AN INTEGRATED FRAMEWORK FOR INTELLIGENT HEALTHCARE DECISION SUPPORT SYSTEM WITH SUSTAINABILITY ASSESSMENT

Submitted by

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This thesis titled, **"AN INTEGRATED FRAMEWORK FOR INTELLIGENT HEALTH-CARE DECISION SUPPORT SYSTEM WITH SUSTAINABILITY ASSESSMENT"**, submitted by Sayma Alam Suha, Roll No.: 1018292005, Session: October 2018, has been accepted as satisfactory in partial fulfillment of the requirement for the degree of MASTER OF SCIENCE in Management of Technology on 19th November, 2022.

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This is to certify that the work presented in this thesis entitled, "AN INTEGRATED FRAMEWORK FOR INTELLIGENT HEALTHCARE DECISION SUPPORT SYSTEM WITH SUSTAINABILITY ASSESSMENT", is the outcome of the research carried out by Sayma Alam Suha under the supervision of Dr. Tahsina Farah Sanam, Assistant Professor, Institute of Appropriate Technology (IAT), Bangladesh University of Engineering and Technology (BUET), Dhaka-1000, Bangladesh.

It is also declared that neither this thesis nor any part thereof has been submitted anywhere else for the award of any degree, diploma, or other qualifications.

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Abstract

Healthcare decision-making is a fundamental and sophisticated field that generally consists of a series of actions taken with the aim of attaining a healthcare service requirement. The decision-making process in this domain can be incredibly challenging due to a variety of aspects such as the diverse branches of the health industry, the presence of multiple stakeholders, the uncertainty of patients' lives, the management of large amounts of health data with complex clinical guidelines, and so on. In such instances, the conventional and mostly manual decision-making process is usually inefficient with slow response in achieving the desired outcome with a proper management of healthcare delivery system. Artificial intelligence (AI) in healthcare decision-making based on clinical knowledge and data are gaining traction as a way to enhance healthcare delivery by making smart decisions. Therefore, the objective of this research is to propose an appropriate and sustainable framework of an intelligent healthcare decision support system (IHDSS) by combining AI-assisted decision-making methodologies with a focus on the most critical aspects of the healthcare sector; which are disease diagnosis & prediction, resource management and treatment management. The study includes three types of AI-based decision-making approaches proposed for the three core stages of the integrated framework where diverse fields of AI have been employed. However, as a test case scenario, the framework has been designed focusing on decision making in healthcare support for burn patients as burns being one of the most prevalent injuries worldwide and leading causes of clinically significant morbidity which can lead to a dramatic physiological reaction with prolonged repercussions, catastrophic organ failure, and death if not properly handled. Thus, for disease diagnosis and prediction phase, the study has proposed a deep convolutional neural network (DCNN) based approach for detecting the severity of burn injury utilizing real-time images of skin burns from victims. At the second phase, the study has proposed a machine learning regression approach to predict the length of stay for patients based on their clinical records with an aim to decision-making in hospital resource management. And, lastly, in the third phase of decision making, the study has proposed a fuzzy logic based model to predict the adequate intravenous fluid resuscitation rate for a burn patient's critical treatment management. Finally, to evaluate the long term sustainability of the proposed system, this research explores the key sustainability indicators for incorporating AI in healthcare decision-making and conducts a systematic assessment to prioritize the indicators based on the perspectives of relevant experts in context of the Bangladeshi health industry.

Chapter 1

Introduction

Decision making is widely regarded as one of the most important aspects of any organizational activity. Indeed, many authors regard decision-making to be the most important function of management, with stakeholders always striving to generate the best decisions and outcomes for their objectives. Making the appropriate decision, on the other hand, is not always an easy task, as it is frequently hampered by personal biases, a lack of information, uncertainty, ambiguity and a variety of other external circumstances [1]. A Healthcare Decision Support System assists healthcare practitioners by systematically analyzing vital health information and making meaningful decisions for quality patient care . In both health policy and medical practice, decision-making is crucial as most of the decisions are made in the presence of uncertainty where the health outcomes are probabilistic. A healthcare decision support system is generally used in a medical environment to assist stakeholders in making decisions and predictions to improve clinical performance and patient care, which can be extremely beneficial by lowering the rate of misdiagnosis, increasing efficiency, improving patient care, and lowering the risk of medication errors. With the expansion of technological involvement, healthcare decision support system now needs to assess a large amount of data in healthcare domain for creating value-based and result-oriented healthcare decisions. It can therefore assist with a variety of healthcare tasks, such as operations, management, and organizational planning as well as it can be used to determine significant trade-offs and ambiguity in the diverse healthcare field. Such kind of healthcare decision support system becomes more significant in least developed or developing countries, where healthcare resources are in limited supply and also their management system is mostly manual.

In a real-world scenario, (a) a patient generally approaches towards a physician for disease detection with a set of symptoms and issues where the doctor would diagnose the issue, provide necessary medications; (b) if required the patient would get hospitalized in the healthcare institutions for critical anomalies; and (c) finally the physicians provide treatment to the admitted patients in the hospitals. Therefore, though clinical and non-clinical healthcare decisions are made in diverse ways, the most critical and essential areas are: disease diagnosis (clinical), treatment management (clinical) and resource management (non-clinical). However, decision-making is very complicated in these areas because of their sensitivity and diversity. But it's very significant towards the stakeholders as physicians must diagnose the disease and make rapid treatment decisions for patients, while hospitals must provide appropriate treatment with limited resources as well as earning maximum profit [2]. Moreover, most patients want their healthcare providers to make an accurate diagnoses with less expenses and effective treatments for all of their health complications. But, a large number of evidence reveals that the traditional healthcare decisions seldom fit patients' expectations, and that medical decisions are placed merely in the hands of physicians. As a result of such conventional decision making system, the patients are rarely consulted about their disease in depth and other alternatives. Also, because of the complexity of healthcare delivery, traditional decision-making processes based on stable and predictable systems are mostly ineffective [3].

In such cases, an evidence-based decision making system that take into account both patient preferences and stakeholder's requirements might help solve this challenge as well as enhance quality of healthcare services with systematic cost-effectiveness. Using Artificial Intelligence(AI) for decision making is one of the most important applications in AI history where the roles of AI have been categorised in numerous ways, with AI systems being used to either support or substitute human decision makers successfully . Numerous applications of AI techniques employing fuzzy inference systems, machine learning, Bayesian networks, deep neural networks, and hybrid intelligent systems have been successfully applied in a variety of healthcare situations and when compared to other sectors, healthcare applications received the most funding in AI research in 2016. Thus, an Intelligent Healthcare Decision Support System (IHDSS) can be an effective technique, allowing the utilization of artificial intelligence to make decisions for a range of healthcare concerns employing relevant health data. But, limited studies have been conducted about the appropriate implementation of such kind of intelligent system. Furthermore, few researchers have merged AI and several computational approaches under one roof for healthcare decision-making, and explored the system's long-term sustainability. For this reason, IHDSS needs more investigation before stakeholders may reap the benefits of such a system practically in healthcare industry.

1.1 Objectives of the Research

The aim of this research is to propose an artificial intelligence-based integrated framework for developing an intelligent healthcare decision support system (IHDSS), focusing on the key areas of healthcare domain including disease diagnosis & prediction, resource management and treatment management; as well as identifying the sustainability indicators to make the proposed system sustainable in context of Bangladesh. Thus, the objectives of this research are as following:

- To propose a framework for intelligent healthcare decision support system (IHDSS) by integrating AI assisted decision-making techniques focusing on the most critical areas of healthcare domain, that will include:
  - Applying computational intelligence for decision making in disease diagnosis and prediction
  - Applying machine learning technique for decision-making in healthcare resource management
  - Applying artificial fuzzy inference system for decision making in treatment management
- Finally, to perform cluster analysis of the major sustainability indicators and conduct a sustainability evaluation for the proposed IHDSS.

1.2 Proposed Framework

Healthcare decision-making is an incredibly challenging field of study because of its complexity, sensitivity, multi-dimensionaity and diversity. Clinical and non-clinical decisions are made in various sectors of healthcare industry, with the most critical areas being disease diagnosis & prediction (clinical), resource management (non-clinical) and treatment management (clinical). Incorporating artificial intelligence (AI) aided decision making solutions in these key sectors of the healthcare industry can result in a much more effective and efficient manner of making vital decisions based on relevant health data. As discussed in [4], sub-fields of AI such as machine learning and fuzzy logic based predictive analysis applied to health data help significantly in determining the interrelationships, as well as meaningful insights for healthcare decision making which is generally difficult to explore manually. Therefore, in this study, an intelligent healthcare decision-making system is proposed, which will use AI-based predictive analytics to make decisions for patient disease diagnosis & prediction using patient data, healthcare resource management using hospital resource data, and treatment management using data from patient's vital sign monitoring; and collectively an integrated solution for decision-making in the healthcare domain will be provided. The suggested integrated framework established in this study is illustrated in Figure 1.1.

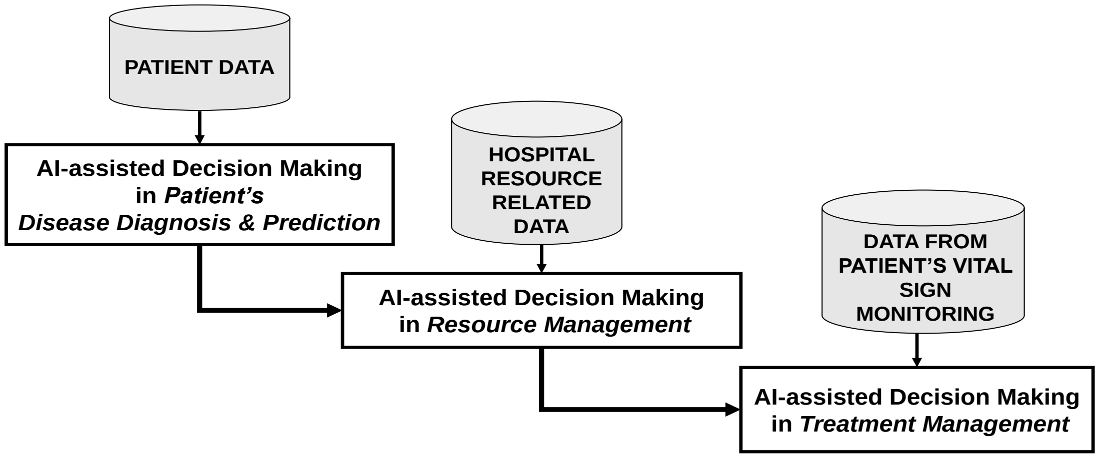


Figure 1.1: Proposed Framework of Intelligent Healthcare Decision Support System

As test case scenario, the study has designed, experimented and validated three AI-based decision providing system emphasizing on burn patients. Here, at first stage (disease diagnosis and prediction) the system would predict the burn severity of victims using real-time image of burnt area; then at second phase (resource management) the system would recommend the duration of days a patient should stay at hospital based on several attributes; and finally at third phase (treatment management) the system would estimate the Intravenous (IV) fluid rate for hospitalized burn patient's fluid resuscitation treatment based on his percentage of total body area burnt (%TBSA) and hourly urine output (HUO). The three types of AI-assisted decision providing systems proposed for three stages of the integrated framework have employed diverse areas of artificial intelligence. For instance, the first phase has employed deep convolutional neural network with transfer learning, the second phase has utilized machine learning regression analysis and finally the third step has used artificial fuzzy inference system for implementation.

1.3 Outline of Experimental Design

The proposed integrated framework of this research mainly consists of three core phases of decision making in healthcare domain followed by a sustainability assessment of the proposed technique. Thus, the outline of the experimental design for different phases of the research has been stated below:

- **Decision making in Disease Prediction & Diagnosis:** In this context as a test case, a Deep Convolutional Neural Network(DCNN) based model has been proposed, trained and tested to detect the burn severity from real-time images of patients as well as make decision in categorizing the burnt area of victims according to their severity into first, second and third degree burns. Section 2.3.1 contains the related works, Section 3.1 demonstrates the methodology and Section 4.1 describes the results and findings in this regard.
- **Decision making in Resource Management:** As a test case, a machine learning regression technique has been developed on hospitalized patients' administrative data in order to anticipate their duration of stay at hospital and thereby provide a smart decision-making system for resource management. Section 2.3.2 contains the related works, Section 3.2 demonstrates the methodology and Section 4.2 describes the results and findings in this regard.
- **Decision making in Treatment Management:** For a test case scenario in this context, a fuzzy neural network model implementing the Mamdani fuzzy inference system has be developed to generate a decision making system for estimating the intravenous fluid resuscitation rate of burnt patients for critical treatment management. Section 2.3.3 contains the related works, Section 3.3 demonstrates the methodology and Section 4.3 describes the results and findings in this regard.
- **Sustainability Assessment:** Finally, expert analysis has been used to conduct a sustainability assessment of the proposed AI-based intelligent healthcare decision support system. Here, the key sustainability indicators of the proposed system has been explored and further considering the significance of the indicators they have been prioritized and grouped in clusters. Chapter 5 of contains the detail demostration regarding the sustainability assessment.

Therefore, the rest of this thesis is organized as follows: Chapter 2 presents the related literature review and background study; the materials and methodology that have been employed in this research are demonstrated in Chapter 3; the result analysis with findings are discussed in Chapter 4; Chapter 5 includes the sustainability assessment of the proposed methodology; and lastly, Chapter 6 contains conclusion that highlights the study's key findings with benefits, limitations, and future goals.

Chapter 2

Literature Review & Background Study

2.1 Decision Making

The act of deciding between two or more courses of action is typically known as decision-making. According to De et al. [5], decision-making is a step in the issue-solving process that involves choosing between different solutions to a problem where decisions can be made intuitively, rationally, or a combination of both. Establishing a choice through acquiring information, and evaluating possible alternatives are generally the steps in the decision-making process. According to Haris et al. [6] the investigation of discovering and selecting alternatives based on the decision maker's values and preferences is known as decision making. The determination of the decision maker(s) and stakeholder(s) in the decision should be the primary step in reducing any disagreements about the problem definition, needs, goals, and criteria. Thus, a general decision making process should have the steps such as: defining the problem, determining the requirements, establishing a goal and identifying alternatives. As organisational decision making are becoming more complicated, the need for information is also becoming increasingly crucial to enable efficient decision-making. On the other side, the growing amount of data available has made it increasingly difficult for humans to organize and comprehend all of it. Technology in such case is playing an increasingly important part in decision-making today, as the sheer volume of data that decision-makers must deal with on a daily basis surpasses what they had to deal with only a few decades ago. Therefore, an effective decision-making system based on the integration of developing technologies has become a critical prerequisite for effective management of decisions in every organization, regardless of sector.

2.1.1 Decision Making in Healthcare Domain

Healthcare decision-making is generally a set of actions that are followed in a certain order with an aim to fulfil a healthcare service requirement . These decisions are made in diverse fields of healthcare domain where the key elements being emphasized are clinical evidences, practitioner's expertise and patients' preference. There can be numerous areas where the healthcare decisions are made, but some of the core areas are healthcare decisions in disease diagnosis or detection, treatment management and resource management which eventually covers so many subareas of the healthcare domain (see Figure 2.1).

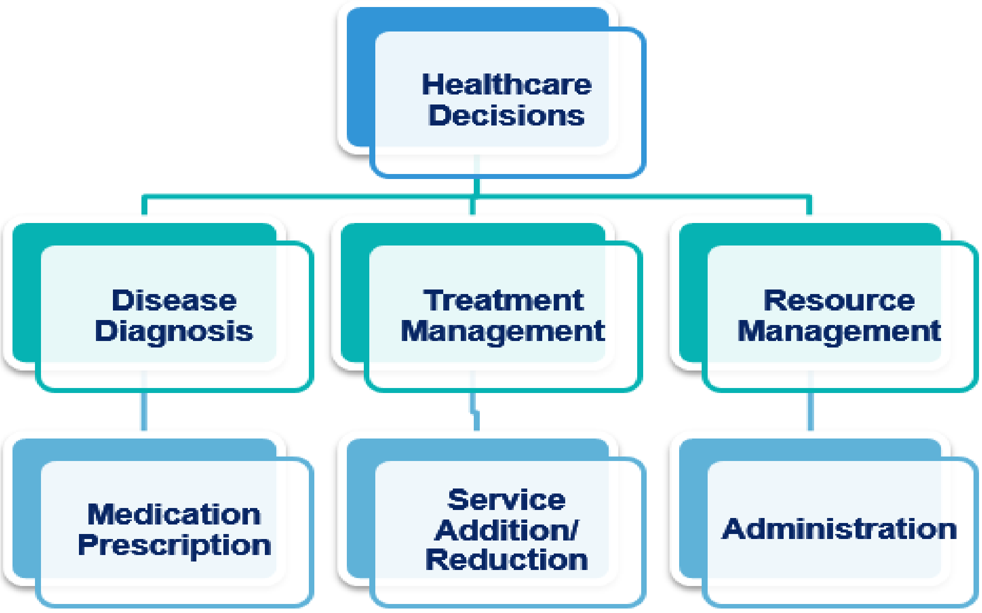


Figure 2.1: Core fields of healthcare decision making

Healthcare decisions have traditionally been determined manually by physicians and the management bodies of the healthcare facilities where the physician's dominance is increasingly being questioned. But, healthcare delivery is changing from care delivered by a single provider and setting to care delivered by numerous providers and locations. These new methods to healthcare delivery introduce significant challenges in terms of how it should be designed, managed and therefore how the critical decisions should be made. For example, managing chronic disease patients in a collaborative way necessitates the incorporation of care delivery processes such as information sharing and decision-making across time and space, as well as among clinicians with varying skill sets and experience. Moreover, technological use in healthcare domain is increasing rapidly day by day. According to the definition of WHO health technology can be defined as the use of organized information and expertise in the form of machines, medications, vaccines, treatments, and services to address a health crisis and increase people's quality of life. Other authors defined health technology to be a broad technology which includes diagnostic, preventive, medicinal, rehabilitative, logistical, data, instructional, and supporting technologies, as well as the medications, equipment, and medical and surgical techniques used in medical treatment, as well as the administrative and supportive mechanisms through which certain health care is delivered to the mass population [7]. Therefore, the decision making in healthcare domain is now strongly associated with various health technologies.

The health system is a broad domain that includes people, organizations, tools, and technology from a variety of disciplines that provide healthcare programs to address the health requirements of a target community with the goal of ensuring patient satisfaction and service quality [8]. Thus, another factor for the complexity of healthcare delivery decision-making is the engagement of a wide range of market forces and stakeholders. Healthcare system is a heavily regulated market having variety of market forces and also governed in a number of ways. For example, there is a lot of concentration on maximizing the financial return in healthcare, rising healthcare costs with higher customer demands are critical source of concern, emerging medical and healthcare research with newer machines and technologies are also needed to be aware of. Additionally there are rules on how they may be marketed and how they can be charged, besides restrictions on the kinds of appliances or medicines that can be placed on the market [9]. For these reasons there is a vast quantities of the stakeholders in the healthcare system that would reflect who are interested or concerned with health services. Health care related business personnel, capitalists/ investors, manufacturers (pharmaceuticals / device companies), healthcare providers, government, insurers, researchers and consumers can be broadly said to be the stakeholders of healthcare system.

Therefore, traditional healthcare decision making approaches are becoming more unmanageable and obsolete as health-care systems become more complex and intertwined with a vast number of stakeholders; necessitating the deployment of newer and more sophisticated health-care delivery decision making models, such as those that put a stronger emphasis on evidence based diagnosis, resource optimization, preventive medicine, primary health care and so on.

2.2 Artificial Intelligence(AI) and its Applications

Artificial Intelligence (AI) is a broad term that refers to the use of a computer to simulate intelligent behavior with little or no human interaction which has the potential to be applied in almost every field of human life. AI can be defined as the ability of a system to accurately interpret external data, learn from it, and apply what it has learned to fulfill specified goals and tasks through flexible adaptation in diverse domain [10]. Economists have defined AI as the purpose of making decisions intelligently that maximize the decision maker's intended outcome with minimal human influence [11]. AI is the oldest and perhaps most broad branch of computer science, encompassing all elements of simulating cognitive capabilities for real-world problem solving and developing systems that learn and think like people. As a result, it is frequently referred to as machine intelligence to distinguish it from human intelligence [12]. Today AI has been utilized in numerous fields of our day to day life, for example : Autonomous planning and scheduling, Speech recognition, Natural Language processing, Robotic vehicles, Logistics planning, Machine Translation etc. are a few instances of AI based systems that exist today. Indeed, as Artificial Intelligence (AI) and other revolutionary technologies advance and become more extensively used, the interplay between organizations, employees, and consumers is fundamentally altering, and the automation of administrative processes and duties is becoming more prevalent [13].

2.3 AI in Healthcare Decision Making

The traditional and manual practice of hospital administration makes effective healthcare decision making exceedingly challenging. With the rapid advancement of AI and other emerging technologies, the utilization of AI applications have increased significantly in the healthcare industry with an aim to provide new opportunities as well as overcome the existing challenges through effective data processing and analysis capability [14]. Through analyzing several real-world examples of AI applications in healthcare, it has been revealed that AI is being optimistically embraced by health facilities in the developed world, who are using AI-enabled systems to augment hospital professionals in patient diagnosis and treatment operations for a wide variety of illnesses as well as maximizing the efficiency of nursing and managerial activities of hospital services [15]. The two primary branches of AI in the healthcare arena are virtual and physical. The virtual branch encompasses informatics approaches ranging from deep learning data management to health management system control, including electronic health records, as well as active physician guidance in treatment decisions. Robotic technologies that aid the elderly patient or the attending surgeon best exemplify the physical branch . Predictive analysis based on AI approaches has recently aroused much attention in the healthcare sector, notably in the decision-making domain, since such methods may consistently aid in managing rapid data expansion and can forecast the future from massive volumes of heterogeneous data [16]. When it is necessary to analyze complex healthcare data in a shorter amount of time with greater precision, or when certain abnormalities cannot be effectively identified by humans, AI-based computational decision making can be very advantageous in revealing hidden interactions or abnormalities that are not noticeable to humans [17]. For example, the researchers in the study [18] proposed an AI-based ensemble architectures to construct deep learning disease quantification model employing computed tomography (CT) scans for decision making in illness quantification, staging, and outcome prediction for COVID-19 patients. Furthermore, numerous researchers across the world have utilized AI-based machine learning strategies to categorize and detect a variety of illness datasets, including diabetes, heart disease, cancer etc. in order to make decision regarding whether or not a patient is infected by the disorder [19, 20]. In the studies [21] various types of AI based regression analysis models have been implemented to make decision about the length of stay or the number of days a patient will stay at hospital for cardiac and critical care patients in ICU which can be very advantageous for resource management in healthcare industry. Therefore, the use of AI in healthcare decision-making is incredibly potential, since it enables precision medicine, illness detection, assisted living for the aged, and managerial support for healthcare institutions, among other things . The following subsections demonstrate some core areas of healthcare domain such as illness detection, resource optimization and treatment management in context of the test cases that has been considered in this research.

