Early Predictive Deep Learning Model For Detecting Overlapping Symptoms of Cardiovascular Diseases in United Arab Emirates (UAE) Hospitals

A Research Proposal Submitted to Department of Information Technology

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DEDICATION AND ACKNOWLEDGMENT

I dedicate this thesis to my parents, friends, and teachers who always supported me to this day of my life.

I am very grateful to my advisor Prof. Dr……., who guided and encouraged me throughout the thesis and opened the doors for me in this research field.

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PREFACE

The hereby Ph.D dissertation of symptoms of cardiovascular disease in UAE which is related to early predictive deep model in which we are going to detect overlapping of symptoms related to the patients in the Hospitals of UAE and going to cover about the medical concerns of people, which is one of the most significant problems in this generation because most of us do not know about the heart issues and deep learning implementations will save themselves from such issues. Within the framework of this study, a hybrid or an ideal model has been compared to check which one is better in terms of symptoms of cardiovascular diseases as provided in the thesis with all formulations along with SPSS output files using deep learning and Neural Network. I want to thank my dissertation advisor Prof. Dr ……………for guiding me during the preparation of this study. I also would like to thank my family and my friends for supporting me.

ACADEMIC DECLARATION

I hereby declare that this master’s thesis titled “Early Predictive Deep Learning Model for Detecting Overlapping Symptoms of Cardiovascular Disease in UAE Hospitals” has been written by me under the academic rules and ethical conduct of the ………… University.

I also declare that the work attached to this declaration complies with the university requirements and is my work.

I also declare that all materials used in this thesis Consist of the mentioned resources in the reference list. I verify all these with my honor.

04-Oct-2021

Student Name

ABBREVIATORS:

Emptysis: EMPT

Dyspnea: DYSP

Fever: FEVE

Headache: HEADACHE

Cyanosis: CYAN

Weakness or Fatigue: WFAT

Discomfort Pressure in Chest: DPCH

Chest Pain: CHEP

Mean Relative Error: MRE

Mean of Mean Relative Error: MMRE

Abstract

To help with data categorization, new illness phenotyping, and complicated decision-making, deep learning (DL), a branch of machine learning (ML), is showing growing promise in medicine. The implementation of deep learning in ML is usually done using multi-layered neural networks. e-commerce, finance, speech, and image identification are all using deep learning to categorize and learn from more complex datasets thanks to recent advancements in computer hardware and algorithms. Signs of cardiovascular disease (CVD) include high blood pressure (hypertension), diabetes, and high cholesterol (hypercholesterolemia). Correct cardiac disease prognosis may save lives, while poor prediction can lead to death. Deep learning methods were used in the research to cover CVD symptoms that overlapped and to accurately identify a specific heart condition. The dataset utilized to train the computer consists of medical records from UAE hospitals, including information on age, symptoms, and cardiovascular disease. As a consequence of the findings, ….

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Chapter I Introduction

1.1.Introduction

In the 21st century, information and communication technology changed the way people live and do business. It would not be incorrect to state that in the current age, information technology has changed almost every element of human lifestyles. Rouse (2016) stated that "health information technology is a study of health information management resources and techniques. This field of study promotes information technology for health, medical practice, medical research and information technology." The use of information technology in the health sector has gained popularity quickly and the advantages of this new paradigm are experienced across the world.

Due to the necessity for a secure and effective administration of medical data, the significance of health information, as is often called, has grown considerably in recent years. The health information technology field is engaged in the effective gathering of medical data, safe archiving and prompt recovery, which enhances the diagnosis and treatment of patients. Health IT also enables appropriate administration, analysis and use of health-related data to provide customers and patients with more Efficient health care delivery and service. The underlying concept of health information is to provide healthcare professionals and patients more control. It also stresses the significance and sensitivity of the responsibilities of healthcare professionals who process and manage data (University of Toronto, 2013).

Also prevalent are other words such as clinical computer science and health information management, which concentrate on how to integrate the power of technology in contemporary health practices and medical data administration. Although the idea has various names, the idea underlying in all is basically the same. It is a process in which data is examined and used to create information that is Effectively used with a view to addressing clinical issues and facilitating fast delivery of medical treatment in a time-sensitive way (Dalrymple, 2011). The complex connection between data, information, and knowledge to which all the above-mentioned disciplines and paradigms are subscribed is shown in Figure 1.1 below. Informatics pyramid developed on the parametric variables containing the numeric information, knowledge and data, which can be implemented using deep learning models, while the state of wisdom in that case comes as non-parametric data which cannot be employed in deep learning models.

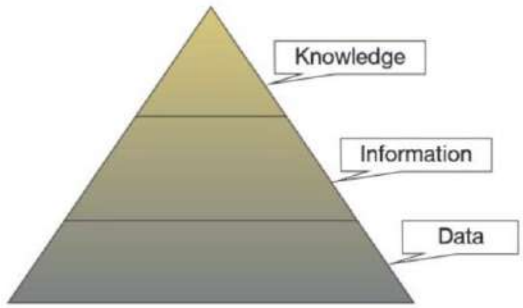


Figure 1.1: Informatics pyramid (Dalrymple, 2011)

The Electronic Health Record (EHR) is an electronic data gathering of individual patients and populations. It may be shared across health care professionals in a certain state or nation (Gunter & Terry, 2005). Health records may contain general health history, patient reviews, patient treatments, medical records, allergies, vaccination status, test findings, radiological pictures and some helpful information for inspection. This large data collection may enable researchers to examine and diagnose illnesses using computer methods. Using EHRs, legacy systems may save costs, improve care quality and increase record mobility or sharing.

The presence of EHRs has led academics to the concept of an electronic healthcare system in which legacy healthcare systems join together and exchange patient information electronically throughout the public infrastructure throughout Canada.

Heart or cardiovascular illness is a kind of heart or blood vessel disease (arteries and veins). Today, most countries face high and rising rates of heart disease, which has become a major cause of worldwide debilitation and death for men and women over the age of 65 and is today regarded as a 'second epidemic' in many countries, replacing infectious diseases as the most important manner of death (Gale Nutrition Encyclopedia, 2011).

Early identification of cardiovascular illness may help decrease the death rate. Echocardiography is one method of diagnosing cardiac illness. Echocardiography, or echo, is an unpaintable test used to make images of the heart on sound waves. The test provides information on the heart size and shape and how Effectively the heart chambers or valves function. Echo may also be used to identify cardiac abnormalities in toddlers and babies (NCBI, 2014).

The study of echo data by specialists takes time, along with the lack of specialists who have expertise about echo data analysis. Automated techniques may thus overcome limitations of conventional diagnostic techniques and provide diagnostic medical knowledge (DAMTEW, 2011). In order to address these and many other health issues relating to the diagnosis of heart disease, one has to find ways to extract information from huge databases gathered in the past. Data mining and machine learning may be a solution via the generation of rules of these huge datasets that can be utilized in echo readings.

Recently, data mining has become one of the most advanced and promising areas for extraction and handling of data for valuable information (Payam Mohebbi, 2016). Often the machine learning process is like data mining. Both use the same techniques and probably overlap. By use of a good research and methodology, machine learning may be differentiated based on the known characteristics learnt from the training data in the dataset, whereas data mining focuses upon on discovery of heretofore unrecognized characteristics of the dataset (Mitchell, 1999).

The idea of machine learning is based on identification of unique data patterns and extraction of viable information (Clifton, et al., 2012). It utilizes extracted data for pattern detection and software Communications to modify them (Rouse, 2016).

Deep Learning is a collection of methods for Machine Learning that have one or more hidden units in neural networks. The hidden layers do not offer direct functions that transfer data for classification, but offer valuable information to cluster a data/data set and extract characteristics and aspects from the spatial domain. Deep learning is a potential area in data mining and machine learning research. In many machine learning applications, deep learning methods have shown excellent results, including voice recognition, image processing, and natural language handling (Najafabadi, et al., 2015). Figure 1.2 illustrates the link between deep learning and machine learning and artificial intelligence. Artificial intelligence utilizes decision-making machine learning algorithms and representation learning is one of its techniques. Deep learning is part of a representational learning system that employs more than one hidden layer to complete the neural networking processes.