2.3.1 Decision Making in Burn Severity Detection

Burn damage is a typical occurrence in which a deep and extensive burn can result in catastrophic consequences such as sepsis from bacterial infection, shock from hypovolemia, massive fluid loss, organ failure, and so on if not treated early [22]. Burn injury can be classified based on its severity, depth of burn and size. Burns that just damage the top layer of the skin called epidermis are classified as superficial or first-degree burns in which the skin turns red and the pain is short-lived; partial or intermediate thickness known as second-degree burns are painful, drier, creates blisters, require dressing with wound care, and may scar, but they do not typically necessitate surgery; and finally a full-thickness or third-degree burns are dry that go through the entire dermis and is usually not painful due to nerve loss, but it does requires fluid resuscitation, protection from infection, and unless the burn is extremely minor surgical care is essential [23]. Figure 2.2 shows the illustration of categorization for burn depth degrees according to its severity . Along with clinical examination, Laser Doppler based techniques such as Laser speckle imaging (LSI) or Laser Speckle Contrast Analysis (LASCA); thermal imaging; Spatial Frequency Domain Imaging (SFDI) etc. are among prominent techniques in medical field for correctly assessing perfusion in burns and burn depth detection. Unfortunately, these procedures need the supervision of qualified specialists, who may not be accessible at the time of the burn injury and thus the burn wound progression may occur rapidly.

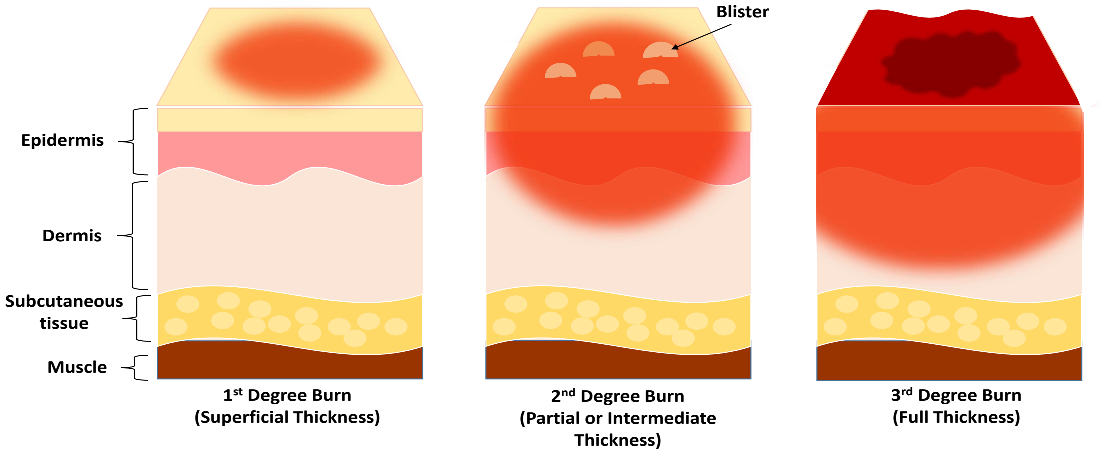


Figure 2.2: Burn Depth Classification

To solve this issue, several researches worldwide have applied various computational techniques to automatically classify the burn images and predict the severity of burn damage from the captured injury images in real-time. In case of image classification based tasks, machine learning approaches are one of the most extensively utilized and promising techniques, which generally analyze and retrieve critical information from enormous quantities of heterogeneous data in order to detect and classify anomalies autonomously . Therefore, employing various machine learning techniques for burn severity assessment is gaining traction nowadays. For example, the study referenced in [24], used 105 burnt photos to develop an automatic segmentation-based classification method to categorize burn images into healthy skin, burned skin, and backgrounds for which they employed four types of clustering approaches for image segmentation and then applied several traditional machine learning classification techniques with an aim to explore the best performing classifier. In the paper [25], an image mining strategy was used to categorize different burn levels of captured burn images into three groups utilizing a comparative evaluation of 20 types of machine learning classification algorithms using both test dataset and 10 fold cross validation approach. In the Study referenced [26], the authors utilized 74 burn images to develop a feature extraction model with several digital image processing steps and then classified the images into two classes using Support Vector Machine classifier. Another related work had been explored in study [27], where a spatial frequency-domain imaging (SFDI) approach was combined with a support vector machine (SVM) machine learning classifier to develop a model that can predict severity of progressive burns in a pig model and to estimate burn severity by measuring the absorbance and scattering characteristics of burn tissue. The work [28] had proposed a method for categorizing burn photos into the second, third, and fourth degrees of severity, in which they used a combination of image processing techniques concentrating on color feature extraction from the images and then SVM classifiers to categorize the images. Another work in [29] suggested a real-time technique for classification of burn depth employing moderate sample sizes based on ultrasound imaging, in which the textural feature set is constructed using a grey-level co-occurrence matrix (GLCM) derived from the ultrasound pictures of the burn tissue; and then utilizing a nonlinear support vector machine and kernel Fisher discriminant analysis, classification is accomplished in porcine skin tissue under four different burn scenarios.

Recently a few studies also applied deep learning technique in this research area for classification and automatic severity detection of burns. For example, the study referenced in [30] proposed a predictive model based on deep neural network, recurrent neural network(RNN) and CNN to determine degree 1, degree 2 and degree 3 of burn images depending on the severity of the burn over a dataset of 104 images. In another study [31], the authors presented a DenseMask Regional convolutional neural network technique, which combined a Mask-region based convolution neural network with dense pose estimation for segmenting the Region of Interest of a skin burn areas from images based on the severity of the burn damage. Another work proposed in the paper [32], applied deep neural network with transfer learning using two pretrained models ResNet50 and VGG16 for the feature extraction from images and then applied SVM classification approach to classify the images into four categories which are healthy skin, first degree, second degree and third-degree burns over 2080 RGB input images. The authors developed a deep learning-based system in work [33], that included precise burn area segmentation and burn depth labeling, as well as proposed a framework for enhanced burn area segmentation and automated burn depth diagnosis based on deep learning methods. Also, the study referenced in [34] suggested an approach for skin burn depth identification in which the pictures are pre-processed using Local Binary Pattern (LBP) operations based on recommendations of a burn specialist, and then an adaptive CNN architecture is used to categorize burn images into four degrees based on their severity.

However, in the earlier studies rarely any researchers have focused on the efficacy of employing CNN architecture with deep neural network over the traditional method of image classification with feature extraction via image processing techniques and conventional machine learning classifiers. Also, the utilization of transfer learning method through various pre-trained models with fine tuning have been explored little. Therefore, this study proposes a CNN architecture that integrates several state-of-art techniques such as transfer learning with fine tuning to effectively classify the burn images according to their severity; and also it conducts the classification analysis through traditional approaches to have a comparative study with the proposed method.

2.3.2 Decision Making in Hospital Patients' Duration of Stay Prediction

Conventional practice of hospital administration makes appropriate management of resources and patients' hospital stay extremely difficult. Thus, many scholars across the world are applying several computational techniques to resolve this issue. For instance, Xin et. al. [35] proposed a model that combined just-in-time learning (JITL) and one-class extreme machine learning for determining the patients' discharge time. Using UK national and hospital-level data, Vekaria et al. [36] demonstrated the utility of three complimentary approaches for predicting length of stay for patients with COVID-19.

Recently, the predictive analysis based on machine learning approaches have gained much interest as such kind of methods can consistently assist in management of the rapid data expansion in the health sector [37]. Machine learning techniques are now considered to be one of the intelligent and efficient predictive analysis approaches in the healthcare sector examining the current and historical facts from huge amounts of heterogeneous data to predict the future. Certain researchers especially focused on applying different machine learning approaches to develop an effective technique to forecast the length of stay (LOS) for patients in the hospital. The studies so far have predicted the LOS using machine learning in two ways: a classification outcome in which the LOS predictions are separated into distinct groups and a regression outcome in which the LOS forecast represents the actual number of days a patient will spend in the hospital. Table **??** summarizes several related studies that have used machine learning techniques to predict LOS. .

Some of the common predictive models used in previous researches are : Decision Tree, Random Forest, Support Vector machine(SVM), Gradient Boosting, Artificial

Table 2.1: Summary of Related Works for Predicting Hospital Patient's LOS using Machine Learning Techniques

Reference	Data Source	Size (no. of records)	Predicting group of patients	Used ML models
Colella et. al. [38]	San Giovanni di Dio e Ruggi University Hospital; Orthopedic and Traumatology dept.	123	Inpatients with lower limb fractures	Decision Tree; Random Forest; SVM; Gradient Boosted Trees;
Alsinglawi et. al. [21]	MIMIC-III dataset developed by the MIT Lab for Computational Physiology.	61,532	Cardiovascular patients in the Intensive Care Unit	Random Forest Regressor; Gradient Boosting Regressor; Stacking Regressor; Deep Neural Network
Mekhaldi et. al. [39]	Microsoft dataset developed for predicting LOS	100000	General patients	Random Forest Regressor; Gradient Boosting Regressor;
Kirchebner et. al. [40]	Swiss forensic institution data	143	Schizophrenic offenders	Boosted Tree; K Nearest Neighbour; SVM
Daghistani et. al. [41]	King Abdulaziz Cardiac Center, Riyadh, Saudi Arabia	16,917	Cardiac patients	Random Forest Classifier; Artificial Neural Network; SVM; Bayesian Network Classifier
Turgeman et. al. [42]	Veterans Health Administration (VHA) data,Pittsburgh, Pennsylvania	20,321	Congestive heart failure (CHF) patients	Cubist tree model
Tanuja et. al. [43]	Super specialty hospital (Location– Not specified)	401	General patients	Multi-layer back-propagation; Naive Bayes;K-NN; decision tree classifiers (by Weka ML environment)

Neural Network (ANN) etc. Here, Decision Tree(DT) is a machine learning structure that resembles like a tree, with leaves representing outcome labels and branches representing input feature combinations that led to those outcomes as predictions; on the other hand, Random Frorest is an ensemble approach that uses bootstrap aggregation to create numerous DTs for prediction [44]. Leo Breiman introduced the Random Forest (RF) model in 2001, which is an adaptive combination of tree prediction algorithms based on statistical learning theory in which the original data is resampled to acquire additional samples, typically using the bootstrap strategy [45]. SVM model is another type of nonlinear machine learning approach that is based on statistical learning theory with a high generalization capacity which can increase learning adaptability by minimizing structural risk [46]. Gradient boosting is also a type of ensemble learning process that combines the outcomes of numerous simple or weak predictors to create a powerful committee with better performance than individual members [47]. The ANN prediction model is a distributed massively parallel processor made up of basic processing units with typically three layers of input, output, and hidden layers to predict the result [48] [49]. There are several varieties of ANN models, among which multilayer perceptron (MLP) model is a feedforward artificial neural network performing fast prediction [50] and the Deep Neural Network (DNN) model is a type of ANN with a higher level of complexity, in which deep nets analyze input in sophisticated ways to make predictions using advanced math modeling [51]. Other than these there are also some predictive models like Linear regressor [52], Linear Lasso regressor [53], Bayesian Ridge regressor [54], Adaptive Boosting regressor [55] etc. which are also employed by researchers for various regression issue predictions.

Analyzing the previous studies, it is evident that, the maximum studies (Colella et al. [38], Kirchebner et al. [40], Gentimis et al. [56] Daghistani et al. [41], Tanuja et al. [43]) treated LOS prediction as a classification problem; estimating a short, medium, or long stay in the hospital but not the exact number of days a patient will spend there. Moreover, the regression analysis studies on this topic also contain number of flaws. For example, the majority of them predicted LOS for a specific medical specialty group of patients, for example, Alsinglawi et al. [21], Turgeman et al. [42] predicted LOS for cardiac patients and so the findings are rarely applicable to general hospital patients with various types of anomalies. Again, while Mekhaldi et al. [39] did regression analysis, they acknowledged the unavailability of a real dataset as a constraint and so they performed the prediction using Microsoft dataset. In addition, the investigations used regression analysis to compare the results of a few different models with limited variety. Furthermore, the previous studies lack potential external validation from healthcare professionals, and as a result, they are rarely implemented and used in actual healthcare institutions [57]. Moreover, in the healthcare industry, data volume with variety is also a major concern where preprocessing the dataset carefully is very important to get efficient performance.m

However, the sort of LOS prediction used in this research is a regression scenario in which the number of days a patient will remain at hospital will be forecasted utilizing Random Forest(RF) Regression model. Random Forest regression model is considered to be one of the robust, significantly faster and better prediction methods to solve regression problems . Leo Breiman introduced the RF model in 2001, which is an ensemble method with adaptive combination of tree prediction algorithms, typically using the bootstrap strategy [45]. Numerous scholars worldwide have implemented this model for regression problem predictions. For example , Liu et al. [58] proposed a regional flood disaster resilience evaluation model based on RF regression model; Singh et al. [59] investigated the water quality and predicted infiltration rate using RF regression model.

Therefore, in this study the proposed methodology utilized RF regression model incorporating different data analytical techniques for forecasting the LOS of general patients with various anomalies. And further a comparative performance analysis is conducted using other types of regression models in several contexts to justify the efficiency of suggested approach.

2.3.3 Decision Making in Burn Patients' Treatment Management for Fluid Resuscitation

For the critically ill patients, intravenous fluid resuscitation treatment to maintain or increase intravascular fluid volume is a routine procedure where the survival of the patients depends highly on the proper maintenance of the fluid rate. This treatment can be utilized in a variety of situations, such as when a patient has severe sepsis or shock with acute dehydration, then the fluid rate in the body needs to be stabilized with fluid resuscitation. Another common application of fluid resuscitation therapy is in the treatment of shock produced by burn injuries. In 1921, burn fluid resuscitation treatment originated with the use of fluids and electrolytes to prevent burn causalities. Burn shock is generally caused by the loss of circulating plasma and red cell components into the burn zone, and thus the treatment and prevention of burn shock include restoring the lost fluid in sufficient quantities to guarantee normal blood flow to the brain, liver, and kidneys . It is evident that with balanced intravenous fluid resuscitation treatment, physicians can successfully resuscitate patients from the shock that occurs with severe burns . But fluid overload or under-load with imbalanced replacement of intravenous fluid can arise multiple dysfunction of organs like cerebral edema, hepatic congestion etc.. And so to decrease the possibility of damage associated with this potentially life-saving treatment, the rate of intravenous fluids must be maintained correctly following a standard guideline [60]. For determining the rate of intravenous fluid, there are various formula or standards suggested by researchers and physicians. One of the widely practiced standard is called Parkland Formula by Dr. Charles Baxter where he has described that the significant number of burn patients will be sufficiently resuscitated if they gain 3.7 to 4.3 ml of Ringer's lactate per kilogram of body weight per %TBSA in the first 24 hours following an acute burn injury [61, 62]. However, the American Burn Association and burn protocol provided by University of Texas recommend calculating the intravenous fluid rate employing 2 to 4 ml per kilogram of the patient's %TBSA as well as taking into account the patient's urine output per hour [63].

Therefore, burn size estimation with %TBSA is a vital part of critical burn management in clinical procedures for directing the amount of fluid resuscitation required for burn patients. For providing burn treatment, the primary task that is generally done by the physicians is to estimate the percentage of total body surface area burned or %TBSA using various clinical techniques to get a rough burn size estimation [64]. According to statistical research, a burn patient's possibility of organ failure increases and survival chances declines as the %TBSA gets higher [65]. The measurement %TBSA, is thus an important part of the treatment, since it informs clinicians about both immediate clinical management and the requirement for fluid resuscitation of the burnt patient. On the other hand, hourly Urine output (HUO) is another routinely monitored parameter for acute burn patients as it plays an irreplaceable role in predicting illness severity, dehydration level and therefore lowering patient's death rates . As one of the goal of fluid resuscitation is to protect the patient from dehydration by maintaining the core organs functioning with adequate fluid, the HUO must be regularly monitored and reported to guide the intravenous fluid resuscitation rate of patients . However, urine output measurements alone do not adequately reflect all of the particular requirements of burn patients; instead, it must be integrated with other shock indicators such as %TBSA to guarantee appropriate fluid replacement [66].

Since most burn treatment management is performed manually, recent studies have focused on improving currently available practices to avoid over or under resuscitation problems, which includes developing innovative resuscitation methods involving computational intelligence for faster decision making. For example, Salinas et. al [67] applied decision-assistance guidelines with a closed-loop system employing computer-controlled feedback technology that provides automated infusion rate management for fluid resuscitation of burn patients to achieve precise titration rates and improved Urinary output regulation. Later Salinas et. al [68] also conducted an original study with computerized decision support system applying the burn protocol algorithm over 32 patients having more than 20% total body surface area burns, where the experiment result showed that the use of a computer-aided decision support system for burn resuscitation in the critical care unit, resulted in better fluid management for burnt patients with better hourly urine output goals. Further Chen et. al [69] proposed a clinical decision support system (CDSS) which can can offer suggestions for the volume of fluid to be injected using information systems and decision support technologies where also the findings revealed that, patients treated with the system had considerably decreased fatality, higher ventilator-free times, and ICU-free days than those treated with conventional fluid resuscitation.

However, the implementation of fuzzy logic in various arena of healthcare sector has gained much popularity in recent days by providing an automated system with efficient and quality service to the patients intelligently in a shortest possible time [70]. Such as, Wang et al. [71] analyzed the limits imposed by hotels for COVID-19 vaccination regulations and proposed a fuzzy multi-criteria based decision-making strategy to assist travelers in selecting appropriate hotel accommodations in post pandemic situation. Shalini et al. [72] suggested a fuzzy logic-based model for correctly and efficiently predicting the presence of glaucoma in eyes from the retinal fundus, as well as assessed its risk level. Arji et al. [73] demonstrated in their review study that various fuzzy logic methods have been employed vastly in over 40 studies to diagnose infectious disorders such as dengue fever, hepatitis, and tuberculosis etc. But, utilizing artificial intelligence and fuzzy logic to estimate burn fluid resuscitation rate is a relatively young concept, with few researchers working on it. Previously, Bates et.al [74] applied fuzzy logic for medical decision making in Intensive Care Unit for fluid resuscitation where they proposed a model to take mean arterial blood pressure and hourly urine output as input and predict the intravenous fluid rate as output of the fuzzy model. But, hardly any research work has been conducted considering the two widely practiced parameters %TBSA and urine output as the indicators of predicting intravenous fluid rate of burn patients intelligently with fuzzy logic methods for clinical decision making. Therefore, in this study these two parameters have been used as the input of the fuzzy logic system which incorporates medical guidelines along with intelligent inference engine to predict the intravenous fluid rate for burn patients.

2.4 Sustainability in Healthcare

Sustainability typically concentrates on fulfilling current demands of the population from a certain industry basing on three aspects: economic, social and environmental; without jeopardizing future generations' capacity to meet their requirements. With the progress of science and technology a slew of newer and advanced technologies emerge every day but only a handful of them are actually able to acquire public recognition, resulting in a long-term financial and environmental stability [75]. As a result, scholars all around the world have emphasized on systematic assessment of emerging technology's long-term sustainability in the relevant industry.

Healthcare sustainability investigates a variety of dimensions for ensuring the long-term viability associated with different healthcare activities; for which several researchers throughout the world have focused on exploring various scopes of healthcare sustainability. For example, the work in [76] explored the social aspects of healthcare sustainability and the momentum toward integrating social practices in the healthcare supply chain as well as identifying the motivating factors of social sustainability in a healthcare supply chain with a focus on four stakeholder groups. Since assessing the sustainability aspects of healthcare system is a challenging and unstructured task, the researchers in [77] proposed a comprehensive and hierarchical framework based on the analytical hierarchical process (AHP) for measuring the sustainability factors in complicated, multi-criteria issues of healthcare systems comprising of multiple stakeholders and decision-making concerns. Moreover, the healthcare industry is considered to be a significant producer of pollutants that may have a negative impact on the environment, therefore the work in [78] proposed an environmentally sustainable healthcare emission research framework based on the present level of healthcare sustainability science and expert opinion, with the goal of improving the healthcare industry's environmental sustainability.The study in [79] utilized an interpretive structural modeling (ISM) technique for determining the triggering factors as well as the interrelationships between the factors to enhance environmental sustainability and hazardous material management while maximizing resource utilization in the healthcare industry's dispensaries sector. Another research in [80] looked into the sustainability of healthcare waste management technologies with the goal of dealing with clinical waste in municipal areas. Thus, analyzing the sustainability of the healthcare industry tends to be an emerging area of research due to its vast, complex and multi-dimensional attributes. .

However, analyzing the related works so far, it appears ,

2.5 Research Gaps

However, analyzing the related works so far, some of the core research gaps have been noticed which are stated below:

- Firstly, the Existing Healthcare Decision models proposed by various researchers are mostly based on manual decision making process, survey results and statistical analysis.
- Although data mining, image processing, AI and other technologies have all been utilized in diverse healthcare applications separately, few researchers has brought them all together under the banner of Healthcare decision making.
- Though AI has been extensively used in diverse areas of healthcare industry, hardly any studies have been conducted to analyze the sustainability factors of applying computational intelligence in the field of healthcare decision making
- Also, researchers have rarely investigated the role of AI in healthcare decision-making in the context of Bangladeshi or other developing nation's healthcare system.

Therefore, this research concentrates on exploring these underlying research gaps as well as ensuring the sustainability of AI based applications in the healthcare decision making field.

Chapter 3

Research Methodology

3.1 Methodology for Decision Making in Disease Detection

Decision making in patient's disease detection or prediction is the initial stage of the proposed framework where AI has been incorporated to make an intelligent decision regarding the patient's disease detection. Among numerous anomalies, burns are one of the leading causes of clinically significant morbidity which can lead to a dramatic physiological reaction with prolonged repercussions, metabolic disturbance, severe scarring, catastrophic organ failure, and death if not properly treated. Therefore, for decision making in disease detection, the test case that has been considered in this study is detecting the burn severity of patients from the victim's image of burnt area. Appropriate burn treatment management is associated with the proper detection of severity of burn wounds which can be extremely challenging to anticipate at an early stage due to various factors using traditional clinical methods. Therefore, this study proposes a Deep Convolutional Neural Network(DCNN) based approach for detecting the severity of burn injury utilizing real-time images of skin burns. The DCNN architecture leverage the utilization of transfer learning with fine tuning employing three types of pretrained models on top of multiple convolutional layers with hyperparameter tuning for feature extraction from the images and then a fully connected feed forward neural network to classify the images into three categories according to their burn severity : first, second and third degree burns. In order to validate the efficacy of the suggested strategy, the study also applies a traditional solution to mitigate this multi-class categorization problem, incorporating rigorous digital image processing steps with several conventional machine learning classifiers and then conducts a comparative performance assessment. The study's findings demonstrate that using pretrained models, the recommended DCNN model has gained significantly greater accuracy, with the highest accuracy being obtained using the VGG16 pretrained model for transfer learning with an accuracy of 95.63% . Thus, through the use of intelligent technologies, the proposed DCNN-based technique can aid healthcare practitioners in evaluating the burn damage condition and providing appropriate treatments in the shortest feasible time, remarkably reducing the unfavorable consequences of burns.

3.1.1 A Deep CNN-Based Approach for Decision Making in Burn Severity Detection from Skin Burn Images

Burns tend to be one of the most prevalent injuries in the world, with consequences that can be deadly or cause a victim to suffer extremely if not treated appropriately. Catastrophic burn injuries are extremely distressing and physically devastating traumas that impact approximately every major organs. According to a report of World Health Organization (WHO), burn injuries cause 180,000 fatalities on average per year, while approximately 11 million people were severely burnt and required medical treatment in the year 2004 [81]. Radiation, electricity, heat, excessive cold, chemical elements etc. can cause burn injuries, where treatments must be ensured carefully according to its severity. With early and adequate treatment, the survival rates of burn victims can be considerably enhanced. Early burn wound excision, skin grafting, skin substitutes are typical treatment techniques that can enhance the prognosis of severe burn patients by lowering fatality rates and minimizing hospital stay days; whereas without correct treatment at the right time poor wound healing, infection, discomfort, hypertrophic scarring, organ failure, and even death can ensue. [82].