Background

Cardiovascular disease (CVD) is a series of diseases involving the circulatory system, including angina pectoris, myocardial infarction, coronary heart disease, heart failure, arrhythmia and else, which is generally related to atherosclerosis. With the social economy development, the population aging and the urbanization acceleration in UAE, some changes have taken place in national lifestyles, which leading to a rise of CVD prevalence. Many advances have been achieved in the research of CVD risk prediction models in recent years, however since the Predicts of epidemiologic risk factors and markers may vary in various groups, the CVD model has a certain degree of demographic specificity. Although there has been no research on a CVD risk forecasting model based on a large cohort demographic in eastern UAE, which would be beneficial. At the same time, a substantial number of current CVD prediction models use the multivariable regression approach to Construct prediction models in a linear way, however the predictive ability of these models is often poor, particularly for specific sub-populations. Machine learning (ML) such as random forest (RF) can improve the performance of risk predictions by exploiting large data repositories to identify novel risk predictors and more complex interactions between them. Many advances have been achieved in the research of CVD risk prediction models in recent years, however since the Predicts of epidemiologic risk factors and markers may vary in various groups, the CVD model has a certain degree of demographic specificity. Although there has been no research on a CVD risk forecasting model based on a large cohort demographic in eastern China, which would be beneficial. At the same time, a substantial number of current CVD computer models use the multivariable regression approach to construct predictive model in a linear way, however the predictive ability of these models is often poor, particularly for specific sub-populations.

Deep learning and machine learning are techniques that use computational models with multiple processing layers to learn from representative data through a hierarchy of multiple concepts. Deep learning and machine learning are techniques that use computational models with multiple processing layers to learn from representative data (LeCun, Bengio, & Hinton, 2015). This information may be presented in a variety of formats, including visual objects (pictures), voice (speech recognition), or sequential data presented in text form. Based on the representation of each data layer, deep learning models create output parameters using backend propagation algorithms (Goodfellow, Bengio, Courville, & Bengio, 2016). Artificial intelligence has proved its potential uses across a wide range of disciplines, as well as in the realms of medical research. The combination of large datasets from hospitals and deep learning methods such as convolutional neural networks may be utilized to develop prediction models for risk management in disease control (Cheung *et al.*, 2020; Usama *et al.*, 2018; Zhu *et al.*, 2020).

The gap between normal human physiological state to diseased state can be potentially filled by examining and monitoring clinical, biomedical, and healthcare wellness data from individuals. Wellness monitoring devices are now available to analyze and share data with health care providers to better understand the disease patterns (Baldi, 2018). Underlying illness trajectories and asymptomatic patients can be stratified using computational biomedical, healthcare, and wellness. In the present thesis, we'll discuss the different deep learning approaches and build a predictive model to detect overlapping symptoms in cardiovascular diseases. The deep neural networks, which in the case can act as alerts and warnings in biomedical depending on the electronic medical record (EMRs). Individual health baselines can bring insights into the identification and significant pathological changes that reduce unnecessary testing. These analyses would play a contributing role in the clinical discussion making and implementation of AI-prescribed medicine and healthcare (Chen *et al.*, 2012; Kohane, 2011; Mirnezami *et al.*, 2012).

In the traditional approach, medical discoveries are made by observing various qualitative and quantitative features such as color, shape, and patterns of a disease to generate hypotheses to run experiments. These experiments then validate the hypothesis, but in the case of novel approaches, artificial intelligence has brought its applications in medical sciences to provide algorithmic analysis of medical data based on multilayer processing neural networks (Poplin *et al.*, 2018).

Chronic Prediction is a deep learning technique that uses user experience to predict the impact of risk factors of non-communicable diseases (Pittoli *et al.*, 2018).