The severity of a burn can be determined depending on the layers of tissues damaged in the human body, with vascular, epidermal, dermal, and muscles among the different tissues typically vulnerable to burn wound . The burn injury is usually classified into one of three categories by the healthcare professional: superficial (first degree burns), superficial-partial or deep-partial burns (second degree burns), and full thickness burns (third degree burns), with each category having different healing times and characteristics [83]. Burn wounds are dynamic and can develop as well as convert to deeper wounds, making an accurate estimate of their depth and severity extremely challenging at an early stage . Sufficient functional and structural investigations are necessary for precise burn intensity diagnosis. To measure the burn severity, modern techniques such as laser Doppler imaging or medical evaluation under the supervision of experienced healthcare practitioners are necessary in traditional clinical practice, but these procedures are constrained by factors such as availability of the devices, distance, time, expense etc. . Because of these obstacles, the burn victims' treatment process may be delayed, resulting in a severe health deterioration. Furthermore, standard manual methods for estimating burn severity, such as visual inspection and physical assessment, not only cause delays, but have also been proven to provide estimations that are only 50-70% correct during the early days after a burn [84]. Early detection of burn depth severity becomes more challenging in remote areas of least developed and developing countries, where healthcare resources and facilities are scarce.

Therefore, the purpose of this study is to develop an autonomous model that can detect burn severity from real-time photographs of the skin burn area and categorize it as first, second, or third degree burns. To attain this objective, a Deep Convolutional Neural Network based machine learning classification model has been designed, trained, and tested using 1530 images of skin burns which intends to use burn photos for detecting and categorizing patients' burn severity. The significant contributions to achieve the goal of this study are listed below.

- A Deep Convolutional Neural Network(DCNN) based approach has been proposed where a Convolutional Neural Network incorporating diferent state-of-the-art techniques like transfer learning with pre-trained models and fine tuning on top of multiple convolutional layers with hyperparameter tuning have been employed for feature extraction from victims' real-time burn photos; and then a fully connected Artificial Neural Network has been used to classify them according to their severity into first, second and third degree burns.

- The classification of the burn images according to their severity have also been conducted through another approach employing traditional machine learning technique where the feature extraction have been conducted meticulously through several image processing stages and then the classification has been conducted using six types of conventional machine learning classifiers.

- To validate the efficacy and potency of the proposed DCNN technique, a comparative analysis have been conducted between the traditional approach and suggested method. Also, three kinds of pre-trained models have been employed and tested in the CNN architecture with an aim to explore the best performing model in this scenario.

3.1.2 Methodology

In this research, a Deep Convolutional Neural Network(CNN) based machine learning classification technique has been proposed, trained and tested that aims to differentiate between the skin burn depth degree of patients utilizing the burn images. Here, the burnt photographs of the victims, captured using a digital camera or a mobile phone camera, have been used as the study's input, with the system predicting the degree of the skin burn. Along with the proposed CNN technique the traditional image classification approach incorporating digital image processing and conventional machine learning classifiers have also been explored in this study for skin burn depth detection in order to assess a comparative performance and efficacy analysis of the suggested technique. The framework of the research methodology followed in this study has been illustrated in Figure 5.1. The stages involved are briefly discussed in the following sections.

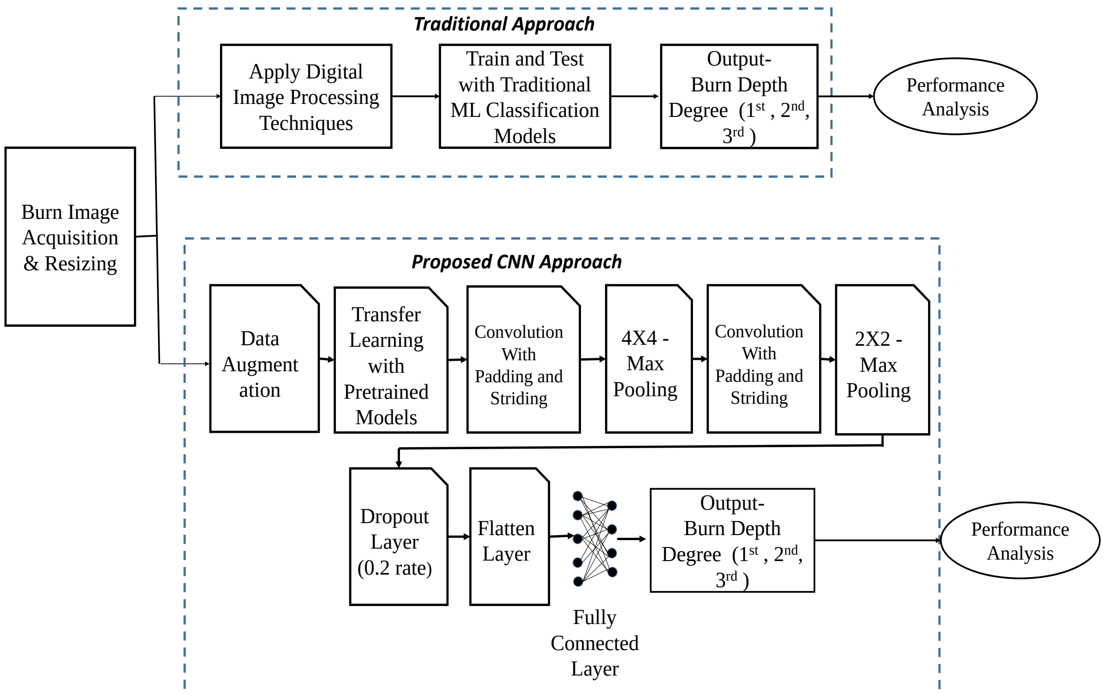


Figure 3.1: Framework of research methodology for decision making in burn severity detection

3.1.2.1 Data Acquisition

The images utilized in this study are digital color images of skin burns captured with camera. There are total 1530 images of skin burns from which 1440 images have been obtained from a publicly available repository of Kaggle [85] and the rest of the images have been collected from the burn units of three hospitals of Bangladesh maintaining their patient privacy concerns. According to their severity, the images are labelled as first degree, second degree, or third degree burns under the supervision of four healthcare practitioner with two burn specialist doctors, where first degree burn photographs depicting less damage and third degree burn being severely damaged. After categorizing them, it has been observed that the dataset contains 670 images of first degree, 347 images of second degree and 513 images of third degree burns. Here, as the digital input images are all RGB coloured images, the number of chanenels for each picture is 3. The pictures' formats and sizes vary since they were retrieved from various sources, rendering them inappropriate for using in predictive analytics. To resolve this issue all the images have been resized to the shape $(224x224x3)$ that contains information about the row, column, and channel of the image and then stored them in a 3D multichannel array. The labelling information for each image has also been stored in another one dimensional array which will be used as the target attribute for the machine learning phase. The examples of one image from each category of input images are shown in figure 3.2.

Figure 3.2: Example of first, second and third degree burnt input images

3.1.2.2 Applying Machine Learning Techniques

In this research, two types of machine learning techniques have been employed to classify the burnt images of patients, where the first one is with several conventional machine learning classifiers and the second one is with the proposed CNN architechture incorporating several state-of-art techniques like transfer learning, fine tuning etc. The Google Colaboratory has been utilized here as the platform for execution, with the scikit-learn and TensorFlow packages from Python. The two approaches are described hereafter.

3.1.2.3 Traditional Approach

Training with a large number of high-resolution images necessitates the processing of large volumes of data, which is troublesome for most traditional machine learning models [86]. For this reason, it is required to perform the appropriate digital image processing steps to extract and highlight the key information from the images before utilizing them in the conventional machine learning classifiers. Thus, in this approach the images are initially pre-processed with digital image processing steps; then splitted into train and test data; and finally employed in the traditional machine learning classifiers.

- **Digital Image Processing Steps:** After the image acquisition and resizing, the first step of digital image processing that has been applied here is the Image Enhancement. This is achieved here via the histogram equalization approach, which enhances the visual perception of information in photographs by giving a more evenly dispersed histogram, resulting in a sharper and clearer image for viewers. As histogram equalization operation cannot be done in colored RGB image space, thus the images are converted to Hue Saturation Value (HSV) format, apply histogram equalization in that HSV imgae and then again converted back to RGB format which will resulted into an enhanced image. The next stage is Noise Removal for which as an image restoration phase of noise reduction, a median filter approach is used; which is a commonly used nonlinear filter with superior edge maintaining capabilities and the potential to minimize impulsive noise. Following that, the required amount of Morphological Erosion and Morphological Dilation operations have been performed where erosion reduces and dilation enhances the pixel numbers on the edges of objects in the images. The final image processing step applied here is Image Segmentation to divide the images into different significant areas. For this, here k-means unsupervised clustering algorithm has been applied that segments the interest area of burn from the background and thus separates the affected area from the healthy skin.

- **Split into Train and Test Data:** After the specified image processing stages are completed, the set of processed pictures are turned into a single dimension array by using OpenCV python function 'FLATTEN'. Each column in this array represents an attribute that contains the image's pixel values. This array with the pixel values has been used as the training's input features, with the one-dimensional array containing the labeling information for each image functioning as the target attribute. Finally, to use this processed dataset in the machine learning classification models, the dataset is divided into 70% train data and 30% test data.

- **Training with Traditional Machine Learning Classifiers:** This study's predictive analysis is a multiclass classification problem where the images can be classified into three classes. Therefore, six different types of conventional classifiers have been employed here with an aim to classify the images into first, second or third degree burn. The classification models are: Logistic Regression classifier, K-Nearest Neighbour(KNN) classifier, Support Vector Machine(SVM) classifier, Decision Tree classifier, Random Forest classifier and Multi-layer Perceptron classifier.

Therefore, in the traditional machine learning approach these above mentioned steps are followed in order to classify the images according to their burn depth severity.

3.1.2.4 Proposed CNN Approach

Convolutional Neural Networks (CNN) are indeed a type of deep neural network with multiple consecutive layers that have shown to perform efficiently in a range of image processing, classification, and segmentation tasks . The advantage of employing CNN is that, it can successfully tackle picture classification problems with higher accuracy since it matches the data point distribution in the picture throughout the neural network training process and can directly utilize the feature maps from the convolutional layers. As a consequence, substantial features from the images can be extracted autonomously without the need for explicit image processing operations [87].

In this research, a CNN architecture with different layers was rigorously built with the goal of classifying burn images. After data acquisition from the repository, the dataset is agian divided into 70% train and 30% test data in this approach; and then the CNN model is built to use this dataset for training. Sequential is the model type that has been employed here to construct the CNN architecture layer by layer with the help of add() function for adding each layer. The layers of the CNN architecture are discussed hereafter.

- **Data Augmentation:** Data augmentation, which comprises generating slightly modified duplicates of images from the original training samples, is an effective strategy for improving performance and minimizing forecast error . In this study, three types of basic image manipulations have been applied to each images to formulate four additional training samples with image augmentation process which includes geometric transformations (random flipping, rotating and shifting);contrast enhancement and sharpening with noise removal.

- **Transfer Learning with Pretrained models** The architecture's first layer after data augmentation is based on transfer learning with fine tuning, a powerful machine learning strategy that aims to improve target learners' performance on intended domains by transferring information from the relevant pre-trained models and then making small adjustment to get the prediction . Here, the pre-trained model's fully connected or dense layer from the source task has been removed using $include\ top = False$ operation and retrained them for the target task using some more convolution and dense layers with hyper-parameter tuning. The basic framework followed for transfer learning has been illustrated in 3.3. In this study, three different types of pre-trained models have been trained, and tested in the transfer learning layer to evaluate which model provides better performance for classification. The models are: VGGNet16 model with 16 layers that has provided best accuracy of 90.1% with Imagenet dataset; MobileNet model with 28 layers that has provided best accuracy of 89.5% with Imagenet dataset; and ResNet50 model with 50 layers that has provided best accuracy of 94.5% with Imagenet dataset.

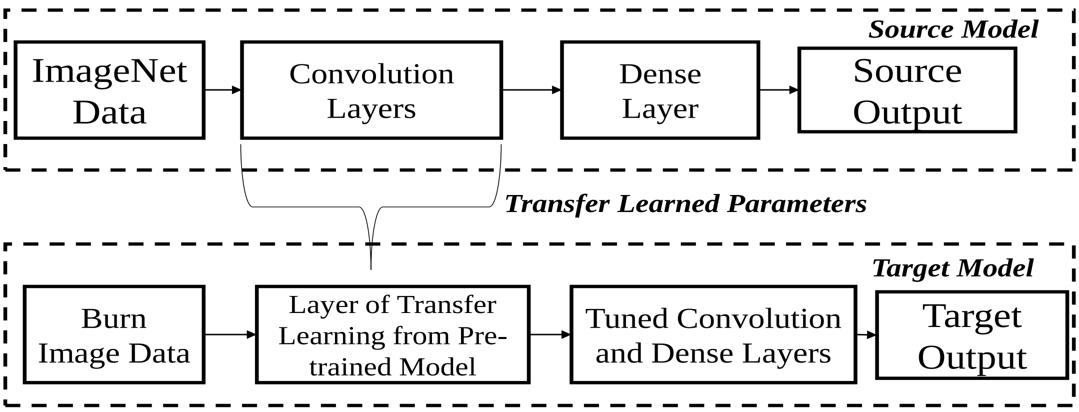


Figure 3.3: Basic framework of transfer learning method

- **Convolution Layer with padding and striding** CNN's essential and fundamental component layer is the next layer which is called Convolution layer that consists of a series of kernels or filters that are mostly smaller in size than the original training picture and whose parameters must be trained throughout time of learning and convolve with the real image . In this study after the transfer learning layer with pre-trained model, the 2 dimensional convolution layer (Conv2D) opearation has been performed two times where the first layer contained 128 nodes and second one 64 nodes. In both cases, the kernel or filter size for convolution has been considered to be $3X3$. Moreover, padding and striding techniques have been used here in the convolution layer to enhance the accuracy of the output; where padding adds one additional layer to the outer image and striding manages the space between two consecutive kernel locations. The value of padding in this CNN architecture is same which indicates padding the input image with zeros evenly to the outer side. The value of stride is 1, which signifies the output size after convolution operation with the filter will be the same as the input size. Then, an activation function is employed in this deep neural network to feed a weighted sum of input signals through and with the result being uutilized as an input to the next layer. In this CNN model, Softmax activation function has been employed which tends to produce useful outcomes that can be applied to multiclass classification problems and provides an output between 0 to 1 range representing the probability classification outcome [88]. The mathematical representation of the softmax activation function has been shown in equation (1).

$$Softmax\ Activation, S(a_i) = \frac{exp(a_i)}{\sum_{j=1}^{n} exp(a_j)} \tag{3.1}$$

- **Pooling Layer:** The Pooling Layer is the following layer in this study's CNN design, which declines the spatial size of the picture while retaining crucial data to progressively reduce the computations and spatial size in the complex and large neural network. [89]. Here, a "Max Pooling" technique has been used to obtain the maximum value for each patch of the feature map. The pooling layer has been employed two times after each of the convolution layers with the first max-pool layer having a pooling window size of $4x4$ and the second max-pool layer having a pooling window size of $2x2$.

- **Dropout Layer:** The Dropout Layer is the next layer, which is a regularization method that significantly reduces overfitting and speed up the learning process by changing input data to 0 for ignoring some nodes at a predetermined frequency rate at each step during the training process. [90]. To conduct the regularization, the dropout rate in this CNN model has been set to 0.2 in the dropout layer.

- **Flatten Layer:** The "Flatten layer" is the next layer, which converts the multi-dimensional outputs of the preceding layer into a one dimensional array to be used in the next classification layer. The input layer of the classifying neural network is built using this one-dimensional array, with the components of the array being provided to each neuron. Therefore, this layer works as the bridge between the convolution and dense layer. The most significant features from the images are also extracted in this layer as a result of the previous layers.

- **Fully Connexted Layer:** The "Fully Connected Layer" also known as "Dense

Layer" is the classifier and final layer of this CNN architecture. This layer is at the bottom of the CNN model, and every neuron inside it is connected to every neurons in the previous and forward layers, adopting the standard multiple-layer perceptron and feed forward neural network technique [91]. As the classification problem here has three classes, the last layer of this dense network will contain three nodes to provide the classification prediction, one for each possible outcome. Here also softmax activation function has been utilized to generate the result from the output neurons possessing the highest possibility.

- **Compiling Model:** Finally, the CNN model has been compiled using three parameters: optimizer, metrics and loss. The optimizer utilized here is the stochastic gradient descent (SGD) optimizer, which is used to regulate the learning rate. Here the learning rate is 0.01. Accuracy has been used as the metrics of the model for assessing the performance of the training. And lastly, for evaluating the loss $categorical\_crossentropy$ function is used as the problem here is a multi-class classification problem. The lower value of loss indicates better performance.

To explore the best performing classification model, the CNN architecture formulated in the above mentioned way is trained with the dataset in four different methods and hyper-parameter optimization : i) without employing transfer learning layer; ii) incorporating VGG16 pre-trained model for transfer learning layer; iii) incorporating MobileNet pre-trained model for transfer learning layer; and iv) incorporating ResNet50 pre-trained model for transfer learning layer. For each type the training has been conducted in 10 epochs and then the models have been evaluated with test dataset.

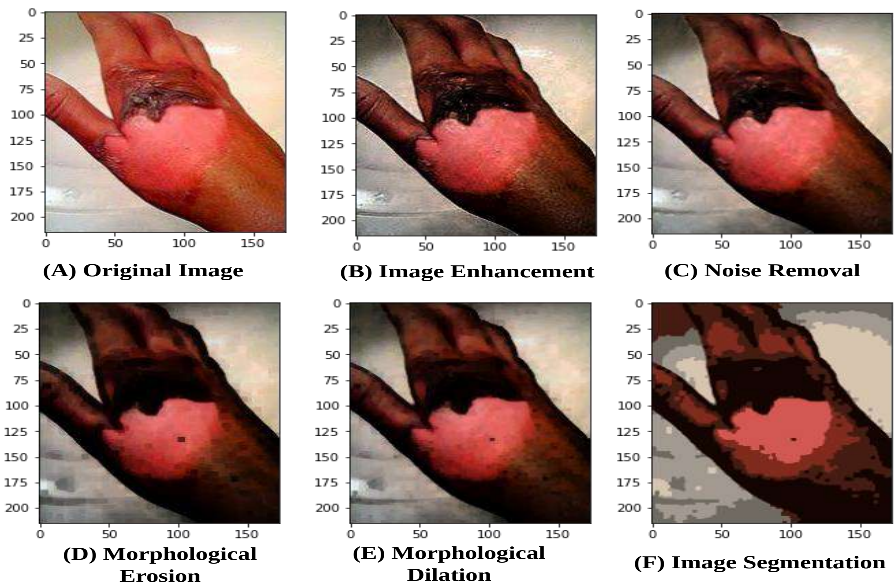


Figure 3.4: Findings from Image Processing Stages

3.1.2.5 Performance Analysis

To evaluate the efficacy of the predictive analysis, the performances of both types of machine learning approaches are assessed using four performance metrics which are the Accuracy, Precision, Sensitivity (recall) and F1 score. The performance indicators are mostly based on a comparison of forecasted and real values from the training dataset, which is separated into four groups: True Positive (TP) that refers to a situation in which both the true and predicted values are positive; True Negative(TN) in which the original value is negative and also the anticipated value is negative.; False Positive(FP) a scenario in which the real value is negative but the anticipated result from the training is positive and finally the actual value is positive, but the forecasted result is negative, leading in a False Negative(FN). The performance metrics can be expressed as following equations (2),(3),(4) and (5) based on these assessments:

$$Accuracy = \frac{TP\ +\ TN}{TP + TN + FP + FN} \tag{3.2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3.3}$$

$$Sensitivity(Recall) = \frac{TP}{TP + FN} \tag{3.4}$$

$$F1 - score = \frac{2 * (Precision * Sensitivity)}{Precision + Sensitivity} \tag{3.5}$$

3.2 Methodology for Decision Making in Resource Optimization

The second step of the proposed intelligent decision making framework is to aggregate artificial intelligence for decision making in healthcare resource optimization. In this case, predicting the length of stay (LOS) of patients autonomously can be an incredibly useful and efficient way for healthcare resource optimization. Numerous hospitals worldwide are confronted with limited resources, including beds to accommodate hospitalized patients. By assuring optimized resource utilization; LOS forecasting can benefit all the relevant stakeholders with improved treatment planning and expenditure prediction. However, traditional hospital management systems fail to estimate the duration of stay for patients at an early stage, resulting in a variety of negative consequences. Therefore, this section of the study proposes a machine learning approach for analyzing patient data and building a reliable decision making model incorporating Random Forest Regression Model to estimate the length of a patient's stay in the hospital. The data utilized in this study is a hospital discharge dataset containing records with various types of relevant information of patients . Two types of feature selection methods (PCA and Chi-square) and interquartile range based outlier elimination strategy have also been employed in the model for efficient prediction. To validate the performance porposed method including the impact of feature prioritization and outlier elimination, the dataset has been applied to ten different machine learning regression models as well as deep learning techniques after requisite data pre-processing. Furthermore, a comparison of multiple prediction models was conducted using various performance metrics in a variety of cases to determine the best performing regression model; in which the Random Forest Regression model outperformed other models.

3.2.1 A Machine Learning Based Approach for Predicting Patient's Duration of Stay at Hospital

The hospital resource management system is a diverse and complicated sector that includes the management of supporting resources based on patient flow and staff capacity. Despite each party's best efforts, inefficiency may persist between medical resource facilities and the huge number of patient requests due to hospital resource mismanagement [92]. This lack of resource management reduces hospitals' chances of providing quality healthcare services. Numerous hospitals worldwide are under severe resource constraints, making it difficult to serve emergency patients. As a result, hospital resource management has become increasingly important worldwide in delivering quality services to patients and can also be beneficial towards all the stakeholders including hospital administration, physicians, patients and healthcare practitioners [93]. Such kind of prediction minimizes the possibility of pharmaceutical adverse effects and increases hospital profit through better resource management [94]. It can help maximizing the use of hospital beds with proper planning of emergency treatment and surgeries based on forthcoming bed availability. Also, The length of stay accounts for about 90% of the difference in hospital expenditures across patients [95]. It becomes more significant in least developed or developing countries, where healthcare resources are in limited supply and also their administrative system is mostly manual.

In such situations, an automated prediction approach for estimating the length of stay of patients can be quite advantageous to develop an efficient resource management system in hospitals. Moreover, machine learning applied to health data enables the detection of patterns and correlations with insightful findings to aid decision-making with huge amount of complex data in healthcare industry [4]. Among various machine learning approaches, Random Forests (RF) are one of the most popular solutions to both classification and regression applications using ensemble machine learning method which is considered as an ideal tool for prediction because of its capacity to handle complicated inter-correlations between input parameters [96]. Moreover, the Random Forest regression model generally surpasses the other regression strategies since it has the potential to estimate nonlinear variables with excellent predictive performance of regression problems [97].

Therefore, the purpose of this research is to propose a robust machine learning-based strategy using Random Forest Regression Model that incorporates several data science techniques for predicting patient's length of stay (LOS) in hospitals. To validate the proposed strategy, this study executed a comparative analysis of several machine learning regression models (including Random Forest Regressor) and deep neural network methodology to estimate the number of days a patient will remain in the hospital. To explore the optimum strategy for prediction, the dataset had been thoroughly analyzed and preprocessed. Furthermore, all the regression models' performances were evaluated in several contexts based on the research analysis, such as with and without outlier data, as well as with and without prioritized features. The comparative study employed multiple performance indicators to determine the best performing regression method using the optimum set of features for forecasting LOS, where eventually Random Forest Regression model outperformed other regression methods.

3.2.2 Methodology

This study had been conducted through several phases to investigate the best performing regression approach with the optimal collection of features for forecasting the duration of stay of patients in a hospital. Several varieties of patient information that are typically available in hospital administration are used as input of this study. The proposed machine learning-based technique would then estimate the LOS of patients in days as output utilizing the patient information. The Google Colaboratory had been used as a platform for implementation incorporating mainly the python scikit-learn and TensorFlow packages. The framework of the methodology used in this research is illustrated in Figure 3.5. The phases involved in this research are described briefly below.

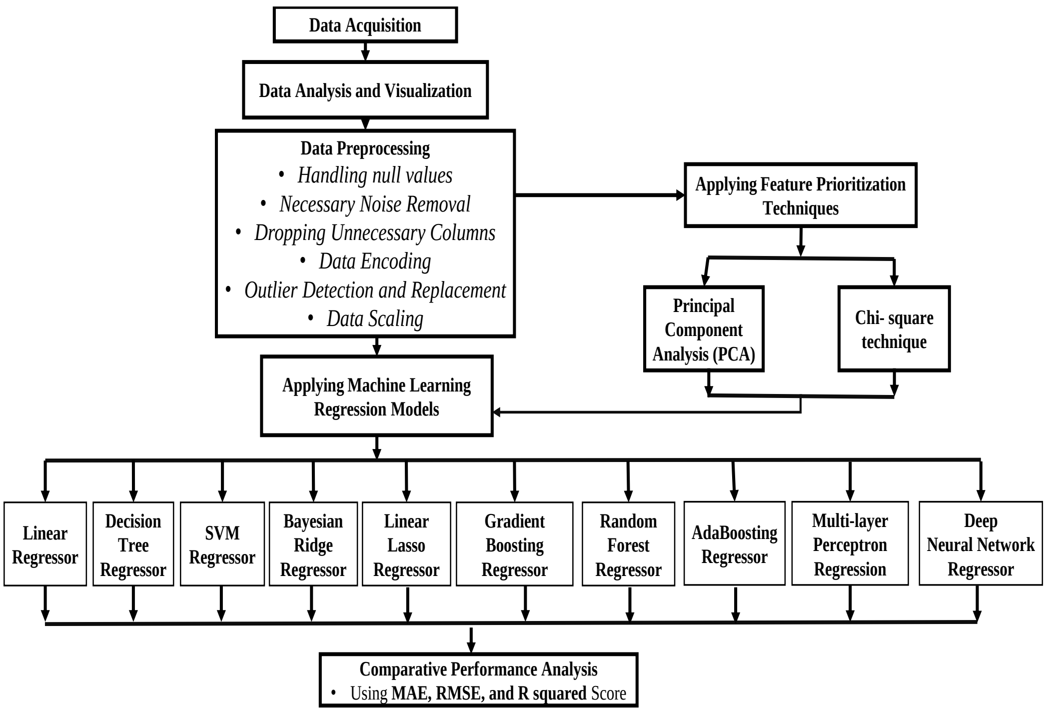


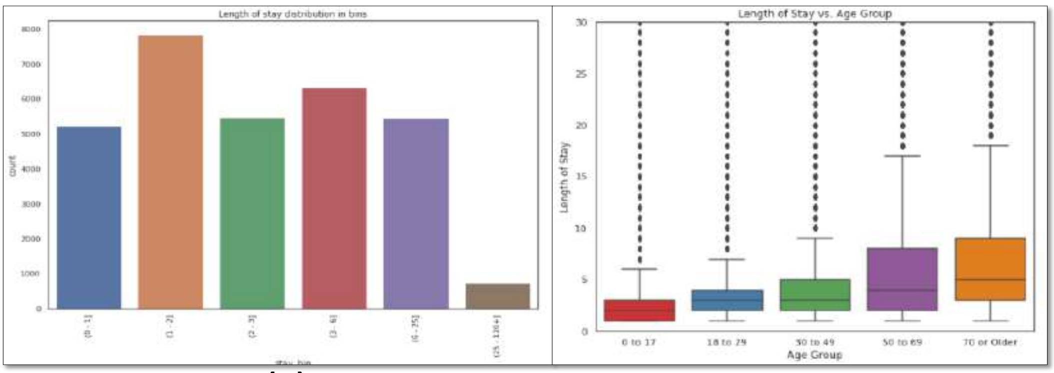
Figure 3.5: Framework of research methodology

3.2.2.1 Data Acquisition

This research has utilized a publicly available data collection of hospital patients from Department of Health, New York State The data repository contains various 'Statewide Planning and Research Cooperative System (SPARCS)' data having the basic record level details for the discharge of patients from various hospitals of New York state. Information on patients' discharges having duration of stays from two hospitals: 'Albany Medical Center Hospital' and 'Women And Children's Hospital Of Buffalo' is collected for this study. The specified dataset, retrieved from the repository to the implementation environment is then stored in a dataframe after importing the necessary library functions.

3.2.2.2 Data Analysis and Visualization

Preliminary investigation on the repository reveals that, the dataset contains 31,413 entries, with 34 columns of features comprising several quantitative and categorical information of hospital patients. The list of the columns is shown in Table 3.1. Here one of the column name is 'Length of Stay' (LOS) which is our target column to predict using the other necessary features. From the target column it has been observed that the days in the LOS column range from 0 to roughly 120 days. To visualize the distribution of data, the LOS days has been divided into bins, as shown in Figure 3.6(A). Similarly, in data visualization phase the relationship of LOS column with other attributes are analyzed in various ways. For example, Figure 3.6(B) depicts the distribution of LOS across patients' age group. Therefore, the data analysis and visualization phase has been carried out in order to develop a better exploration idea for appropriately preprocessing the dataset.



(A) (B)

Figure 3.6: (A) Distribution of days from LOS column, (B) Distribution of LOS vs patients' age group

3.2.2.3 Data Preprocessing

One of the core challenges in data science is that, the data quality in practical world environment is flawed and imperfect, with missing or inconsistent data samples, noises, complicated failures, and so on; lowering the forecast accuracy [98]. As a result, preprocessing the dataset meticulously is an essential aspect before applying any machine learning models. The following steps are applied to the dataset for preprocessing it.

Handling Null Values: In this research, at first the presence of null values in the dataset

Table 3.1: List of Columns from the dataset

Numerical Data Columns (11 col.)	Categorical Data Columns (23 col.)	
Operating Certificate No.	Health Service Area	CCS Procedure Description
Facility(Hospital) Id	Hospital County	APR DRG Description
Discharge Year	Facility(Hospital) Name	APR MDC Description
CCS Diagnosis Code	Age Group	APR Severity of Illness Description
CCS Procedure Code	Zip Code - 3 digits	APR Risk of Mortality
APR DRG Code	Gender	APR Medical Surgical Description
APR MDC Code	Race	Payment Typology 1
APR Severity of Illness Code	Ethnicity	Payment Typology 2
Birth Weight	Length of Stay	Payment Typology 3
Total Charges	Type of Admission	Abortion Edit Indicator
Total Costs	Patient Disposition	Emergency Department Indicator
	CCS Diagnosis Description	

has been investigated. It is observed that, 'Payment Typology 2' and 'Payment Typology 3' has too many null values (13916 and 25791 respectively) and so these columns are entirely dropped from the dataset as they won't provide any significant information for prediction. Then some other columns with a few null values and so the rows or entries containing those null values were discarded.Thus, after this phase the dataset are free from any null or missing values.

Necessary Noise Removal: A few columns in the dataset has unwanted symbols or noises in the data that needs to be eliminated. For example, 'Total Costs' and 'Total Charges' attributes has a '$' symbol. So such kind of irrelevant symbols are discarded from each entries of these columns and converted them to be numerical columns.

Dropping Unnecessary Columns It is necessary to check whether there are any columns that are unnecessary or redundant which need to be removed in order to improve prediction accuracy. It has been observed that, some pair of columns provided the same information and so one of them has been kept and the other redundant one is dropped from the dataframe. The examples of such kind of columns are shown in Table 3.2.

Again, there are some attributes not providing any valuable information. For example, 'Operating Certificate Number' containing the patients' ID numbers ; 'Discharge Year' with just one value that is '2015'; 'Ethnicity' column having very less information which is identical to 'Race' column etc. Thus, at this step, all of the unnecessary columns has been removed, leaving only the significant attributes for the next phases.

Data Encoding: To use machine learning methods and achieve the optimal outcome, practitioners frequently need to encode categorical values in their datasets and convert

Table 3.2: List of Redundant Columns with Same Information

Column Name	Redundant Column Name
Health Service Area	Zip Code - 3 digits
Facility Id	Facility Name
CCS Diagnosis Code	CCS Diagnosis Description
CCS Procedure Code	CCS Procedure Description
APR DRG Code	APR DRG Description
APR MDC Code	APR MDC Description
APR Severity of Illness Code	APR Severity of Illness Description

them into numerical information [99]. Here, after dropping unnecessary columns there are still some columns having categorical values which needs to be encoded. As a consequence, the columns having binary values like ‘Y/N’ and ‘M/F’ are first converted to 1/0 to make it numerical. After that, the attributes which represents some groups has been replaced with relevant group codes. For example, the age group ‘0 to 17’ are replaced with 1; ‘18 to 29’ with 2 and so on. The remaining categorical columns are then encoded using ‘one-hot encoding’ technique, which converts categorical data into numerical vectors with minimal processing [100]. Thus, after this phase, all the attributes in the dataframe will contain numerical values being suitable for prediction.

Outlier Detection and Replacement In the data analysis and visualization phase, it has been clearly observed that most of the LOS data is between 0 to 25 days stay at hospitals. Thus, the remaining few longer days of LOS records can be considered as outliers of the dataset since they are inconsistent and very less comparing the rest of the data [101]. Detection and replacement of these outlier data can be beneficial for the prediction. So, the interquartile range strategy has been used here to detect outliers in the target parameter ’Length of Stay’ and then substituted those values with mean of rest of the data in that column [102]. However, in the performance analysis phase, the prediction performance of various models with and without outlier elimination is compared to better understand its impact.

Data Scaling: As the dataset contains a variety of measurement units for different features, the values has to be rescaled using the data scaling approach to avoid feature sensitivity as well as a higher risk of misprediction and a misleading outcome [103]. To do so, the dataset is normalized using the MinMax Scalar method in this research before splitting them to train and test data for implementation [104] .

3.2.2.4 Applying Feature Prioritization Techniques

Feature prioritization is a great method for removing unnecessary properties from a data set in order to improve accuracy by enhancing its quality. After the preprocessing phase, the dataframe now contains 48 attributes; among which the unnecessary ones may degrade the quality of the predcition. Thus,in this research, two types of feature selection techniques have been applied to find out the optimal set of features from the preprocessed dataframe. One of them is chi-square feature selection technique which is one of the most frequent feature selection strategies used in machine learning [105]. Another technique used for feature selection is the Principal component analysis (PCA) method, which is an efficient dimension reduction tool for feature prioritization utilizing numerical analysis [106].

However, the most relevant attributes for LOS prediction are determined using these approaches, and the performance of machine learning models with and without feature prioritizing is compared.

3.2.2.5 Applying Machine Learning Regression Models

Ten different machine learning models has been applied to the dataframe after it is preprocessed and separated into train and test data.The prediction strategy is here all regression models since the forecast output is a continuous value of LOS in days. The ten models can be classified as classical machine learning models [107], ensemble machine learning models [108] and artificial neural network models [109]. Table 3.3 illustrates the list of machine learning regression models applied in this research. For designing the deep neural network (DNN) regressor model, TensorFlow package with Keras API has been used. Three hidden layers are created in the DNN model using the 'relu' activation function, while the output layer is created using the 'linear' activation function and for compiling the DNN model 'mae' was considered as the loss function with 'adam' optimizer. The model has been trained with the train data using 300 epochs and the batch size being 5. For implementing the other regression models, the scikit learn package has been utilized.

Table 3.3: List of Machine Learning Regression Models

Model Type	Model Name
Classical ML Models	Linear Regressor Decision Tree Regressor SVM Regressor Bayesian Ridge Regressor Linear Lasso Regressor
Ensemble ML Models	Gradient Boosting Regressor Random Forest Regressor Adaptive Boosting
Artificial Neural Network Models	Multilayer Perceptron Regressor Deep Neural Network Regressor

3.2.2.6 Performance Analysis for Evaluating Regression Models

The most commonly used performance metrices of regression model analysis are utilized to evaluate the performances of several machine learning approaches applied to the dataset, and those are: mean absolute error (MAE), root mean square error (RMSE) and R squared values [110]. Here,

$$MAE = \frac{\sum_{i=1}^{n} |p_i - t_i|}{N} \tag{3.6}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (p_i - t_i)^2}{N}} \tag{3.7}$$

$$R^2 = 1 - \frac{SSR}{TSS} \tag{3.8}$$

where, p_i is the predicted observation, t_i is the true value, and N is the total number of pairs between the testing true data and prediction result [111]. Also, in R squared equation (3), SSR is the Sum of Squared Regression and TSS is Total Sum of Squares [112] .

3.3 Methodology for Decision Making in Treatment Management

The Third phase of the proposed healthcare decision making framework is to make decision through artificial intelligence for treatment management of hospitalized patients. Among various fields, appropriate burn treatment management is a critical area of medical field that can help to rescue patient's life by dramatically minimizing burn progression and severity. Initial acute burn treatment involves intravenous fluid resuscitation, which must be administered meticulously to restore fluid loss and maintain essential organ function. But, a number of factors must be addressed quickly to make a decision for determining the required rate of intravenous fluid that will replenish the bodily lost fluid owing to the burn injury. Therefore, this research proposes a fuzzy logic based model to predict the decision making regarding adequate intravenous fluid resuscitation rate for a burn patient intelligently considering the patients' percentage of total body surface area burned (%TBSA) and hourly urine output (HUO). To attain the objective, a fuzzy logic system (FLS) has been developed in the study aggregating the clinical burn protocol as the knowledge base of the fuzzy inference engine where the %TBSA and HUO measurements are considered as inputs and intravenous fluid rate will be the output of the FLS. Multiple forms of fuzzy membership functions and different types of defuzzification methods have been applied to the same system in order to compile a comparative study of different models with various modifications. To explore the best performing fuzzy approach, three different test cases have been considered for which both the manual calculation under the supervision of physicians and fuzzy fluid resuscitation model's assessment have been performed and compared for determining the optimum amount of intravenous fluid rate necessary for burn patient's resuscitation.

3.3.1 A Fuzzy Model for Decision Making in Burn Patients' Treatment Management of Fluid Resuscitation

Burn injury management is typically a critical area of medical science as the burn shock caused by the major burns in the patients develops the mix of hypovolaemic and cell shock and as a consequence of the patho-physiological mechanisms happening after the trauma, it provokes rapid fluid loss in the body through the cell wounds [113]. Managing the treatment of burn patients within the first 24 hours is one of the most challenging aspects which significantly impacts on the amount of damage and mortality rate of patients [114]. Therefore, fluid resuscitation therapy in this period is considered to be essential in the treatment management of patients with dehydration caused by burns and shocks [115]. Fluid resuscitation therapy can be conducted in various ways. Among them, intravenous fluid resuscitation technique is a universally practiced medical treatment for critically ill patients which replenishes bodily lost fluids caused by various causalities with required fluids directly through patient's vein [116]. Maintaining an adequate amount of fluid in the body necessitates a proper amount of fluid resuscitation, where especially for burn patients, under or excess fluid resuscitation can be life-threatening, resulting in a variety of abnormalities.

Medical decision making in such kind of cases is very sensitive because it involves patients' future health consequences, uncertainties, complex trade-offs, quantitative and qualitative information overload, interrelated behaviors, and so many other factors [117]. It often becomes humanly impossible to make such complex decisions about the treatment of burn patients manually in a shortest possible time considering so many factors and statistical data. A computer assisted decision support system incorporated with medical guidelines and artificial intelligence can be a wonderful solution to resolve these issues. However, fuzzy logic based approaches has recently gained much interest for its capability to deal with healthcare related problems that are difficult, obscure, or ambiguous to predict [118]. Therefore, this study proposes a fuzzy logic based model to predict the required amount of intravenous fluid that is necessary for the resuscitation of a burn patient for maintaining an optimal amount of fluid in the body. To attain this objective, a fuzzy logic-based prediction model has been developed in this study that takes into account the percentage of total body surface area that has been burned (%TBSA) and the patient's hourly urine output (HUO) as inputs with some required clinical rules to estimate the quantity of intravenous fluid rate (IFR) necessary in 24 hours for a burn patient.

However, in most of the earlier studies, several formulae have been devised to assist resuscitation in severely burnt patients involving manual fluid dosage, which can lead to mistakes and inferior results [119]. A few researchers used a conventional computer-assisted decision-making system based on fluid resuscitation formulas to predict the fluid demand for burn patients, with little utilization of artificial intelligence [120, 121]. Barely any researcher has explored the fuzzy logic based system in this arena to predict IFR for burn patients employing the key indicators such as %TBSA and HUO. Thus, in this research, an intelligent fuzzy model based on Mamdani fuzzy inference system [122] have been employed that imitates the human brain's process of combining information from the burn protocol knowledge base and input parameters(%TBSA and HUO) to arrive at a final decision about the quantity of the IFR. The proposed model has been implemented using different membership functions for fuzzification and different methods for defuzzification in three test case scenario to explore the best performing model. To validate the correctness of the model's outcome, the intravenous fluid rate for test cases has been estimated manually with standard formula under the supervision of expert physicians and then that outcome has been compared with the fuzzy system's outcome for exploring the optimum model. Thus, if this system can be implemented practically in the burn units of the hospital, it will be able to assist the healthcare providers in making decision quickly about how the intravenous fluid rate (IFR) should be adjusted within shortest time for burn patients with lesser risk of over or under resuscitation. However, it is recommended that, healthcare practitioners should not solely rely on the output readings of the suggested fuzzy logic system proposed here; instead, they should validate the fuzzy system's outcome with their practical medical expertise before making the final decision for critically burned patients.

3.3.2 Methodology

The proposed conceptual framework of fuzzy inference system for predicting Intravenous fluid resuscitation (IFR) rate for burn patients is presented in Figure 5.1. Here, two input variables has been used to demonstrate the fuzzy inference system, which are: percentage of Total Body Surface Area burned (%TBSA) and hourly urine output (HUO). Initially, these two input variables work as the crisp input set of the system where these input values have the characteristics of being countable or finite. %TBSA has been considered as crisp input set A, HUO has been considered to be crisp input set B and Intravenous Fluid Rate (IFR) has been considered to be the output of the system.

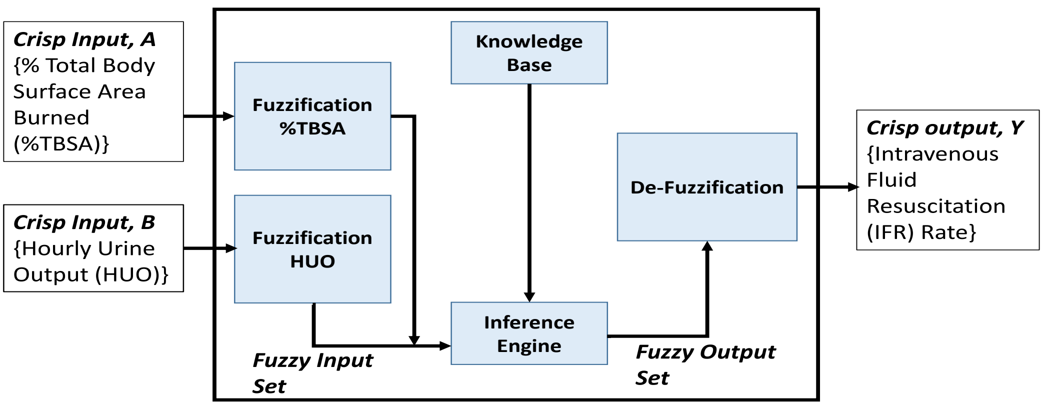


Figure 3.7: Conceptual Framework of research methodology

The modeling steps of the proposed framework are as follows:

- The initial step is called the fuzzification step. The two input parameters at first enter into the blocks of fuzzification process where the crisp values are converted to fuzzy values using various membership functions to use them as the fuzzy input set for the model. Therefore, at this step the two fuzzy input sets of the model with %TBSA as fuzzy set A and HUO as fuzzy set B are generated.

- Now an appropriate set of rules following proper medical guidelines to predict the fuzzy output of IFR based on different combination of fuzzy input parameters are formulated to be used as the knowledge base of the model.
- This set of rules has been aggregated intelligently with the fuzzy input set in the Mamdani fuzzy inference engine to acquire the fuzzy output set of intravenous fluid resuscitation rate (IFR).
- The final step is the defuzzification phase where the fuzzy output set of IFR gets converted into crisp value of IFR employing using various defuzzification techniques. Thus, the predicted value of IFR can be generated.

The procedure of estimating intravenous fluid resuscitation rate in this method employs the most significant indicators (%TBSA and HUO) as well as the clinical formula of fluid resuscitation of burn patients that are typically practiced in the real-world burn treatment and therefore, this approach might be efficiently applied the practical healthcare applications. Each steps of the methodology applied in this study has been discussed hereafter.