Non-Communicable diseases such as cardiovascular diseases, including heart attacks, stroke, arrhythmias, coronary artery disease, and cardiomyopathy, are the main reasons for the rise of disease in the developed world, which needs to be managed and controlled by regulating their behavioral and biological risk factors. Cardiovascular diseases such as coronary artery disease is the basic cause of death in females all around the world, according to the World Health Organization (J. Wang *et al.*, 2017). Chronic Prediction utilize Bayesian Networks to assess risk factors in order to know the causative's of no Communicable diseases (Pittoli *et al.*, 2018). Usage of multiple BNs to import risk factor-based automated alerts are still going to develop. The fundamental aim of chronic Prediction is to analyze training data to provide statistically validated Prediction similar to that of actual conditions. Another primary objective of neural models is to provide the real-time impact of risk factors onto the user actions (Pittoli *et al.*, 2018). The leading cause of death worldwide is cardiovascular disease, and the electrocardiogram (ECG) is a significant instrument for diagnosis. (Zoni-Berisso *et al.*, 2014). It is a more difficult process to detect cardiac failure relative to deciding if electrocardiography is normal or not. The conventional study and classification of the ECG signal depend on advice from experienced medical practitioners, which is a time-Consuming and Labor-Consuming task. Consequently , the need for completely automated ECG analysis utilizing machines is rising (J. Zhang *et al.*, 2019).

Furthermore, AI techniques such as deep learning can not only give predictions built on raw data but can learn the patterns and make decisions based on that layered patterns, which can be more Productive than a human brain (Al'Aref *et al.*, 2019; Krittanawong *et al.*, 2019; Krittanawong *et al.*, 2017). Biomedical data such as, medical history, genetics, gut microbiome, and social media can be exploited into cognitive computing to provide precision medicines.

Like deep learning, cognitive computing involves three kinds of pattern learning techniques as supervised, unsupervised, and reinforcement learning to bring productive precision results in clinical trials (Krittanawong *et al.*, 2017). The Precision Medicine Platform of the American Heart Association, for example, is a fine example of such AI techniques. (Platform, 2021). Clinical experts have put a lot of time and resources into designing and improving statistical tools to determine disease status, which is also challenging for doctors to reliably describe (W. G. Baxt & Skora, 1996). For example, myocardial infarction (MI) is frequently difficult to diagnose in patients who present to the emergency room with anterior chest pain. As a Consequence, robust statistical models capable of forecasting MI incidents are highly desirable. With the assumption of a linear relationship between risk factors and disease, many risk scoring systems based on generalized linear models have been developed (W. G. Baxt & Skora, 1996). However, in the majority of circumstances, the disease's root mechanism is multifactorial and subtle, with non-linear causal dynamics. In this regard, using a linear model in the presence of nonlinearity would result in incorrect modelling. As a result, generalization and prediction accuracy suffer as a result of this. As a Consequence, to describe and forecast an illness, a non-linear method, such as machine learning techniques, will be more fitting. Machine learning (ML) is a subset of artificial intelligence that proposes a series of computer-based methods for automated knowledge processing and pattern/concept recognition based on repetitive learning from training data (Rogan *et al.*, 2008). It is capable of defining the non-trivial/non-linear interaction between the predictors and the result, as well as developing models for data-driven prediction. Data-driven forecasts provide the benefit of offering recommendations for relatively rare chronic or sub-clinical disorders that could elude a practitioner but can be elucidated by the data-driven aggregation of infinite interactions by multiple doctors and patients (Chawla & Davis, 2013).

1.2.Statement of The Problem

The incidents and mortality rates due to cardiovascular diseases are increasing in recent years, where how to diagnose and prevent such diseases has become a challenging situation. Acute forms of a cardiovascular catastrophe such as thrombosis, atherosclerosis plaque formation involve 15-20 years. Such long periods of silent symptoms has made it difficult to diagnose early screening for health care physicians (Escárcega *et al.*, 2018). Most cases, such as ischemic cardiomyopathy and acute coronary syndrome, reached progressive phases of the condition at the first appointment. And though AS plaques are discovered, it is a struggle to address whether or not lesions need involvement or weakness in clinical practice (Cao *et al.*, 2019). Meanwhile, some of the CVDs may share similar characteristic symptoms like chest pain, irregular heartbeat, shortness in breath, Pain in the neck, jaw, throat, upper abdomen or back, and numbness, which increases the chances of physicians diagnosing misleading.