3.3.2.1 Fuzzification

As the first step of fuzzy inference system is to fuzzify the crisp input set, thus here firstly the two variables having crisp input set have been converted into fuzzy set values using membership functions (MF). Membership functions are considered to be the building blocks of fuzzy logic system which are represented by graphical patterns to quantify fuzziness of the crisp set inputs [123]. For this research mainly three types of membership functions have been used, those are: Triangular, Trapezoidal and Gaussian membership functions. Here, triangular membership function can be represented using 3 parameters; which are a lower limit p, an upper limit r, and a middle value q, where $p < q < r$. The mathematical representation of triangular membership function has been shown in equation 1.The second membership function used here is the trapezoidal membership function that can be represented using 4 parameters; which are a lower limit p, an upper limit s and in between these two points a lower support limit q, and an upper support limit r, where $p < q < r < s$. The mathematical representation of trapezoidal membership function has been shown in equation 2. The third membership function in this study is the Gaussian membership functions that can be defined using two parameters; where one is specified by a central mean value m , and another one is the standard deviation σ (where $\sigma > 0$). Here the output membership function looks like a bell shape, where the smaller the value of σ, the narrower will be the bell shape. The mathematical representation of Gaussian membership function has been shown in equation 3. The brief description about the input and output variables of the system are described in the following sections.

$$\mu_{triangular}(x) = \begin{matrix} 0;\ x \leq p \\ \frac{x-p}{q-p};\ p \leq x \leq q \\ \frac{r-x}{r-q};\ q \leq x \leq r \\ 0;\ x \geq r \end{matrix} \tag{3.9}$$

$$\mu_{trapezoidal}(x) = \begin{matrix} 0;\ x \leq p \\ \frac{x-p}{q-p};\ p \leq x \leq q \\ 1;\ q \leq x \leq r \\ \frac{r-x}{r-q};\ r \leq x \leq s \\ 0;\ x \geq s \end{matrix} \tag{3.10}$$

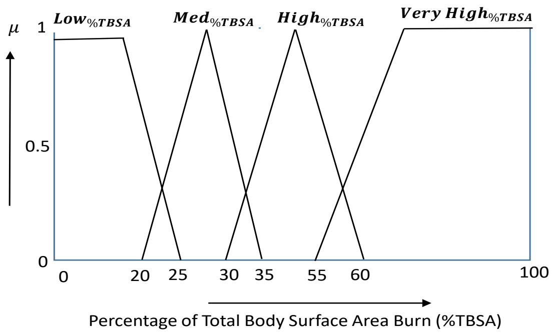
$$\mu_{gaussian}(x) = \left\{ e(\frac{1}{2}(\frac{x-m}{\sigma})) \right\} \tag{3.11}$$

Input A- Percentage of Total Body Surface Area Burned (%TBSA):

In this research, for predicting the intravenous fluid rate for a burn patient in 24hours, the first parameter that has been considered is %TBSA. %TBSA works as the input linguistic variable in the FLS, where the crisp input has been converted to fuzzy value using membership function in the fuzzification phase. The range of possible crisp values can be divided into four parts to represent the required fuzzy quantity which can be specified as: low burn (%TBSA is $< 25\%$), medium burn (%TBSA is $20 - 35\%$), high burn (%TBSA is $30 - 60\%$) and very high burn (%TBSA is $> 55\%$). It is to be mentioned that, these measurements may vary physician to physician as there is no fixed range of %TBSA measurement. An example of the fuzzification of %TBSA using membership function and range of crisp values are illustrated in Figure 3.8. Here, the linguistic values have been represented using their individual triangular or trapezoidal membership functions following their assumption of crisp value's range.

Input B- Hourly Urine Output (HUO):

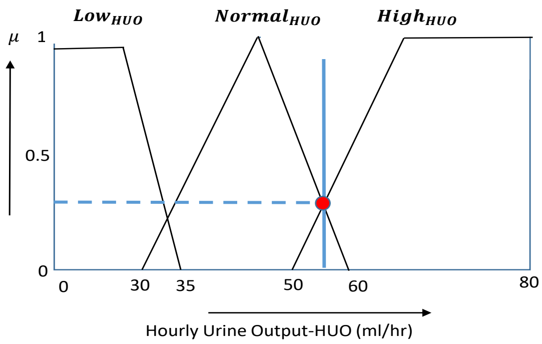
The another input variable of interest, Hourly Urine Output (HUO) has been considered



Crisp input %TBSA	Fuzzy Set
<25 %	Low
20-35 %	Medium
30-60 %	High
>55%	Very High

Figure 3.8: Fuzzy Sets for %Total Body Surface Area Burned

in this study in the fuzzy inference system, as illustrated in Figure 3.9 .To calculate a patient's urine output, the physicians need to know the volume of urine they generated, and how long it took them to produce it. Thus the general rule for measuring hourly urine output of a patient is urine output (measrured in ml)/number of hours. For adult burn patients, hourly urine outputs of 30 to 50 mL are generally regarded sufficient for preserving proper organ functioning, and the fluid resuscitation rate should be adjusted to maintain this level [124]. Here the range of possible crisp values of HUO has been divided into three parts : low ($< 35ml/hr$ urine), normal ($30 - 60ml/hr$ urine) and high ($> 50ml/hr$ urine).



Crisp input HUO (ml/hr)	Fuzzy Set
<35	Low
30-60	Normal
>50	High

Figure 3.9: Fuzzy Sets for Hourly Urine Output

Output- Intravenous Fluid Rate (IFR): The intravenous fluid rate (IFR) should be provided timely with accurate measurements for the burnt patients, which depends on various factors. Here for this research, the IFR will be predicted as the output of the fuzzy system based on the input variables %TBSA and HUO. The output of the fuzzy logic system (FLS) in this study, determines the quantity of IFR required for per kilogram of body weight. For example, if the system predicts the IFR should be $90ml/kg$ then any patients of 50kg body weight will need $(90 \times 50 = 450ml)$ intravenous fluid in 24 hours. According to the clinical burn protocol the linguistic output variable IFR can assumed to be divided into following five linguistic values:

- IFR-Low ($< 80ml/kg$)
- IFR-Maintain ($55ml/kg$ *to* $115ml/kg$)
- IFR-Moderate ($95ml/kg$ *to* $170ml/kg$)
- IFR-High ($130ml/kg$ *to* $340ml/kg$)
- IFR-Very High ($> 260ml/kg$)

3.3.2.2 Knowledge Base & Inference Engine

Here for this study the percentage of Total Body Surface Area(%TBSA) burned and Hourly Urine Output(HUO) have been considered as the inputs variables of the system for predicting the Intravenous Fluid Rate(IFR) rate of a patient at a given time using fuzzy inference system. For constructing the knowledge base of the system, the burn resuscitation protocol considering %TBSA and urinary output goals suggested by McGovern Medical School, University of Texas; incorporating the Parkland Formula for measuring the total fluid requirement in 24 hours for any adults $(4ml \times \%TBSA \times BodyWeight(kg))$ have been employed [62,125]. With the crisp input sets of %TBSA and HUO being fuzzified, each time a fresh pair of measurements of fuzzy values from %TBSA and HUO comes for a patient, which enable to describe the diagnostic condition of the individual. For each pair of fuzzy linguistic input parameter sets, the rate of fluid must be determined accordingly.

For example if the value of %TBSA is low and HUO is High, that means the urinary output is higher with lower burned area and thus the necessity of fluid rate is less. So the output in this case will be 'Low' rate of fluid resuscitation. On the other hand if the value of %TBSA is Very High but the HUO is Low, that means the urinary output is lower with highly affected burned area in the body and thus the necessity of fluid rate is much higher to recover the bodily lost fluid. So the output in this case will be 'Very High' rate of fluid resuscitation. Therefore, considering practical medical guidelines from physicians as well as from the burn resuscitation protocol by McGovern Medical School, University of Texas; the rule table for the fuzzy logic controller of this study has been constructed which is shown in Table 3.4. The rule table illustrates the different combinations of linguistic input values of %TBSA and HUO stated before, as well as the output created as linguistic values of IFR according to the clinical guidance.

Based on the rule table from Table 3.4, numbers of rules can be generated which are listed below:

Table 3.4: Rule Table of the Fuzzy logic controller

	%TBSA LOW	%TBSA Medium	%TBSA High	%TBSA Very High
HUO-Low	IFR Maintain	IFR Moderate	IFR Very High	IFR Very High
HUO-Normal	IFR Low	IFR Maintain	IFR High	IFR Very High
HUO-High	IFR Low	IFR Low	IFR High	IFR High

- Rule 1: If %TBSA is Low; And HUO is Low; then IFR is Maintain.
- Rule 2: If %TBSA is Low; And HUO is Medium OR High; then IFR is Low.
- Rule 3: If %TBSA is Medium; And HUO is Low; then IFR is Moderate.
- Rule 4: If %TBSA is Medium; And HUO is Medium; then IFR is Maintain.
- Rule 5: If %TBSA is Medium; And HUO is Low; then IFR is Low.
- Rule 6: If %TBSA is High; And HUO is Low OR Medium; then IFR is High.
- Rule 7: If %TBSA is High; And HUO is High; then IFR is Moderate.
- Rule 8: If %TBSA is Very High; And HUO is Low OR Medium; then IFR is Very High.
- Rule 9: If %TBSA is Very High; And HUO is High; then IFR is High.

These rules work as the knowledge base of the fuzzy system in this study which has been aggregated with the input fuzzy sets of %TBSA and HUO in the fuzzy inference engine to determine the fuzzy output of IFR intelligently. Therefore, the fuzzy output set for the IFR is generated after these phases.

3.3.2.3 Defuzzification

Utilizing the output fuzzy set with relevant membership function, defuzzification is the process of creating a measurable outcome in crisp logic. It is the procedure for converting a fuzzy set to a crisp set by selecting the appropriate crisp value from the fuzzy output of a fuzzy inference system [126]. For this study, after obtaining the fuzzy

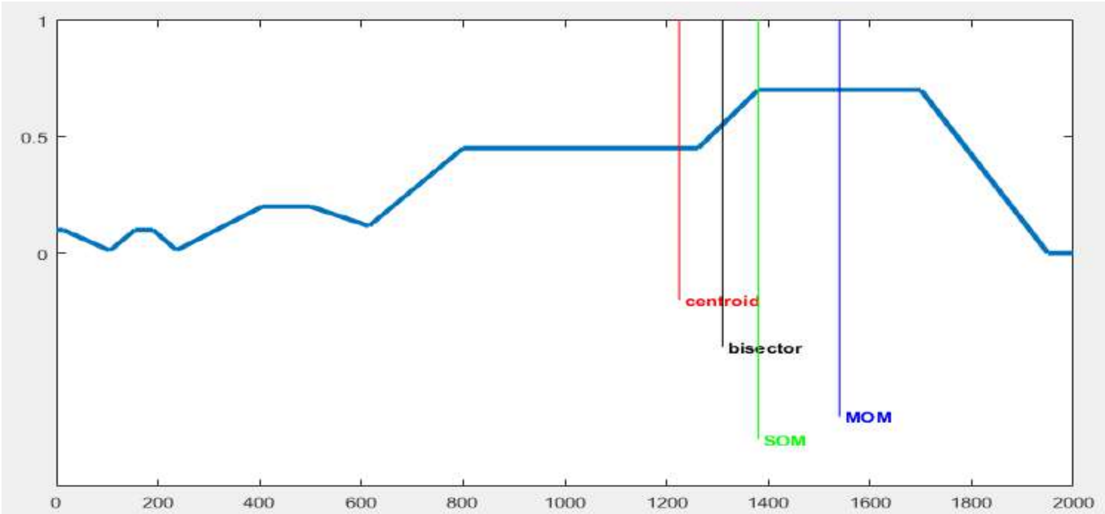


Figure 3.10: Different types of Defuzzification methods

output set for IFR, the crisp value has been generated using four kinds of defuzzification methods:BOA (bisector of area), COA (center of area), MOM (medium of maximum) and SOM (smallest of maximum) which are shown in an example in Figure 3.10.

Chapter 4

Results and Findings

4.1 Experimental Results for Disease Detection

4.1.1 Result Analysis of Deep CNN-Based Approach for Decision Making in Burn Severity Detection from Skin Burn Images

4.1.1.1 Findings from The Traditional Machine Learning Approach

Employing the traditional ML approach, the images have been pre-processed with required digital image processing stages to retrieve the significant information before applying them into machine learning classification algorithms. One of the examples of a burnt image with each steps of image processing technique has been illustrated in Figure 3.4. From the figure it is visible that, after applying the digital image processing steps the affected burnt area is more prominently detected in the final segmented image in comparison to the original image. Similarly, all the images are processed in

Table 4.1: Performance analysis results obtained from the test data with traditional machine learning approach

Machine Learning Model	Accuracy	Precision	Recall	F1-score
Random Forest Classifier	0.773	0.784	0.734	0.744
Support Vector Machine Classifier	0.767	0.762	0.740	0.747
Decision Tree Classifier	0.706	0.692	0.692	0.692
K-Nearest Neighbour Classifier	0.661	0.796	0.571	0.517
Logistic Regression Classifier	0.642	0.619	0.601	0.601
Multi-Layer Perceptron Classifier	0.530	0.595	0.580	0.524

this way and then employed to the machine learning classifier as train and test image data. The performances of the six types of machine learning classifiers with different performance metrices have been shown in Table 5.1. From the performance analysis in Table 5.1, it can be observed that among all the classifiers, Random Forest classification model comparatively outperforms others in terms of performing with highest accuracy (77.3%) whereas the Mult-Layer Perceptron provides the least accuracy (53.0%).

4.1.1.2 Findings from the Proposed CNN Approach

The proposed CNN architecture has been slightly modified with hyperparameter tuning in four different ways to explore the best performing model for burn depth prediction where each method has executed over 10 epochs for training. Figure 4.1 shows how the accuracy of the model increases and the loss decreases per epoch of the training. Table 5.2 shows the performances of the proposed CNN technique on the test dataset with four methods; which consists of without including transfer learning from pretrained models as well as including three different pre-trained models as transfer learning process. From the table, it is apparent that all of the CNN approaches with the proposed technique have achieved substantially higher accuracy, with the transfer learning model using the VGG16 pre-trained model outperforming the other models with 95.63% accuracy. Moreover, it is also noticiable that, the performance of the classification model enhances significantly while employing transfer learning technique as the CNN model without tranfer learning has acquired only 72.01% accuracy.

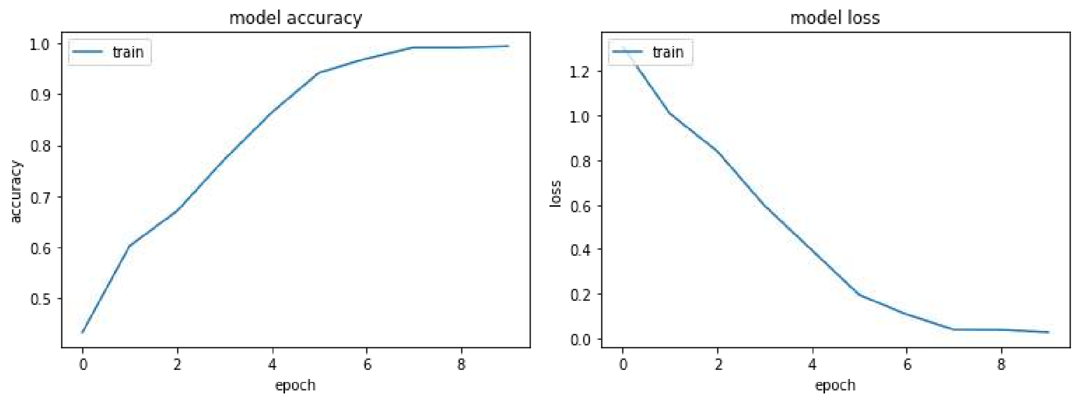


Figure 4.1: Accuracy and loss obtained per epoch from the proposed CNN technique

The comparative accuracy analysis of employing traditional and proposed CNN technique with different machine learning models have been illustrated in Figure 4.2. From the comparative performance analysis it is evident that, the accuracy of the models with traditional approaches is much lower in comparison to the CNN techniques. Furthermore, the traditional technique entails several tedious image processing phases that

Table 4.2: Performance analysis results obtained from the test data with proposed CNN machine learning approach

CNN Architechture	Accuracy	Precision	Recall	F1-score
CNN without Transfer Learning	0.7201	0.72	0.69	0.71
CNN with Transfer Learning-**(VGG16)**	0.9563	0.96	0.94	0.94
CNN with Transfer Learning-**(MobileNet)**	0.8751	0.90	0.83	0.87
CNN with Transfer Learning-**(ResNet50)**	0.9236	0.92	0.91	0.92

need meticulous adjustments whereas the CNN technique can provide excellent performance without any explicit image processing steps as the neural network itself extract the significant features from the images at the time of training. Therefore, the suggested method, which integrates transfer learning with pre-trained VGG16 model, can be used effectively in clinical practice to estimate the depth of burn from captured photos of skin burn injury.

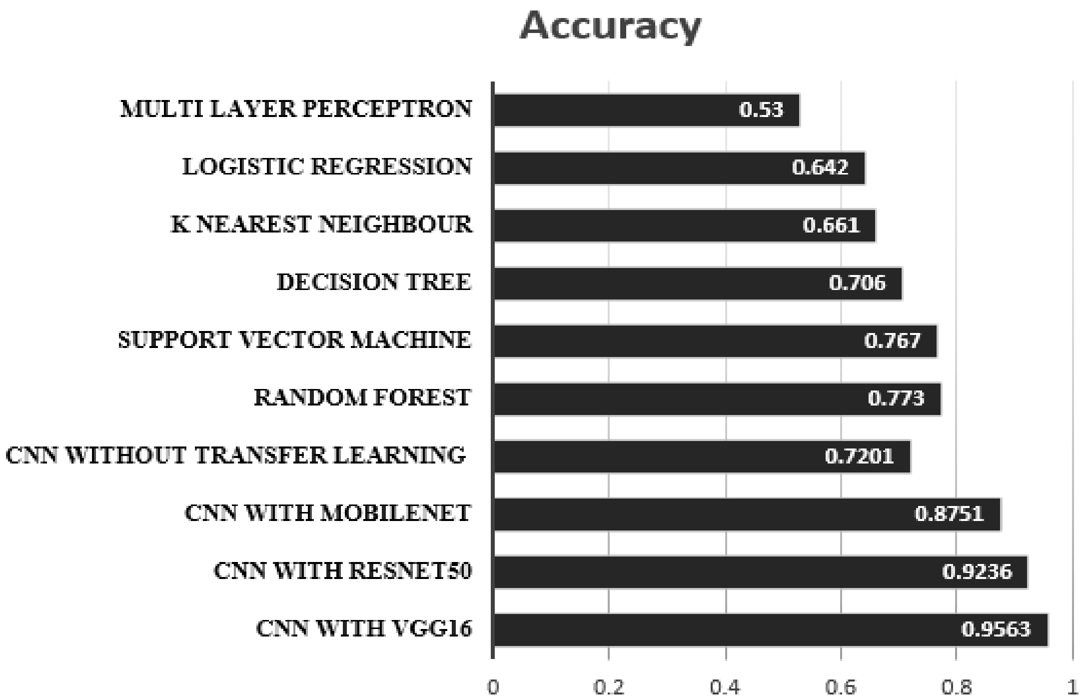


Figure 4.2: Comparative accuracy analysis

4.1.2 Discussion

This research has proposed a DCNN based model with transfer learning and fine tuning for effective identification of skin burn degrees according to their severity from real-time burn images of victims. The architecture employs transfer learning from pretrained models and then multiple convolutional layers with hyperparameter tuning for feature extraction from the images which are then utilized in a fully connected feed forward neural network to classify the images into three categories. To validate and evaluate the efficacy of the proposed technique, the traditional approach incorporating digital image processing and conventional machine learning classifiers has also been applied to solve this multi-class classification problem. Accuracy, precision, recall and F1-scores are the matrices that have been utilized to conduct the performance analysis. The findings from comparative analysis indicates that the proposed technique shows much higher accuracy in comparision to the traditional approach and also incorporating transfer learning outperforms other techniques in terms of accuracy.

Therefore, the suggested DCNN based computational model can assist medical practitioners and healthcare providers in evaluating the injury condition and suggesting suitable therapy in a quickest possible time depending on the degree of the skin burn. Through the utilization Artificial intelligence and advanced technologies, this approach can also provide telemedicine support to diagnose and treat patients remotely, especially in rural areas of least or developing countries where professionals may be scarce. This method can also be utilized in the healthcare facilities where there is limited resources to conduct appropriate clinical diagnosis for detecting skin burn severity. However, this study may be expanded in the future by integrating additional samples, which will allow for the distinction of superficial-partial and deep-partial burns, as well as the estimation of the Total Body Surface Area (TBSA%) of burn for improved clinical assessment for burn patients. However, the proposed methodology for this phase of the thesis has been published in one of the reputed peer-reviewed journal [127].

4.2 Experimental Results for Resource Optimization

The following sub-sections have been organized to present the findings from the interpretation of research results for resouce optimization.

4.2.1 Comparative Analysis of ML Models with and without Outlier Data

From the data analysis and visualization phase, it is visually clear that the dataset contains the majority of the length of stay values in the range of 0 to 25 days. Additionally, to justify this, the interquartile range of the LOS data was evaluated, revealing that the 25th percentile (lower quartile) value of LOS is 2.00 days and the 75th percentile (upper quartile) value of LOS is 5.00 days. Then, the upper quartile value have been multiplied with 5 to consider as the maximum value of LOS which results in 25 days of stay and the minimum value of LOS is 0 days. The results reveal that out of 31,413 entries, only 561 have a LOS of more than 25 days, which are subsequently adjusted with the mean of the remaining entries.

The ten types of regression models are then ran on both the original dataset with all of the outlier values and after the outlier data had been processed. Table 4.3 presents the comparative performance analysis of all the models with and without outlier data. Figure 4.3 graphically illustrates the comparative analysis of MAE output using testing data with different models with and without outlier data. The comparative analysis reveals that in both cases the Random Forest Regression model perfroms best with least errors. Also after processing the outlier data, the error rate for most of the models drops significantly and they acheive better accuracy.

To further analyse the impact of outlier elimination, Figure 4.4 has been used here as an example. The figure shows the predicted vs. true value of the Random Forest Regressor model, where Figure 4.4(A) shows the outcome without outlier data of LOS and Figure 4.4(B) shows the outcome after replacing the outlier data. In the figure the data points that are closer to the straight line represent predicted values that are more identical to the real values. Here, it is visible that containing the outlier data in the training dataset, numerous predicted values (in Figure 4.4 A) are less comparable to the true value which is revealed by their sparse distribution from the straight line. On the other hand, when outlier data is replaced with the mean of other values; the projected values are more similar to the actual values. As a consequence, the overall findings show that, removing outlier data improves the performance and decrease the errors of regression models.

Table 4.3: Comparative Analysis of ML Models with and without Outlier data

Machine Learning Models	**Including Outlier Data of LOS**						**Replacing Outlier Data of LOS**					
	Training Dataset			Testing Dataset			Training Data.			Testing Data.		
	MAE	RMSE	R-2	MAE	RMSE	R-2	MAE	RMSE	R-2	MAE	RMSE	R-2
Random Forest Regressor	0.401	1.0752	0.98	1.09	2.6888	0.86	0.361	0.7446	0.98	1.00	2.0533	0.88
Gradient Boosting Regressor	1.308	2.4599	0.91	1.36	2.7642	0.85	1.211	2.1126	0.74	1.26	2.2758	0.71
Decision Tree Regressor	0.000	0.0000	1.00	1.44	3.6286	0.76	0.000	0.0000	1.00	1.28	2.8498	0.55
Deep Neural Network Regressor	1.876	3.3417	0.82	1.91	3.7066	0.80	1.503	2.4743	0.84	1.54	2.6888	0.83
Adaptive Boosting Regressor	3.242	5.9308	0.47	3.25	6.0531	0.33	1.706	2.7365	0.55	1.71	2.7661	0.57
Linear Regressor	1.918	3.7207	0,79	1.89	3.6719	0.75	2.088	3.2855	0.36	2.13	3.3586	0.38
Bayesian Ridge Regressor	1.918	3.7209	0.79	1.89	3.6715	0.75	2.091	3.2870	0.36	2.14	3.3604	0.37
SVM Regressor	3.129	7.5182	0.15	3.09	6.9893	0.10	2.316	4.0212	0.04	2.40	4.1589	0.04
Linear Lasso Regressor	3.368	7.3365	0.19	3.27	6.5199	0.22	2.464	3.7543	0.16	2.53	3.8746	0.17
Multi-Layer Perceptron Regressor	3.368	7.3365	0.19	3.27	6.5199	0.22	2.475	3.7543	0.16	2.55	3.8746	0.17

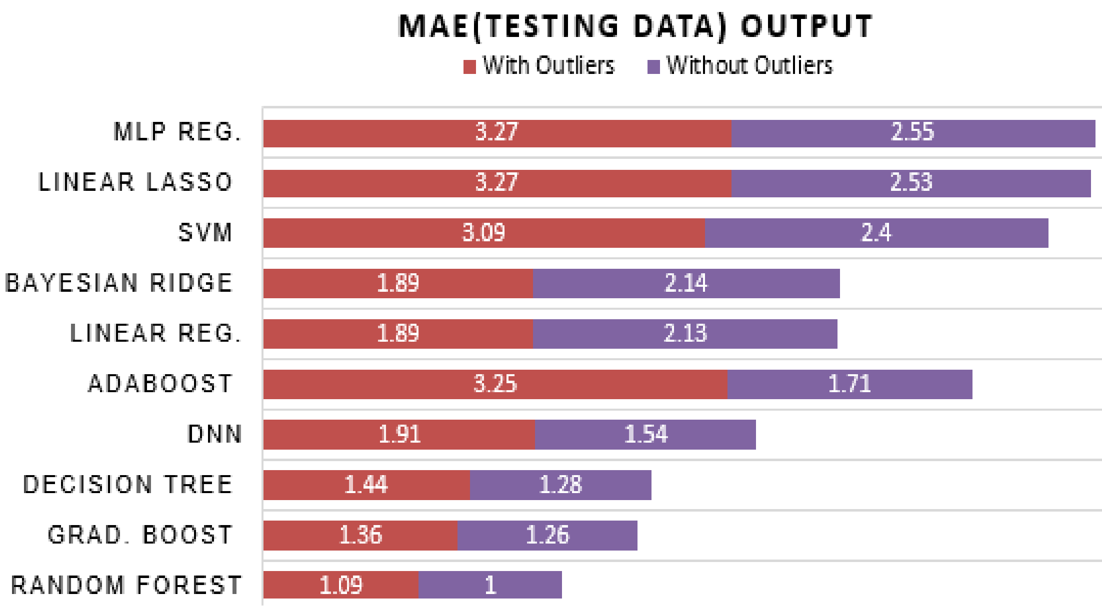


Figure 4.3: Comparison of MAE from ML models with and without outlier data

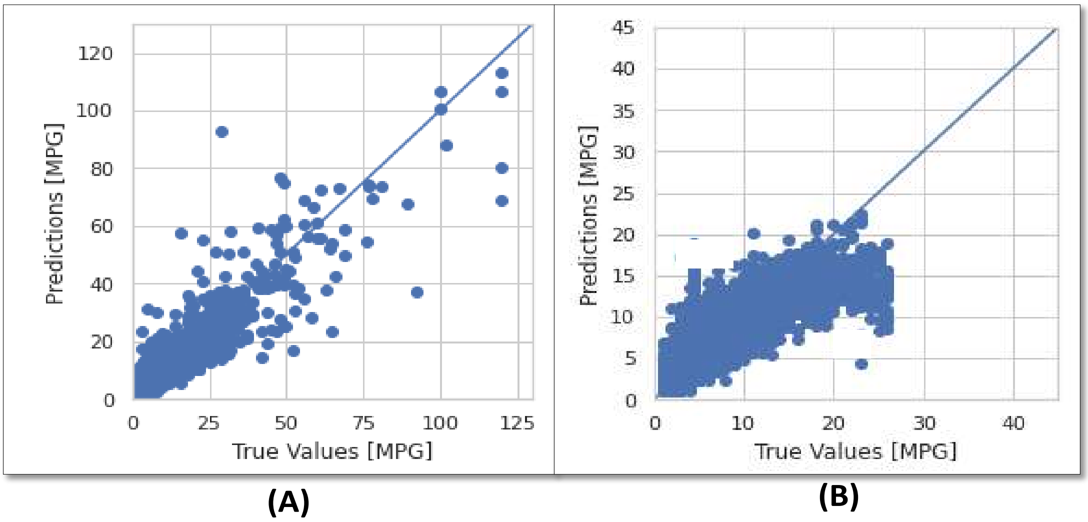


Figure 4.4: Comparison of RF Prediction (A) With Outlier (B) Replacing Outlier

4.2.2 Comparative Analysis of ML Models with and without Feature Prioritization

In this study, two types of feature prioritization techniques have been used, one is PCA and another is Chi-square method. After the pre-processing step, the dataframe contains 48 features with one target attribute(Length of Stay). The both feature prioritization techniques selects the top 38 features according to their own algorithms and it is to be mentioned that the 38 features selected by PCA technique are quite different from features selected by Chi-square technique. Then, the above mentioned ten types of regression models were run on dataframe with all features (without feature selection) and dataframe with reduced features (selected as a consequence of feature prioritization approaches). Table 4.4 presents a comparative study of the performances (MAE, MSE, and RMSE) of several models using the testing dataset. Figure 4.5 graphically illustrates the comparative analysis of MAE output with different models with and without feature selection.

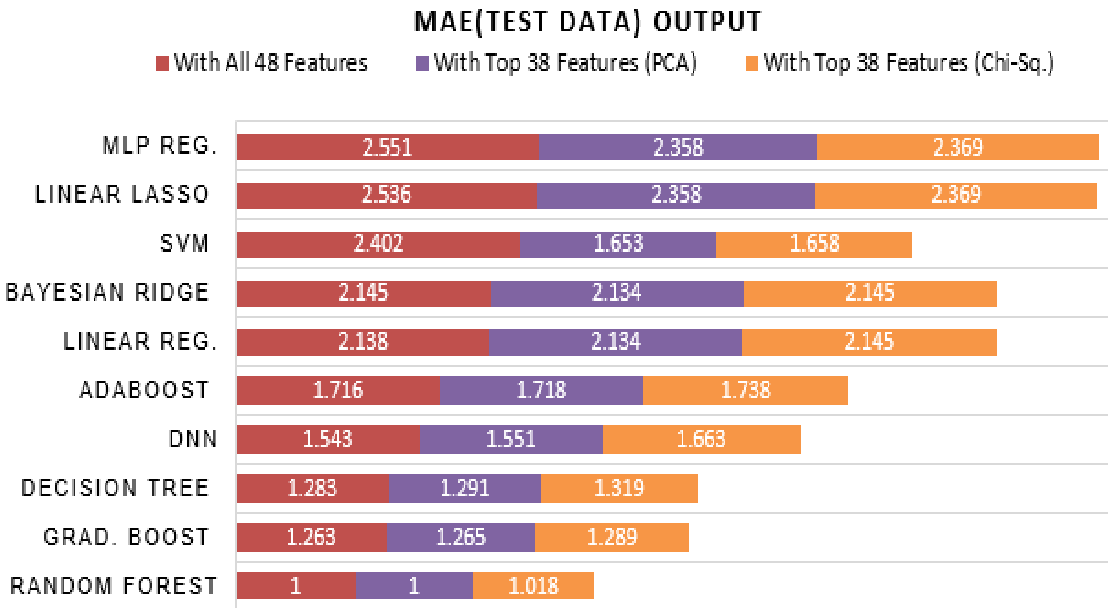


Figure 4.5: Comparison of MAE with & without feature selection

It's apparent that the models' performances using the PCA feature selection approach using 38 attributes are almost same, if not slightly better; than the models' performances utilizing all features. Conversely, when compared to the other two scenarios, the models' performance utilizing the Chi-square feature selection approach displays relatively worse results with higher error rate. So, as the findings of this investigation, it can be stated that utilizing PCA feature selection technique to predict the duration of stay for patients in days with this dataset can produce superior performance utilizing less number of features.

4.2.3 Performance Analysis of Different Models

Upon observing the results of several models, it is noticeable from Table V and VI that Random Forest Regression model have the least error rate comparing to other models in all kinds of scenarios (with and without outlier data, with all features, with features selected by PCA technique and features selected by Chi-Square technique). Following the Random Forest model, the Gradient Boosting, Decision Tree, and Deep Neural Network Regression models show relatively better performances with less error rates. On the other hand, Linear Lasso and Multi-Layer Perceptron Regression models performs worse with higher error rates in all cases.

Table 4.4: Comparative Analysis of ML Models with and without Feature Prioritization

Machine Learning Models	**With All Features**			**Features Selection (PCA)**			**Feature Selection (Chi-Square)**		
	Testing Dataset			Testing Dataset			Testing Dataset		
	MAE	RMSE	R-2	MAE	RMSE	R-2	MAE	RMSE	R-2
Random Forest Regressor	1.000	2.0533	0.78	1.000	2.0539	0.77	1.018	2.1036	0.76
Gradient Boosting Regressor	1.263	2.2758	0.71	1.265	2.2760	0.71	1.289	2.3088	0.71
Decision Tree Regressor	1.283	2.8498	0.55	1.291	2.8923	0.56	1.319	3.0011	0.50
Deep Neural Network Regressor	1.543	2.6888	0.83	1.551	2.7630	0.81	1.663	2.8836	0.79
Adaptive Boosting Regressor	1.716	2.7661	0.57	1.718	2.7663	0.57	1.738	2.8116	0.56
Linear Regressor	2.138	3.3586	0.38	2.134	3.3599	0.37	2.145	3.3797	0.37
Bayesian Ridge Regressor	2.145	3.3604	0.37	2.134	3.3591	0.37	2.145	3.3793	0.37
SVM Regressor	2.402	4.1589	0.04	1.653	2.8585	0.55	1.658	2.8729	0.54
Linear Lasso Regressor	2.536	3.8746	0.17	2.358	3.6667	0.25	2.369	3.6820	0.25
Multi-Layer Perceptron Regressor	2.551	3.8746	0.17	2.358	3.6667	0.25	2.369	3.6820	0.25

Analyzing the computing time required to run the machine learning models, it's evident that Random Forest delivers the best results in less amount of time in comparison to other good performing models. For example, the Deep Neural Network(DNN) produces the outcome using 300 epochs which takes almost 36 min to execute. Figure 4.6 depicts how the value of MAE and loss in the DNN model decreases over time per epochs to achieve the optimal prediction where finally the MAE for test data is 1.54. On the other hand, the Random Forest regression model takes 16 seconds time to execute and then the value of MAE for test data is 1.00. Thus, the findings indicates that that the Random Forest regression model outperforms the other models in terms of not only the lowest error and highest prediction rate but also the shorter execution time to forecast LOS for patients.

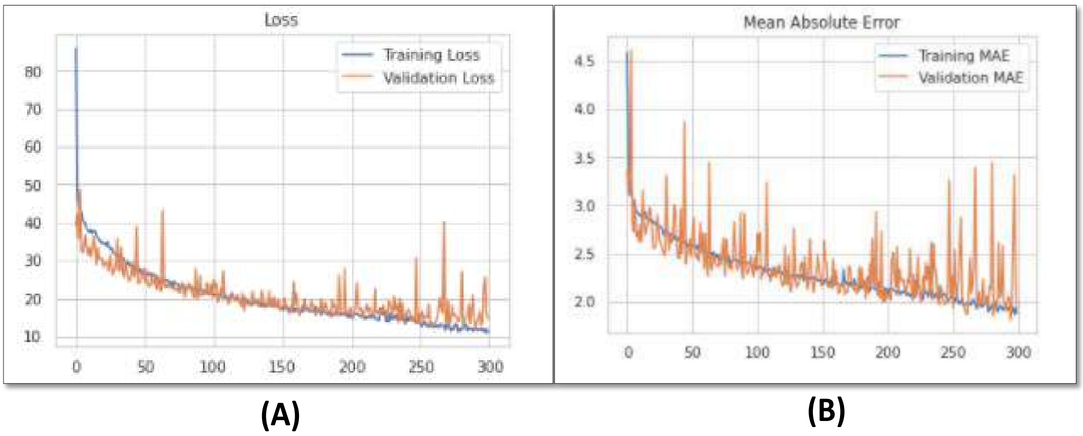


Figure 4.6: Loss and MAE values for each epoch in DNN Model

4.2.4 Discussion

Predicting the length of a patient's stay in the hospital is a potentially useful practice for hospital resource management and the provision of high-quality healthcare. In this research, to estimate the length of a patient's hospital stay, a machine learning technique using Random Forest Regression model with Principal Component Analysis (PCA) feature selection and interquartile range based outlier identification and elimination approaches is proposed. To validate the suggested methodology including the effects of feature prioritization and outlier elimination; the dataset had been preprocessed very meticulously and then ten different regression models including the Random Forest model were executed in a variety of scenarios such as with and without selected feature sets as well as outlier data.

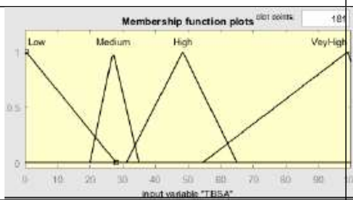
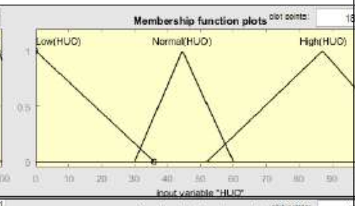
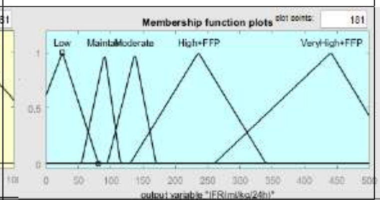
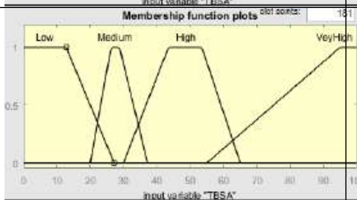
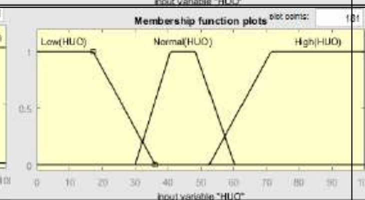
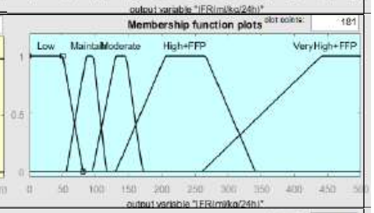
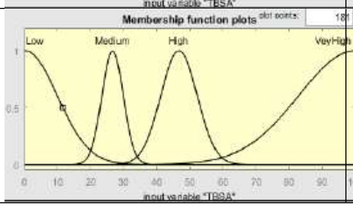
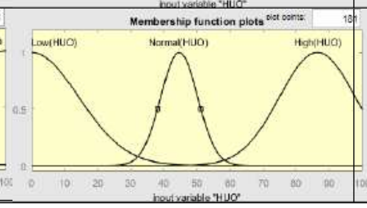
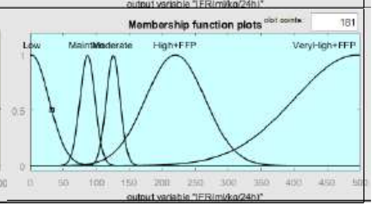
The experimental findings reveal that, the Random Forest regression model performs better with the least MAE and RMSE and a higher R2 score in a reasonable amount of execution time in comparison to all other models. The findings of the comparative analysis of several types of scenarios also demonstrate that detecting and eliminating outlier data may substantially lower the error rate in all regression models. It has also been observed that after applying the PCA feature selection approach to the dataset and using a reduced feature set, almost all regression models perform better.

The findings of this study will greatly benefit healthcare providers in predicting the length of a patient's stay at an early stage, which will aid in delivering excellent service while assuring adequate resources for the patients. Patients can also get benefited from knowing their expected duration of stay in the hospital, estimating treatment expenditures, and managing their other personal affairs accordingly. Furthermore, the investigation results can also be highly advantageous to other researchers to acknowledge the performance of different regression models, as well as the impact of rigorous preprocessing, outlier removal and feature selection approaches for preferable prediction. However, the proposed methodology for this phase of the thesis has been published in one of the reputed conferences [128]

4.3 Experimental Results for Treatment Management

The implementation of the fuzzy fluid resuscitation model has been done using MATLAB following the proposed methodology. Here, %TBSA and HUO are considered to be the inputs and IFR is considered to be the output. Applying different types of membership functions and deffuzzification methods in fuzzy inference system the output of the system has been determined and then the predicted value of IFR has been compared with the manual calculation which is typically followed by the physicians. Three types of membership functions has been applied to the input and output parameters of the fuzzy logic system are shown in the Table 4.5. Furthermore, the comparative result analysis has been conducted considering 3 test case scenarios for different input values of %TBSA and HUO. The analysis results of this study are discussed hereafter.

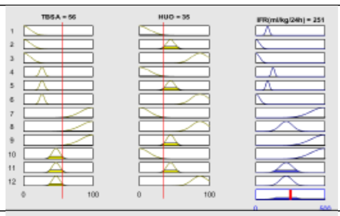
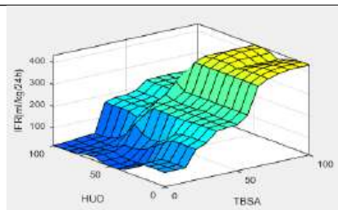
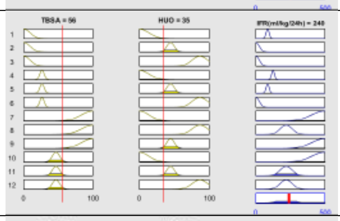
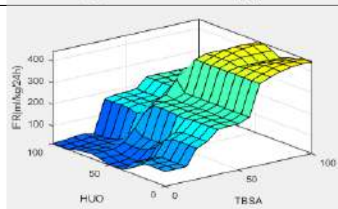
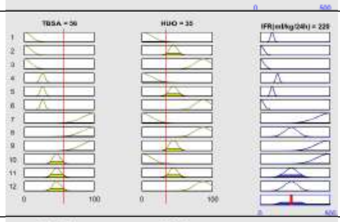
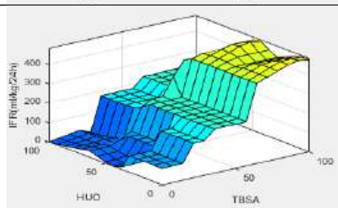
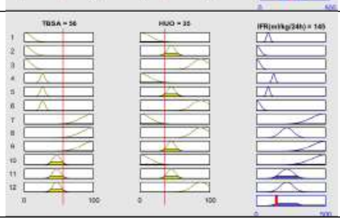
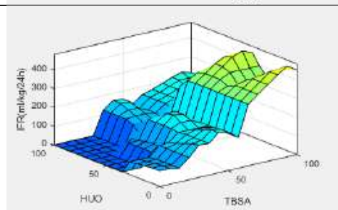
Table 4.5: Fuzzy Input and Output Variables with Different Membership Functions

MF	%TBSA	HUO	IFR
Triangular			
Trapezoidal			
Gaussian			

4.3.1 Test Case 01 (56% %TBSA and 35ml/hr HUO)

As the first test case, a random scenario has been considered that a patient's clinical data represents %TBSA being 56% burned with 35ml/hr HUO. Now the output of the intravenous fluid rate per kilogram weight of this patient in 24 hours for this scenario will be predicted using fuzzy fluid resuscitation model proposed in this study applying different defuzzification methods and membership functions. Further, the manual calculation for determining the IFR will be conducted under the supervision of a doctor to justify the correctness of the acquired result.

Table 4.6: Findings for Test Case 01 with Gaussian Membership Function and Different Defuzzinfication methods

Defuzzification methods	Results (Rule View)	Results (3D View)	IFR Crisp Output
Center of Area			251 ml/kg
Bisector of Area)			240 ml/kg
Medium of Maximum)			220 ml/kg
Smallest of Maximum			145 ml/kg

Fuzzy Fluid Resuscitation Model Results: The clinical data %TBSA = 56% and HUO= 35ml/hr has been first applied to the fuzzy resuscitation model as the crisp inputs. The crisp input values are then converted to the fuzzy input values using membership functions in the fuzzifiction phase. Three sorts of different models were created utilizing three types of membership functions for comparative analysis. Aggregating the fuzzy knowledge base and the fuzzy input sets, the fuzzy inference engines generate a fuzzy output of the IFR. Finally, each of these model's fuzzy output values have been tested with four different types of defuzzification procedures. Table 4.6 illustrates an example of the fuzzy fluid resuscitation model outcome where Gaussian membership functions has been used to fuzzify the input and output parameters for test case 01. Here four types of deffuzzification methods (COA, BOA, MOM, SOM) have been applied to compare the results. The table also includes the results in rule based view and the 3D surface view of the model. The output from this model reveals that with the same input and output parameters the four different defuzzification methods provide different types of output values for IFR such as, COA method predicts the IFR to be 251ml/kg, BOA predicts 240ml/kg, MOM predicts 220ml/kg and SOM predicts 145ml/kg. In a similar manner the predictions for IFR have been determined using triangular and trapezoidal membership functions in the fuzzification steps.

Manual Calculation Result:

By following the clinical burn protocol with parkland formula and the according to the urinary output of the patient, the manual calculation for this case has been done under the supervision of two physicians who have expertise in treating critically burnt patients. Here, the general protocol follows that if the burn is $> 30\%$ and the hourly urine output is in normal range (30ml-50ml), then the IFR will be $(4\times\%TBSA)$ amount of Lactated Ringers or Isolyte etc. in addition to $(0.5\times\%TBSA)$ amount of fresh frozen plasma (FFP). Thus for this case, the total amount of intravenous fluid according to the physician's measurement is approximately $[(4 \times 56) + (0.5 \times 56)] = 252ml/kg$ in 24 hours for the burn patient.

Comparative Analysis:

Table 4.7 represents the IFR output values that have been obtained from various types of fuzzy resuscitation models with various sorts of defuzzification procedures as well as the output from manual calculation. From the table it is evident that with different types of models and defuzzification techniques the output of IFR varies significantly. Therefore, to explore the best performing fuzzy model and justify the outcome, an external validation under the supervision of a doctor is necessary here; for which the manual calculation for the test case scenario has been conducted. The comparative analysis reveals that, considering the general medical practice the tentative amount of IFR for per kg weight of patient in 24 hours would be 252ml/kg for 56% TBSA burn with 35 ml/hr urine output. It can be observed that, the output of IFR using COA defuzzification technique is closely similar to this manually computed result in all the three types of models: triangular MF is 248 ml/kg, trapezoidal MF is 255 ml/kg, and Gaussian MF is 251 ml/kg. Following that the BOA deffuzzification technique shows next closely related results (245ml/kg, 245ml/kg, 240ml/kg) and MOM being the following one (235ml/kg, 238ml/kg, 220ml/kg). It can also be seen that SOM provides the least closely related value in this case to the manually calculated result (170ml/kg, 170ml/kg, 145ml/kg). Thus, in context of defuzzification methods utilized here, the COA defuzzification technique offers the best outcome in this specific test situation and it becomes remarkably identical when Gaussian membership function has been utilized as input and output fuzzification.