Such post-determined symptoms and silenced indications for cardiovascular diseases can be estimated and assessed using the deep learning neural networks. Deep Belief Networks, Medical

Image Segmentation, and Bayesian Networks can use the large clinical dataset to predict risk factors' impacts. In this Research the researcher is going to develop a predictive model based on machine learning algorithms to assist and predict precisely early symptom of heart diseases in United Arab Emirates (UAE).

1.3.Research Objectives.

Fundamental computational biology is purposed to characterize a system numerically, which is also quantified in terms of explanatory variables. The study aims at developing a deep learning model for early predictions of related symptoms of cardiovascular diseases. The deep neural networks may use large datasets to create algorithms that predict, and extract outputs based on trained topics, as literature has clarified. The authors here focused on using UAE clinical dataset as a predictor of risk factors and the impact of overlapping symptoms in cardiovascular diseases and contribution in the literature to improve the diagnostic measures for CVDs.

Research objectives:

- To define the precision of the early prediction of CVDs in the Deep Learning Model.
- To develop a profound learning model for the predictive analysis of overlapping CVD symptoms.
- To enhance the Efficacy of the prediction of simultaneous symptoms of CVDs.
- To evaluate and analyze the accuracies of the proposed model.

1.4.Research Questions

The Research would have full answers to the following concerns:

RQ1 What is the precision of the early Prediction in Deep Learning Model?

RQ2 Can the profound learning model solve overlapping in cardiovascular diseases symptoms exists?

RQ3 Do deep learning models are Efficient in the early Prediction of overlapping symptoms of cardiovascular diseases?

RQ4 What is the Chest Pain of predictive deep learning in the early detection of overlapping symptoms of cardiovascular diseases?

RQ5 Can deep learning models be accurate in using deep learning models in the early Prediction of cardiovascular overlapping symptoms?

Research Question	**Research Objective**	**Research Methods**
What is the precision of the early Prediction in Deep Learning Model?	To define the precision of the early prediction of CVDs in the Deep Learning Model.	Training Method including Naïve Bayes, Vector Machine and Random Forest.
Do deep learning models are Efficient in the early	To develop a profound learning model for the	Multilayer Perceptron to find out the overlapping in in symptoms of CVD.

Prediction of overlapping symptoms of cardiovascular diseases?	predictive analysis of overlapping CVD symptoms.	
Can deep learning models be accurate in using deep learning models in the early Prediction of cardiovascular overlapping symptoms?	To evaluate and analyze the accuracies of the proposed model	Analysis Mann-Whitney U test, and T-test method to compare accuracies

1.5.Significance of the Study

In the current age, information technology has practically changed every area of human existence. The use of IT in the health sector is gaining popularity quickly and the advantages of this new paradigm are being recognized across the world. This development generated enormous amounts of patient data that can be used by computer technology and machine learning methods and converted into valuable information and knowledge. These data may be utilized to build expert systems to diagnose life-threatening illnesses such as cardiovascular illnesses with lower costs, time and enhanced diagnostic accuracy. Although contemporary medicine produces a lot of data every day, nothing has been done to utilize this accessible information to address difficulties in diagnosing cardiac illnesses successfully. Identifying the need to investigate the use of robust data mining methods in the detection of heart disease and other weakening illness by health professionals.

A fundamentally new way of doing simulation that focuses on limited human insight is the enormous machine learning area (Bishop, 2006). A change is going on in the world of machine learning. Over the last few decades, it has changed from a specialized field to a significant economic development driver as innovation revolutionizes web browsing, speech-to-text, and many other economic significance fields (He *et al.*, 2015; Silver *et al.*, 2016). Computational models are beginning to be used by biomedical researchers to interpret knowledge and define the fundamental concepts (Jonas & Kording, 2017).