Table 4.7: IFR output from the FLS with Test Case 01

	Triangular MF (ml/kg)	Trapezoidal MF (ml/kg)	Gaussian MF (ml/kg)	Manual Calculation (ml/kg)
COA	248	255	251	252
BOA	245	245	240	252
MOM	235	238	220	252
SOM	170	170	145	252

4.3.2 Test Case 02 (25% %TBSA and 15ml/hr HUO)

As the second test case scenario it has been considered in this research that, a patient's %TBSA being 25% burned with 15ml/hr HUO. Here similar to the first test case scenario, several models with different membership functions and defuzzification techniques as well as the manual clinical calculation have been performed to predict the IFR. According to manual calculation, when the %TBSA is in between 20-29% and the urine output per hour is less then the sufficient, then the rate of intravenous fluid will be according to Parkland Theorem $(4 \times \%TBSA)$ with additional 20% fluid. So according to physicians' calculation output value will be approximately $[(4 \times 25) + 20\%] = 120ml/kg$ IFR for a patient in 24 hours. Now, applying different models of the proposed fuzzy resuscitation model, the IFR has been determined. The output obtained from these calculations are illustrated in Table 4.8. Here also it can be seen that COA defuzzification method provides closely similar values to the clinical assumptions (triangular MF- 125ml/kg, trapezoidal MF- 127ml/kg , Gaussian MF- 123 ml/kg). After COA, in this case SOM method provides closely matched values (118ml/kg, 122ml/kg, 115ml/kg) followed by MOM (135ml/kg, 138ml/kg, 130ml/kg) and BOA (139ml/kg, 135ml/kg, 132ml/kg) methods.

Table 4.8: IFR output from the FLS with Test Case 02

	Triangular MF (ml/kg)	Trapezoidal MF (ml/kg)	Gaussian MF (ml/kg)	Manual Calculation (ml/kg)
COA	125	127	123	120
BOA	139	135	132	120
MOM	135	138	130	120
SOM	118	122	115	120

4.3.3 Test Case 03 (75% %TBSA and 59ml/hr HUO)

Finally, the third test case scenario that has been considered for calculation here is that, a patient's %TBSA is 75% burned with 59ml/hr HUO. According to manual calculation, here the burn is higher with $\%TBSA > 55\%$, and the urine output is also higher than the usual (more than 50ml). Thus, in this case, the fluid rate will be decreased by 20% from the parkland theorem as the urine output is higher, with added Fresh Frozen Plasma-FFP (0.5 * %TBSA) as the burn rate is also high. Thus, the fluid rate will be tentatively $[(4 \times 75) - 20\% + (0.5 \times 75)] = 277.5ml/kg$ in 24 hours according to clinical decision. Now similar to the previous test cases, these input values of %TBSA and HUO are applied to different models of fuzzy resuscitation CDSS. The output obtained from these calculations are illustrated in Table 4.9. In this case also COA defuzzification method shows better result with closely matched values of IFR (triangular MF-276ml/kg, trapezoidal MF- 274ml/kg, Gaussian MF- 277 ml/kg) followed by BOA, MOM and SOM methods.

Therefore, the comparative analysis acquired from the 3 test cases implies that, fuzzy fluid resuscitation model can provide satisfactory results comparing the critical manual assessment for burn resuscitation. The results also indicate that COA defuzzification method provides a better result in all the cases irrespective of the membership function used. On the other hand, when it comes to membership functions, table 4.7, 4.8, and 4.9 show that using a Gaussian membership function to fuzzify the input and output sets produces less error than using triangular or trapezoi-dal membership functions. Therefore, the comparative result analysis from different models with different test cases indicates that utilizing %TBSA and HUO as crisp inputs and then using Gaussian MF in the fuzzification process with COA defuzzification method can formulate the best performing fuzzy model with the proposed methodology for forecasting IFR with better accuracy.

Table 4.9: IFR output from the FLS with Test Case 03

	Triangular MF (ml/kg)	Trapezoidal MF (ml/kg)	Gaussian MF (ml/kg)	Manual Calculation (ml/kg)
COA	276	274	277	277.5
BOA	265	260	268	277.5
MOM	246	248	230	277.5
SOM	155	160	115	277.5

As the results from the three test cases have revealed that, the fuzzy model employing Gaussian MF and COA defuzzification technique provides best performance, additional seven test cases with different values of %TBSA and HUO are again simulated using the best performing model. The evaluation result has been shown in Table 4.10. The Table also demonstrates the clinical instructions provided by the physicians according to the values of input variables for each test cases and the prescribed manual calculation of IFR. From the evaluation results of Table 4.10, it is apparent that for all the test cases the predicted values of fuzzy model using Gaussian MF and COA defuzzification method are significantly close enough to the clinically calculated ones. This result indicates that, the proposed model performs good in predicting the IFR of burn patients which can also be implemented in the real-time scenario.

Table 4.10: IFR output from the proposed FLS with multiple Test Cases employing Gaussian MF and COA defuzzinfication technique

Test Case No.	%TBSA	HUO (ml/hr)	Fuzzy Model Prediction (ml/kg) (MF-Gaussian, Defuzz-COA)	Clinical Instruction	Manual Calculation (ml/kg)
4	20%	15	83	Maintain standard Fluid rate	(4x20) = 80
5	35%	30	139	Maintain standard Fluid rate	(4x35) = 140
6	30%	75	91	Decrease Fluid rate by 20% from standard	{(4x30)-20%} = 96
7	50%	25	228	Maintain fluid rate and add FFP by (0.5x%TBSA)	{(4x50)+(0.5x50)}=225
8	60%	20	291	Maintain fluid rate and increase FFP by 50ml/hr	{(4x60)+50}=290
9	70%	60	309	Maintain fluid rate and add FFP by (0.5x%TBSA)	{(4x70)+(0.5x70)}=315
10	85%	30	394	Maintain fluid rate and increase FFP by 50ml/hr	{(4x85)+50} = 390

4.3.4 Discussion

The standard medical procedure for calculating intravenous fluid rate requires careful and tedious calculations based on the patient's urine output and the percentage of his body that has been burnt. When predicting the appropriate volume of fluid required for resuscitation, this procedure can often be extremely tricky to perform manually. In such cases, a fuzzy fluid resuscitation model can serve as an intelligent decision support system, assisting in the speedy and accurate prediction of the required intravenous fluid rate for the patients. Such kind of automated system will be beneficial to both the healthcare providers and the patients. Through this approach the physicians will be able to anticipate intravenous fluid requirements quickly from this fuzzy automated model, and therefore the burnt patient's treatment procedure can be initiated immediately by replenishing the fluid loss to prevent fatalities.

However, in clinical decision support system, results must be very close with the traditionally practiced outputs and specially in case of fluid resuscitation the estimated IFR should be close enough to the real-time clinical calculation. The proposed system has been designed supporting this concept. Fuzzy logic has gained much acceptance with higher success in various fields including clinical decision providing system as the fuzzy model resembles reasoning capability like a human. As the fuzzy logic system does not require any training to learn. The comparative study of the proposed system has been conducted through simulation. Here, the testing of the proposed system has been conducted through simulation employing three different membership functions and four different defuzzification methods which have been experimented through multiple test cases for comparison, validation as well as determination of the best model. Moreover, by using the traditional formula with the help of a couple of physicians, the traditional calculation of IFR has been determined and compared with the proposed system outputs for validation.

The proposed fuzzy model for anticipating intravenous fluid rate can be implemented in the future with a suitable user interface, so that physicians can provide inputs to the system and the system will automatically generate an output to predict the required intravenous fluid rate in the practical medical field. However, in this study, one output variable was utilized to predict the amount of intravenous fluid required per kilogram of body weight in 24 hours for a patient. In the future, the fuzzy system's output variable may be separated into two parts: one output variable will forecast fluid requirements in the first 16 hours (which are typically higher), and the second output variable will predict fluid requirements in the latter 8 hours (which is generally lesser) to imitate the more accurate practice of burn fluid resuscitation in the hospitals. Furthermore, researchers hope to construct fuzzy fluid resuscitation models for additional types of causalities in the future, other than burn victims.

Today, with the advancement of research and technology, medical science is increasingly incorporating various intelligent and innovative computational approaches, allowing more people to get benefited from less manual mistakes. Thus, developing an effective and usable fuzzy fluid resuscitation model for burn patients can assist the clinical system in overcoming fluid deficiencies of burn patients in the quickest period feasible precisely with the least degree of danger. However, the proposed methodology for this phase of the thesis has been published in one of the reputed peer-reviewed journal [129].

Chapter 5

Sustainability Assessment of Proposed Methodology

Healthcare decision-making is a complicated aspect that requires collaboration among stakeholders, whilst ensuring its sustainability is essential for addressing the requirements of healthcare facilities. Artificial intelligence (AI) in healthcare decision-making based on clinical knowledge and data are gaining traction as a way to enhance healthcare delivery by making smart diagnosis and treatment decisions. However, there are indeed a number of factors that require comprehensive inspection to ensure a sustainable AI-based decision making system in the healthcare domain. Therefore, this research explores 15 key sustainability indicators for incorporating AI applications in healthcare decision-making and performs a systematic assessment to prioritize the indicators according to the viewpoints of 35 relevant experts in context of the Bangladeshi health industry. Professional judgements on the level of significance for each indicators have been converted into quantitative data and plotted graphically in terms of their relative importance and divergence of opinions. Furthermore, the indicators have been categorized into three groups using two types of clustering techniques: K-means and agglomerative clustering approaches. According to the findings of the investigation, among the three clusters, one of them consisting of six indicators have considerably greater relative importance values with lesser opinion divergence, and hence are extremely crucial factors for ensuring sustainability. Thus, this research will guide healthcare practitioners with deeper perspective in undertaking appropriate strategies, focusing on the critical indicators for embracing AI-based techniques in developing nations' healthcare decision-making arena.

5.1 Sustainability Assessment of Artificial Intelligence in Healthcare Decision Making: An Emerging Country Context

Decision making is a cognitive method that entails obtaining information and evaluating different solutions with an aim to determine a decision from two or more operations in a relevant field. Healthcare decision making is a complex area of health industry that involves a collaborative interaction between healthcare providers, investors, govt., policy makers as well as individuals who seek treatment, including patients and their caregivers; where the satisfaction and preferences of the person accessing the healthcare should be at the forefront of decision-making [130]. The healthcare industry is more complicated arena since it brings together a wide range of stakeholders and typically integrates operational, environmental, experiential, clinical, and organizational goals with dynamic nature [131]. Healthcare industry being an irreplaceable and precious commodity, the finest decisions in this field including how to distribute resources or which treatments and medicines to prescribe, are challenging to make and justify manually, since decision-making methods tailored to healthcare issues must be extensive, transparent, and clearly combine social and health-care aspects. Furthermore, governments, donors, and technical support partners are increasingly focusing on the outcomes of cost analyses as well as other economic evaluations such as budgeting, financial planning, and benchmarking of expenditures corresponding to many factors with wide variations in the techniques and data in healthcare decision-making process . As a result, it is crucial to implement a sustainable decision-making system that can meet the demands and requirements of healthcare facilities as well as the expectations of stakeholders.

In recent times, researchers have been using various multi-criteria decision making (MCDM) methodologies such as the Analytic Hierarchy Method (AHP) to handle real-time challenges in healthcare decision making; but unfortunately including various stakeholders in such decision-making process in healthcare industry becomes much complex for establishing a sustainable solution, and it may make attaining agreement much more challenging as well as time consuming, as each stakeholder may have different interests, priorities and perspectives. Moreover, health-related information is constantly evolving due to factors such as volume, velocity,heterogeneity, and complexity of real-time data, making it difficult to make decisions based on such high-dimensional data. In such cases, Artificial Intelligence(AI) based computational decision providing applications not only provides a smart alternate solution for managing the entire healthcare decision making system in a quickest possible time, but also aids in accurate diagnosis and prediction of various critical health issues, assigning healthcare professionals, providing effective resource management, offering home care advice, and prescribing personalized medication etc. [132]. AI has boosted robotics and automation breakthroughs, which has far-reaching ramifications in almost every aspects in real life context. Although using healthcare knowledge and data to generate AI-based decision-making systems that can enhance healthcare delivery with improved diagnosis and treatment decisions has the potential to dramatically improve the global healthcare systems with increasing interest and investments of the stakeholders; there are indeed a number of ethical, regulatory, and financial factors to consider for ensuring its sustainability .

Therefore, the objective of this research is to perform a comprehensive sustainability assessment of deploying AI-based applications in healthcare decision making area, taking into account the perspectives of relevant experts in adopting AI-based healthcare decision making practices in context of the Bangladeshi health industry. To accomplish the objective, the important sustainability indicators for applying and adopting AI-based applications in healthcare decision making have been investigated by observing the functional healthcare domain of Bangladesh as well as performing an extensive literature study. Following that, a questionnaire survey analysis have been carried out, with 35 experts from relevant sectors who has provided their opinions on the relevance and importance of each sustainability indicator. The survey results are then transformed into quantitative data in order to determine the standardized relative importance and opinion divergence of each indicator; which are further plotted graphically to divide them into groups or clusters. The indicators are thereby split into three categories using two types of clustering techniques: K-means and agglomerative clustering methods. As a result of the cluster analysis, the group of indicators with high relative importance values and low opinion divergence can be claimed to be the most important aspects to consider for ensuring sustainability. Therefore, the research can provide valuable insights to the stakeholders as well as assist healthcare professionals in understanding which factors should be prioritized when implementing an AI-based decision making system in Bangladesh's healthcare sector and also can direct the practitioners in taking appropriate actions to fulfil the requirements. The key contributions of this research has been highlighted hereafter:

- The essential sustainability indicators for applying and adopting AI-based applications in healthcare decision making arena have been explored.
- A survey analysis have been conducted employing relevant experts to investigate the significance of the indicators.

- The indicators are categorized into clusters employing clustering algorithms based on their relative importance and opinion divergence from expert judgments.
- The cluster comprising the most significant factors is addressed in depth, which are crucial in ensuring long-term viability of AI in healthcare decision-making.

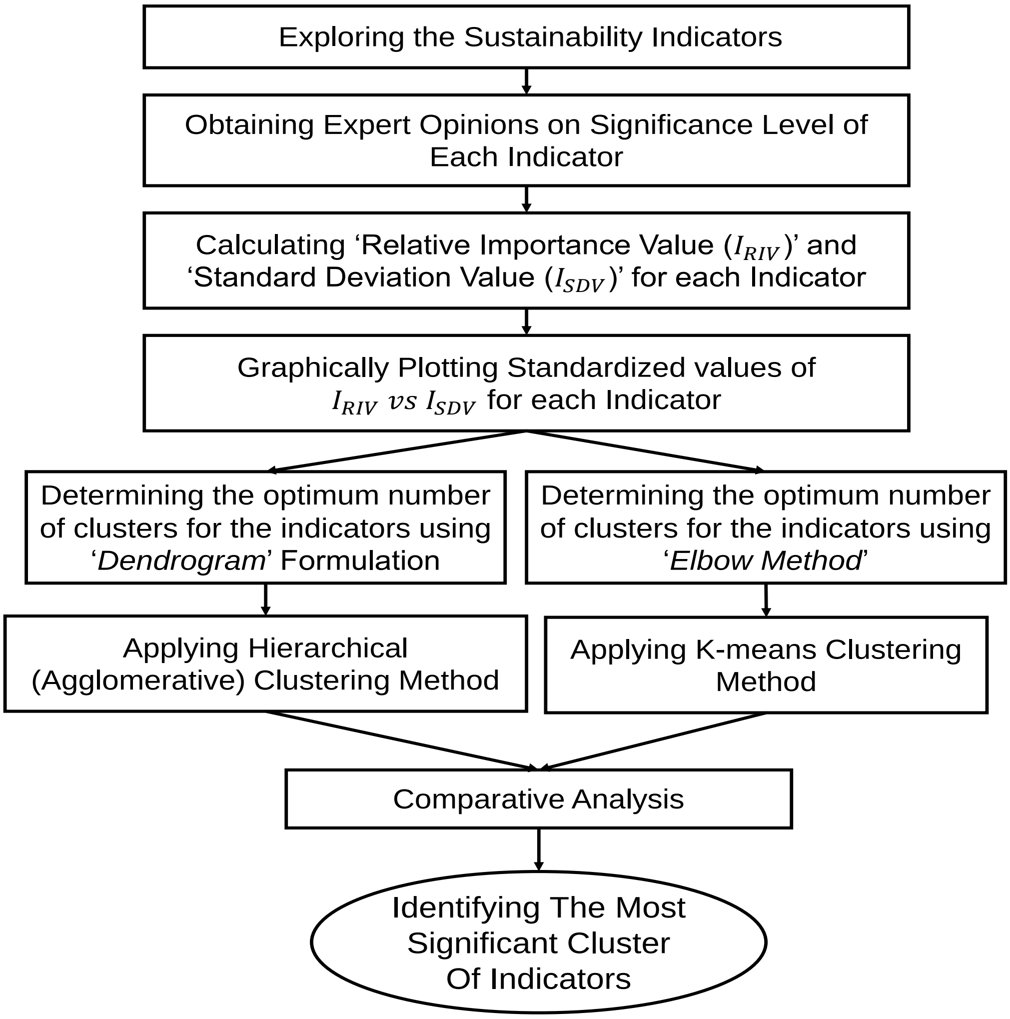


Figure 5.1: Framework of research methodology

5.2 Methodology for Sustainability Assessment

This research has been carried out in multiple stages to assess the sustainability indicators for incorporating applications of AI in healthcare decision-making in developing countries, particularly in the context of the Bangladeshi healthcare system. The framework of the methodology used in this research is illustrated in Figure 5.1 and described briefly below.

Table 5.1: List of the sustainability indicators

Code	Sustainability Indicators	Ref.
I0	Clinical performance of the system	[134], [135]
I1	Infrastructure support for establishing & running the system	[134], [135], [136], [137]
I2	Consistency & relevance with the existing clinical practices	[137], [138]
I3	Managerial performance of the system	[134], [77]
I4	Social impact, cultural perceptions with acceptance and trust of adopters	[135], [139]
I5	Individual competency of associated healthcare personnel to handle the system	[139], [140]
I6	Environmental impact of the system	[141], [142]
I7	Patients' satisfaction from the system	[134], [135]
I8	Structured implementation with continuous monitoring & maintenance to run the system	[136], [140]
I9	Healthcare professionals' & investors' satisfaction from the system	[136], [143]
I10	Acquiring accreditation of the system	[77]
I11	Cost- effectiveness of the system with efficiency, utility & quality of service	[143], [144]
I12	Maintenance of clinical data accessibility & privacy with availability, authenticity, correctness	[145], [146]
I13	Consideration of 'ethical' issues in decision making	[147], [148]
I14	Policy settings & supports from Govt. & healthcare institutions as per the contextual need of the system	[143], [149]

Initially, the sustainability indicators or factors that are necessary for ensuring the long term viability of combining AI in healthcare decision making sector have been investigated by monitoring the practical healthcare domain of Bangladesh as well as conducting a comprehensive literature review. After extensive inspections, the 15 crucial sustainability factors have been explored by the authors which are listed in Table 5.1. The research data for this assessment has been gathered by a questionnaire survey approach from relevant experts, based on the sustainability indicators provided in Table 5.1. The survey questions are set on the sustainability indicators of integrating AI into healthcare decision-making, which ask about the experts' perspectives on the level of significance for each indicator. Every expert who took part in the survey has been asked to assess the indicators based on a Likert scale ranging from 1 to 5, which is a commonly practiced method for obtaining perspectives about the importance of a topic [133]. The linguistic and numerical representation of five-point Likert scale followed in this study is shown in Table 5.2.

A total of 35 experts took part in the survey, which had been performed both online (through email) and offline (in face-to-face interviews). The participants of this study were from various backgrounds and professions mostly related to healthcare sector. Among the expert participants, 17 were physicians who are currently working in various government and private hospitals of Bangladesh; 5 were engineers as well as researchers and experts in technology management field; 4 were information technology specialists having expertise in various fields of computer science; and 9 were researchers as well as university faculties who typically conducts various AI related researches. However, the participants were also asked to provide their suggestions or recommendation to develop a sustainable AI based decision support system in healthcare domain of Bangladesh.

Table 5.2: Level of significance scores

Level of importance (linguistic representation)	Numerical score
Not Important(NI)	1
Less Important(LI)	2
Neutral (N)	3
Important(I)	4
Very Important(VI)	5

After gathering the expert opinions about the level of significance for each of the sustainability indicators, the next phase is to identify the relative importance of each indicators through 'Relative Importance Value (RIV)' as well as the difference of expert perspectives among the participants about the same indicator through 'Standard Deviation Value(SDV)' measurements. If the selected sustainability indicators are represented as I_i where $i = 1, 2, 3...15$, the number of responses are n and the numerical scores given to indicator I_i by the participants are represented as x_j; then the equations for calculating the Relative Importance Value (RIV) and Standard Deviation Value(SDV) for each indicator are as follows [150]:

$$I_{RIVi} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{5.1}$$

$$I_{SDVi} = \sqrt{\frac{\sum_{j=1}^{n} (x_j - I_{RIVi})^2}{n}} \tag{5.2}$$

Now, to standardize the values of features (I_{RIV} and I_{SDV}) from diverse dynamic ranges into a a particular range, the Z-score standardization approach has been utilized in this study that converts normal variants into a standard score form. The formulas for standardization are as follows, where m represents the number of indicators:

$$\bar{I}_{RIV} = \frac{\sum_{i=1}^{m} I_{RIVi}}{m} \tag{5.3}$$

$$\bar{I}_{SDV} = \frac{\sum_{i=1}^{m} I_{SDVi}}{m} \tag{5.4}$$

$$Z(I_{RIVi}) = \frac{I_{RIVi} - \bar{I}_{RIV}}{\frac{1}{m}\sum_{i=1}^{m} |I_{RIVi} - \bar{I}_{RIV}|} \tag{5.5}$$

$$Z(I_{SDVi}) = \frac{I_{SDVi} - \bar{I}_{SDV}}{\frac{1}{m}\sum_{i=1}^{m} |I_{SDVi} - \bar{I}_{SDV}|} \tag{5.6}$$

Here, $\bar{I}_{RIV}$ and $\bar{I}_{SDV}$ represents the mean of relative importance values and standard deviation values of the indicators. And, $Z(I_{RIVi})$ and $Z(I_{SDVi})$ represents the standardized values of relative importance values and standard deviation values of the indicators which are then plotted graphically keeping $Z(I_{RIVi})$ in the X-axis and $Z(I_{SDVi})$ in Y-axis.

5.2.1 Clustering the sustainability indicators

Following that, to identify the group of indicators which are relatively more important to consider, the indicators have been separated into clusters. The clustering is conducted over the graphical representation that has been formulated using the standardized relative importance value $Z(I_{RIV})$ and standard deviation value $Z(I_{SDV})$ of the sustainability indicators. For clustering the data points, two types of unsupervised clustering techniques have been employed here, which are K-means clustering and hierarchical or agglomerative clustering methods. The Google Colaboratory was utilized as a platform for developing both types of clustering techniques using the Python Scikit-Learn tools.

The first clustering technique here has been the K-means clustering algorithm, for which the optimum number of groups has been determined using the heuristic 'Elbow method' where K is the number of clusters. For several values of K, the elbow technique depicts the sum of squared distances between each point in a cluster and the centroid, resulting in an arm-like graphical structure with the optimal number of clusters at the point of inflection or the 'elbow' of the curve . Thus, after determining the optimum number of clusters, the K-means clustering technique is applied to the data-points to group the sustainability indicators.

To validate the clustering result of the k-means approach, the second clustering technique that has been utilized here is the agglomerative clustering. To identify the optimum number of clusters in the agglomerative clustering approach, a binary merge tree known as 'dendrogram' is formulated which represents the hierarchical relationship. The tree is formulated in agglomerative clustering in a bottom-up manner, beginning with the single data items placed at the tree's leaves and merging the pair with the most identical sub-sets to store at nodes until the tree's root is reached, which contains all the data elements [151]. From the dendogram tree which data points are in which cluster can also be determined easily. Therefore, the data points are divided into clusters according to the agglomerative tree structure.