Deep learning techniques for overlapped symptomatic cardiovascular diseases and risk heterogeneity must not only be reliable to be useful, but they will need to offer visibility about where they are likely to deliver false outcomes and be explainable in the way that health care professionals can appreciate when the model obtains a given outcome. These proposed methods assist in guaranteeing that the model can be extended diligently to the population about which it is most precise (Schlesinger & Stultz, 2020). Deep learning can derive actionable insights from patterns in troves of data. Computer Aided Diagnosis (CAD) has been used to help radiologists interpret medical images in clinical practice for decades. Deep learning algorithms outperform classical algorithms on benchmark image recognition tasks and are only recently being implemented into medical imaging research.

The use of machine learning and deep learning inside the health industry has quickly acquired worldwide significance. In recent years the significance of health informatics has increased Considerably since medical data needs to be managed securely and Efficiently. Health information technology also makes it possible to properly store, analyze and utilize health related data for the more Productive delivery of healthcare. It is also crucial to assist doctors discover successful therapies and patients get better and better healthcare services that are more inexpensive (Zarb, 2016). As far as health informatics is concerned, the useful use of the data categorization should determine whether an admitted patient improves or deteriorates in a hospital.

1.6. Terms Defenition

This section defines the basic terms that has been used in this study as follows:

Artificial Intelligence: Artificial intelligence (AI) refers to the simulation of human intelligence in machines that are programmed to think like humans and mimic their actions.

Cardiovascular Diseases: Cardiovascular diseases (CVDs) are a group of disorders of the heart and blood vessels.

Computer Aided Diagnosis: In medical imaging field, computer-aided detection (CADe) or computer-aided diagnosis (CADx) is the computer-based system that helps doctors to take decisions swiftly.

Convolutional Neural Networks: A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other.

Decision Tree: A decision tree is a decision support tool that uses a tree-like model of decisions and their possible Consequences, including chance event outcomes, resource costs, and utility.

Deep Belief Network: In machine learning, a deep belief network is a generative graphical model, or alternatively a class of deep neural network, composed of multiple layers of latent variables, with connections between the layers but not between units within each layer.

Deep Learning: Deep learning is a subset of machine learning in artificial intelligence that has networks capable of learning unsupervised from data that is unstructured or unlabeled.

Deep Neural Network: A deep neural network (DNN) is an artificial neural network (ANN) with multiple layers between the input and output layers.

Electrocardiography: Electrocardiography is the process of producing an electrocardiogram. It is a graph of voltage versus time of the electrical activity of the heart using electrodes placed on the skin.

Machine Learning: Machine learning is the study of computer algorithms that improve automatically through experience and by the use of data.

Multilayer Perceptron: A multilayer perceptron (MLP) is a class of feedforward artificial neural network (ANN). The term MLP is used ambiguously, sometimes loosely to any feedforward ANN, sometimes strictly to refer to networks composed of multiple layers of perceptron's.

Naïve Bayesian: In statistics, naive Bayes classifiers are a family of simple "probabilistic classifiers" based on applying Bayes' theorem with strong independence assumptions between the features.

Neural Network: A neural network is a series of algorithms that endeavors to recognize underlying relationships in a set of data through a process that mimics the way the human brain Operates.

Non-Communicable Diseases: A non-Communicable disease (NCD) is a disease that is not transmissible directly from one person to another.

Recurrent Neural Networks: A recurrent neural network (RNN) is a class of artificial neural networks where connections between nodes form a directed graph along a temporal sequence. This allows it to exhibit temporal dynamic behavior.

1.7.Chapter Summary

Machine learning is becoming more popular as technology and hardware power improve, and it is being used in a variety of fields ranging from stock research to medical picture processing. Forecasting of heart failure is one of the applications of computer education that may be made. This research would also study the different machine learning algorithms and quantify the results using additional output indicators such as accuracy, precision, and a recollection of the results.

Chapter II Literature Review

2.1 Introduction

This chapter discusses the currently available research on deep learning algorithms, how they relate to medical diagnostics and how they are employed in early cardiovascular disease prediction. This section contains literature on prior research of the issues mentioned, a theoretical framework connected to data analysis, philosophy, obstacles, errors, best practices and highlights knowledge gaps.