Furthermore, the clustering results obtained using the two techniques are compared, and the cluster with the higher relative importance values and lower standard deviation values is considered to be the most significant cluster of indicators for ensuring the long-term viability of AI in healthcare decision-making in context of Bangladesh.

5.3 Result Analysis

The following sections have been organized to present the findings from the interpretation of research results.

5.3.1 Data Analysis

After exploring the sustainability indicators, the 35 experts of this study provided their opinions on the level of significance for each indicators via a survey which have been summarized in Table 5.3. For example, here the for the Indicator I0 which is 'Clinical performance of the system', 17 experts identified it to be a very important (VI) indicator, 11 of them marked it as important(I), 7 of them found it to be Neural(N) and none of them marked it as less important(LI) or not important(NI).

Applying equations (1) to (6) for each indicator's expert significance values of Table 5.3, the values of I_{RIV}, I_{SDV}, $Z(I_{RIV})$ and $Z(I_{SDV})$ have been calculated which are listed in Table 5.4. For all the indicators at first I_{RIV} and I_{SDV} have been calculated using equation (1) and (2). Then their mean values $\bar{I}_{RIV}$ and $\bar{I}_{SDV}$ have been generated from equation (3) and (4). Finally from equation (5) and (6) standardized values $Z(I_{RIV})$ and $Z(I_{SDV})$ have been calculated. Positive $Z(I_{RIV})$ and $Z(I_{SDV})$ values of Table 5.4 indicate that they're on the right side of the mean value whereas negative $Z(I_{RIV})$ and $Z(I_{SDV})$ values represent they are on the left side of the average value.

Table 5.3: Expert responses about the level of significance for each indicators(35 response)

Indicator Code	NI	LI	N	I	VI
I0	0	0	7	11	17
I1	0	0	4	9	22
I2	0	4	14	10	7
I3	5	9	10	9	2
I4	2	8	15	8	2
I5	0	2	5	13	15
I6	6	12	10	5	2
I7	0	1	6	12	16
I8	3	6	8	10	8
I9	0	0	8	15	12
I10	7	11	5	9	3
I11	0	1	5	13	16
I12	0	6	9	10	10
I13	0	2	11	10	12
I14	1	8	9	9	8

5.3.2 Cluster Analysis

The values of $Z(I_{RIV})$ and $Z(I_{SDV})$ generated in Table 5.4 for each of the indicators are plotted in graphical form which has been illustrated in Figure 5.2. Here, the x-axis of the graph represents the standardized relative importance $Z(I_{RIV})$ and the y-axis represents the standardized standard deviation $Z(I_{SDV})$ values for each indicators. The acquired data-points in Figure 5.2 are then grouped into clusters using two different types of clustering techniques which are k-means clustering and hierarchical or agglomerative clustering technique.

For determining the optimum number of clusters in the k-means clustering method, elbow technique had been used which has been shown in Figure 5.3(A). Here, the point of inflection is at $k = 3$ which indicated the optimum number of clusters with this data points should be 3. Thus, considering $k = 3$, the k-means clustering algorithm has been applied to the data-points of $Z(I_{RIV})$ vs $Z(I_{SDV})$ for each of the indicators which has divided the them into 3 groups illustrated in Figure 5.3(B).

Now for validating the clustering result obtained from k-means algorithm as well as to determine which data points have been included in each clusters, the agglomerative clustering technique have been employed. The dendrogram tree structure obtained from agglomerative clustering has been illustrated in Figure 5.4(A) and and thereby the clustering of the data points using this hierarchical algorithm has been shown in Figure 5.4(B) which shows similar result of clusters as the previous technique. The advantage

Table 5.4: Data characterization and standardization values

Indicator Code	I_{RIV}	I_{SDV}	$Z(I_{RIV})$	$Z(I_{SDV})$
I0	4.286	0.777	1.163	-1.219
I1	4.514	0.692	1.502	-1.76
I2	3.571	0.935	0.069	0.325
I3	2.828	1.133	-1.493	1.033
I4	3.00	0.956	-0.493	0.186
I5	4.171	0.877	0.955	-0.583
I6	2.571	1.103	-1.962	0.839
I7	4.228	0.831	1.059	-0.879
I8	3.4	1.247	-0.452	1.619
I9	4.114	0.747	0.851	-1.409
I10	2.714	1.277	-1.701	1.945
I11	4.257	0.805	1.211	-1.043
I12	3.686	1.063	0.069	0.588
I13	3.914	0.937	0.542	0.479
I14	3.429	1.153	-0.399	1.059

of hierarchical clustering is that from the dendrogram tree the data point distribution to the clusters can be clearly estimated. Here, as the cluster findings from the two techniques in Figure 5.3 and Figure 5.4 have resulted to be same, therefore it can be said that the optimum clustering have been formed with the data points of sustainability indicators.

5.3.3 Implications of the findings

Here analyzing the dendrogram and the plots of clustering it can be anticipated that the Cluster 1 with higher values of standard deviation and lower values of relative importance contains 3 indicators which are I10,I3,I6. Cluster 2 with comparatively medium standard deviation as well as relative importance includes 6 indicators which are I8,I14,I4,I13,I2,I12. And finally the rest of the 6 indicators which are I1,I5,I7,I9,I0,I11 have been grouped to in Cluster 3 having lower values of standard deviation and higher relative importance.

The cluster analysis result obtained from the expert opinions over the 15 sustainability indicators reveals that some of the indicators which are in cluster 3 have lower opinion divergence with higher relative importance and therefore they are very crucial to consider in case of ensuring the sustainability of AI-based applications for healthcare decision making. So these six indicators in cluster 3 have been considered to be highly significant indicators. The three indicators in Cluster 1 with higher opinion divergence and lower relative significance, on the other hand, have been designated as less signifi-

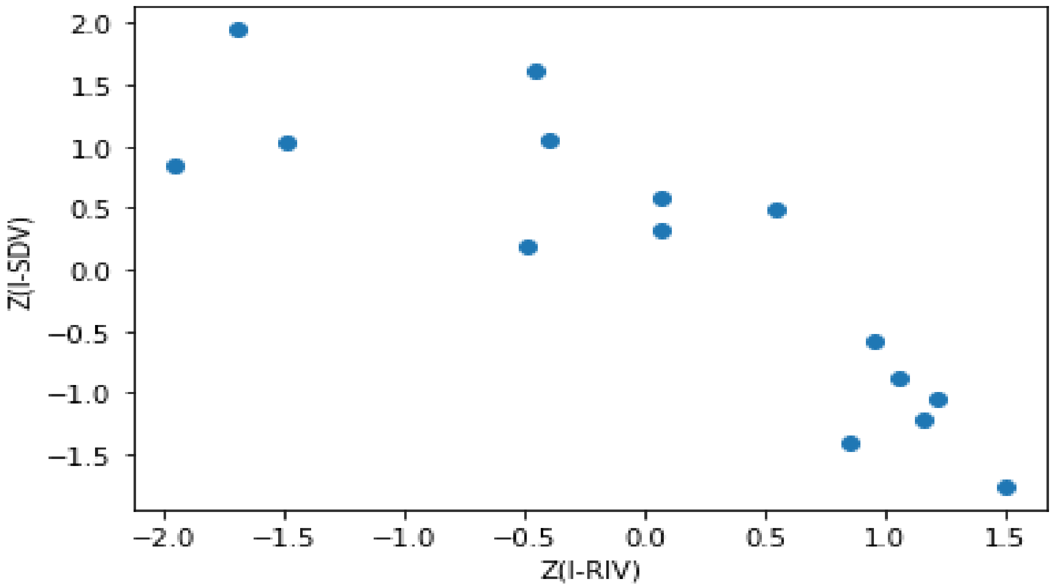


Figure 5.2: Graphical Representation of standardized relative importance $Z(I_{RIV})$ vs standard deviation $Z(I_{SDV})$ values for each indicators.

cant indicators for maintaining the sustainability of the relevant field. Finally, the rest of the six indicators which goes to cluster 2 have medium values of opinion divergence and relative importance and therefore they can be considered to be moderately significant indicators. The sustainability indicators that have been explored to be highly significant are demonstrated briefly hereafter.

- I0:'Clinical performance of the system': This has been revealed to be a highly significant indicator which indicates that the AI systems for healthcare decision making must perform well in terms of accuracy, precision, and responsiveness in case of executing any clinical activities or making sensitive clinical decisions.
- I1:'Infrastructure support for establishing and running the system': This indicates that the healthcare facility must have the capability to provide the required resources, hardware & software compatibility and availability, technical facilities, equipment supply etc. with an overall strong infrastructure support to implement AI-based applications in healthcare decision making field.
- I5:'Individual competency of associate healthcare personnel to handle the system': This is a key factor which implies that relevant healthcare personnel's skills, knowledge, and absorptive ability should be proficient enough with technical competence to conduct and operate the innovative AI-based healthcare decision-making system.
- I7:'Patients' satisfaction from the system': This is another highly significant sus-

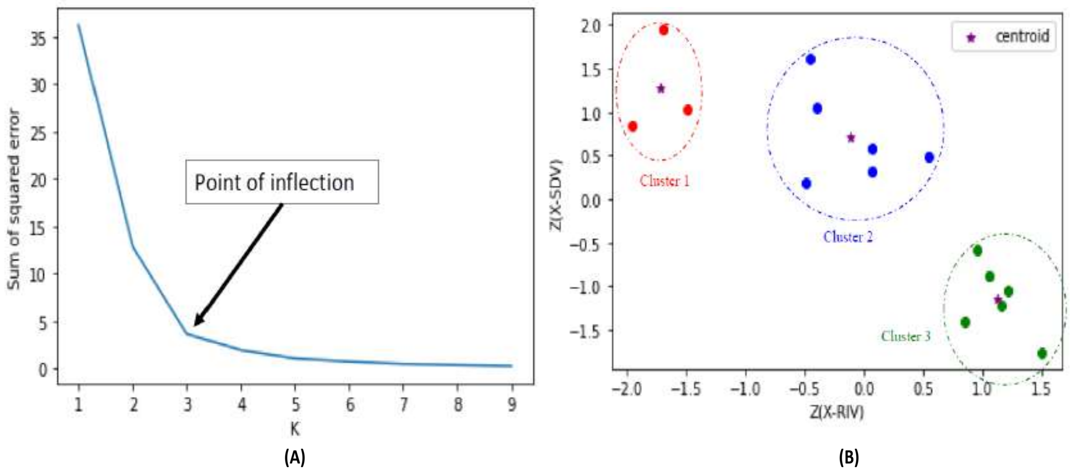


Figure 5.3: Clustering data points using K-means clustering algorithm

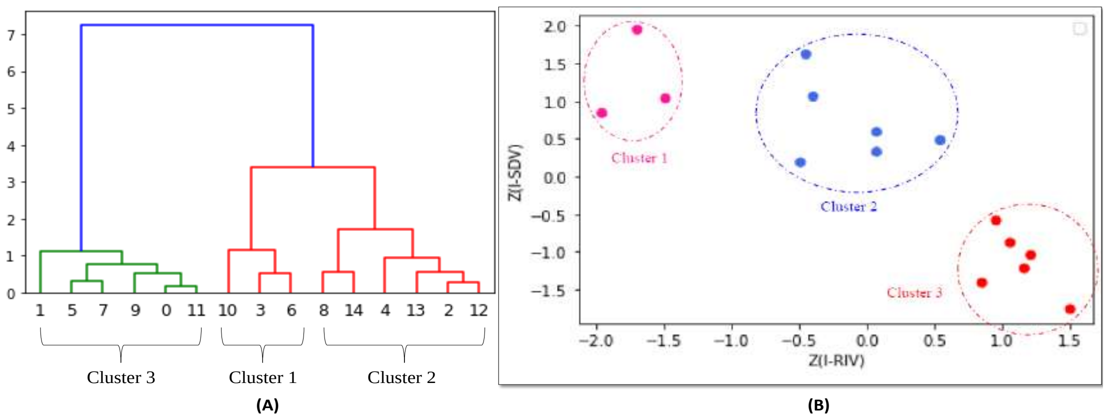


Figure 5.4: Clustering data points using Agglomerative clustering algorithm

tainability indicator that has been emphasized by the experts in this research. As the core aim of the healthcare industry is to provide quality treatment and services to the patients, therefore, it is vital to maintain patient satisfaction with the AI-based healthcare decision making system in terms of comfort, quicker treatment, reliability, privacy protection, and safety maintenance.

- I9:'Healthcare professionals' & investors' satisfaction from the system': The AI-based system should be user-friendly, effective, and efficient enough to keep abreast with healthcare practitioners' opinions, perceptions, attitudes, and system aspirations as well as catch the interest of local investors and stakeholders.

- I11:'Cost-effectiveness of the system with efficiency, utility and quality of service': In terms of developing countries, the deployment and maintenance costs of advanced AI based technological applications become increasingly difficult to bear. As a result, the AI-based decision-making system must be cost-effective enough yet to give high-quality services to patients.

Therefore, the six indicators listed above must be addressed first in order to ensure a long-term sustainable healthcare decision-making system based on AI applications. The expert analysis in this research claims that after concentrating on these indicators, innovators should focus on another six groups of indicators in the following phase which are 'Consistency and relevance with the existing clinical practice'; 'Social impact, cultural perceptions with acceptance and trust of adopters'; 'Structured implementation with continuous monitoring & maintenance to run the system'; 'Maintenance of clinical data accessibility & privacy with availability, authenticity, correctness';'Consideration of 'ethical' issues in decision making'; 'Policy settings & supports from Govt. & healthcare institutions as per the contextual need of the system'.

Finally, according to the analysis, after ensuring all of this above mentioned factors before deploying an AI-based application in healthcare decision making the practitioners lastly should focus on three indicators which are:'Managerial performance of the system'; 'Environmental impact of the system' and 'Acquiring accreditation of the system'.

5.4 Discussion

In this research fifteen key factors that needs to be addressed in order to develop a sustainable AI-based healthcare decision-making system in context of Bangladesh have been explored. In addition, to prioritize these sustainability indicators, they were evaluated by a systematic questionnaire survey that included 35 relevant experts who rated the importance of the sustainability indicators. Furthermore, the survey results were transformed into numerical values and grouped into clusters based on the relative significance and opinion divergence of each indicator. The clustering was performed using both K-means and hierarchical (agglomerative) clustering techniques to verify the correctness of the clustering outcome.

The experimental findings revealed that, the data points of the indicators reflecting standardized relative importance vs. opinion divergence were clustered into three groups by performing both types of clustering algorithms. Among them, one of the clusters including six indicators had a greater relative importance with reduced opinion divergence; indicating that the majority of the experts thought these factors were crucially significant and that their opinions on the importance of these sustainability indicators differed little. With the help of dendrogram tree it had been revealed that these highly significant six sustainability indicators for establishing AI-based healthcare decision making system in context of Bangladeshi healthcare industry would be: clinical performance of the system; infrastructure support for establishing and running the system; individual competency of associate healthcare personnel to handle the system; patients' satisfaction from the system; healthcare professionals' & investors' satisfaction from the system; and finally cost-effectiveness of the system with efficiency, utility and quality of service. Therefore, a research like this would be able to reflect the revolutionary effect of AI-based applications in the healthcare sector of developing countries like Bangladesh, providing deeper insight into the long-term sustainability of implementing such advanced technology especially in healthcare decision making domain. Finally, the findings of the study will aid healthcare practitioners and policymakers in formulating appropriate strategies for promoting AI-based technology adoption in the healthcare decision-making arena with an aim to stay up with the current world in terms of technological advancement.

Chapter 6

Conclusions

This research aggregates the advanced techniques of Artificial Intelligence and proposes a framework for intelligent healthcare decision support system focusing on decision making in the three core domains of healthcare sector, which are disease prediction, resource management and treatment management, followed by a sustainability assessment to ensure the system's long term validity. The research has been conducted mainly focusing on the burn patients as test case scenario; where the first phase would predict the burn severity, the second phase would predict the number of days a patient should stay at hospital and the third phase would estimate the required intravenous fluid rate for burn patients' treatment management. At the first step, the proposed DCNN-based decision providing model can aid medical practitioners in evaluating the injury status of burn patients and suggest appropriate therapy in the shortest feasible period depending on the burn severity. At the second stage, based on various attributes of the patient, the hospital administration can make decision about the patients' expected duration of stay in the hospital through our proposed machine learning model that can aid in hospital's effective resource management. And, finally, if the patient gets admitted, our proposed fuzzy fluid resuscitation model can be extremely beneficial for the treatment management of the burnt patients though intelligently providing the decision about the required amount of intravenous fluid rate necessary for the patient to replenish the bodily lost fluids.

Establishing strategic choices and critical decisions in healthcare activities with the assistance of intelligent technologies has the potential to be a valuable solution for successful treatment management as well as the delivery of high-quality healthcare. Yet, ensuring the long-term sustainability of such technological engagement in the healthcare industry requires rigorous investigation as it is a delicate area dealing with people's lives and so the research also includes a systematic sustainability assessment of the proposed system employing relevant experts; through which the key sustainability indicators have been explored that are necessary to implement such kind of intelligent system in context of Bangladesh.

Bangladesh being a poverty stricken and densely populated country, the healthcare system here is mostly manual with lack of responsiveness, management and adequate resources. In recent days, it has already been proved several times that our healthcare system is insufficient to deliver proper health service to the public. According to an estimation of WHO there are only 3 physicians and 2.8 nurses or midwives for per 10,000 population in our country. According to another report of Directorate General of Health Services or DGHS Bangladesh it has been investigated that against each bed available at the hopitals there are more than 10,000 patients at each districts of Bangladesh; which clearly indicates our massive lack of resources [152]. Furthermore, due to a shortage of intensive care unit services in the hospitals, the capacity to treat critically ill patients is severely limited. Also because of scarcity of proper treatment management; a huge population of our country are still dependent on informal or non-allopathic health service providers like medicine shopkeepers, local non-certified physician etc. and even for treating serious illnesses like cancer, heart attack a lot of people cannot take proper medical treatment from physicians.

This is not a circumstance that can be rectified overnight, but an effective and smart decision providing system as proposed in this research can be an extremely beneficial alternative for dealing with such situations. If the IHDSS framework that has been proposed in this research is implemented in the real-world clinical practice while maintaining the core sustainability factors, it can be a pioneer to execute an appropriate technology for decision making in healthcare sector. Such kind of AI-assisted decision making system can be extensively helpful towards all the stakeholders in numerous ways, for instance with increased physician's and patient satisfaction, better adherence to treatment plans, improved hospital's resource allocation, better avoidance of errors and misdiagnosis, greater and faster treatment facility with low cost, implementation of remote healthcare providing services, evidence based healthcare practice with minimal corruption and thereby an improved, consistent and effective healthcare management system. Therefore, the proposed system is predicted to deliver higher quality in healthcare decision-making and, as a result, can assist in the development of a better and more sustainable smart hospital management system, which would pave the way for a rapid industry 4.0 adoption possibility in Bangladesh.

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Appendix A

Sustainability Assessment Questionnaire and List of Participants

SURVEY QUESTIONNAIRE

Titile: Prioritizing the Sustainability Indicators for Applying Artificial Intelligence in Healthcare Decision Making.

Please fill up the following information:

- **Name:**
- **Occupation:**
- **Designation and Organization:**
- **Email:**

Abstract: Healthcare decision making is an universally relevant and significant activity in the healthcare industry that entails specified actions for decision making in a desirable sequence to efficiently deliver care to patients. Incorporating Artificial Intellect (AI) into healthcare decision-making, on the other hand, has the potential to augment human intelligence and enable smarter decision-making. AI is anticipated to play a larger influence in healthcare decision-making processes in the near future of industry 4.0 by making smarter, faster, more accurate, and consistent decisions. However, it is crucial to investigate the sustainability indicators for using AI in healthcare decision making, as these may serve as the measurement for its long-term survival in human and environmental well-being. Therefore, we are gathering valuable opinions from relevant professional in this expert survey in order to prioritize the sustainability indicators identified from several researches. The objective of this survey is to collect data for M.Sc. thesis purpose under Bangladesh university of engineering & Technology (BUET).

Guidelines for filling and establishing relative importance The researchers of this study identified the following 15 sustainability indicators of using AI for healthcare decision making in context of Bangladesh. Each indicator can be rated according to its degree of relative importance. Please select an option as per your valuable opinion regarding the level of significance of these indicators according to their importance. You can also add your own opinion on adding any other sustainability indicator.

Indicator 1: Clinical Performance (Efficiency, Accuracy, Accessibility, Responsiveness) of the system.

- Negligible
- Less Important
- Moderately Important
- Important
- Very Important

Indicator 2: Infrastructure support (availability of resources, hardware software compatibility, equipment supply etc.) for establishing running the system.

- Negligible
- Less Important
- Moderately Important
- Important
- Very Important

Indicator 3: Consistency Relevance with the existing medical practice

- Negligible
- Less Important
- Moderately Important
- Important

- Very Important

Indicator 4: Managerial Performance of the system

- Negligible
- Less Important
- Moderately Important
- Important
- Very Important

Indicator 5: Social Impact cultural perceptions with acceptance and trust of adopters

- Negligible
- Less Important
- Moderately Important
- Important
- Very Important

Indicator 6: Individual competency (technical skill knowledge, adaptive capacity, training etc.) of associated healthcare personnel

- Negligible
- Less Important
- Moderately Important
- Important
- Very Important

Indicator 7: Environmental impact (efficiency in waste and pollution management, consumption of energy etc.) of the system

- Negligible
- Less Important

- Moderately Important
- Important
- Very Important

Indicator 8: Patient Satisfaction (Comfort ,Reliability, Safety Privacy with ensuring Information security of the patients)from the system

- Negligible
- Less Important
- Moderately Important
- Important
- Very Important

Indicator 9: Structured and systematic implementation process with robust monitoring and continuous technical maintenance

- Negligible
- Less Important
- Moderately Important
- Important
- Very Important

Indicator 10: Employee (physicians, healthcare investors, nurses, other hospital staffs) satisfaction with their beliefs, attitude, perceptions, interests, emotions expectations towards the system

- Negligible
- Less Important
- Moderately Important
- Important
- Very Important

Indicator 11: Acquiring accreditation of the system (getting accredited by any standard like ISO or govt. organization)

- Negligible
- Less Important
- Moderately Important
- Important
- Very Important

Indicator 12: Cost- effectiveness of the system with efficiency, utility and quality of service

- Negligible
- Less Important
- Moderately Important
- Important
- Very Important

Indicator 13: Availability, authenticity, correctness of clinical data with maintenance of data accessibility and confidentiality

- Negligible
- Less Important
- Moderately Important
- Important
- Very Important

Indicator 14: Consideration of ‘Ethical’ issues and compliance with ethical standards while decision making

- Negligible
- Less Important

- Moderately Important
- Important
- Very Important

Indicator 15: Policy Settings and supports from the Govt. and the healthcare institutions according to the contextual need and practice

- Negligible
- Less Important
- Moderately Important
- Important
- Very Important

Please write down your opinion if you want to add any more sustainability indicator of using AI for healthcare decision making in context of Bangladesh. **Comments:**

Thank you so much for your contribution as an expert.

Please feel free to contact with us if you face any trouble.

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