2.2 Deep Learning

Cardiovascular disease (CVD) is a significant hazard to human health and the world's leading cause of mortality. In 2016, CVD caused 17.6 million deaths, up from 2006 to 2016 by 14.5 percent (H. Thomas *et al.*, 2018). Unfortunately, CVD mortality and morbidity rates grow annually, particularly in emerging nations. Studies have indicated that almost 80 percent of CVD-related fatalities occur in nations with low and moderate revenues. These fatalities also occur at a younger age than in nations with high incomes (Wu *et al.*, 2016). Population aging may also raise cardiovascular risk factors and raise the prevalence of CVD. Patients and society as a whole were heavily burdened by CVD. At the moment, artificial intelligence (AI) can tackle this issue. However, more than 60 years have passed since the AI idea was introduced (Y. Yan *et al.*, 2019).

In the early identification and diagnosis of CVDs as well as outcome prediction and prognosis assessment, artificial intelligence (AI) approaches, such as machine learning (ML), deep learning (DL), and the cognitive computer may play a vital role. A wide-ranging data gathering from electronic medical records has generated massive data sets (quantitative, qualitative, and transactional data) that require interpretation by AI algorithms (EHRs). AI approaches may also help doctors make better clinical judgments, allowing the early diagnosis of subclinical organ malfunction, by using information that is clinically relevant in the vast data volume, and so enhancing the quality and Chest Pain of the delivery of healthcare. Telemedicine and deep learning health (mHealth) are also increasingly significant when it comes to preventing CVD and improving healthcare in general. The Internet of Things (IoT) may also be a dramatic shift to heart disease in health care; patients' collected data may be Communicated to remote doctors who are continually able to learn the physical state of patients in real-time. Cardiac imagery has a major role in cardiovascular disease diagnosis (CVD). Its usefulness has so far been restricted to the visual and quantitative evaluation of heart anatomy and function. However, new possibilities arise with the advent of Big Data and machine learning to Construct artificial intelligence systems to help the doctor immediately diagnose CVDs.

Deep learning (DL) is a branch of Machine Learning (ML), which shows increased promise in medicine, helps to classify data, phenotype new diseases, and making difficult decisions. It is usually performed using neural networks with several layers. It has been accelerated by recent developments in computer hardware and algorithms and is rapidly being used to learn and categorize complicated datasets in e-commerce, banking, and picture identification.

Deep Learning (DL) mirrors the complexity of a human brain in which data that have several abstract levels may develop complicated hierarchical representations. The programmer inserts known data into the system so that algorithms can appropriately react, even in the face of completely new input (Seetharam *et al.*, 2019). The neural network learning via experience, reading data, building hierarchical structures, and offering higher degrees of input and output. It can record intricate nonlinear links between variables of input-output. Average results error and their forecasts may be reduced by estimating input weights and outcomes data. Doctors diagnose their expertise, experience, and cultural background. Deep learning might at this moment be highly Productive, extending and increasing medical knowledge, especially for non-expert doctors. DL may use more hidden layers to investigate more intricate data than standard neural networks. This is why DL has lately been popular in medical research as a result of the increasing number and complexity of data, notably in the field of imaging analysis (Romiti *et al.*, 2020).

Chronic Prediction is a thorough learning methodology that utilizes experience to forecast the influence of non-Communicable disease risk factors (Pittoli *et al.*, 2018). The primary reasons for an upsurge of disease in the developed world, which should be managed and controlled with regulating behavioral and biological risk factors, are non-Communicable diseases like cardiovascular diseases, including heart attack, stroke, rhythmia, coronary artery disease, and cardiomyopathy. Cardiovascular disorders such as coronary artery disease are the fundamental cause of mortality in women worldwide, says the World Health Organization (J. Wang *et al.*, 2017). Chronic prediction Use Bayesian networks to evaluate risk variables to know the causes of non-Communicable illnesses. The use of numerous BNs to import automatic warnings depending on risk factors is currently in progress. The basic objective of chronic prediction is to assess training information to give statistically verified predictions comparable to those in real situations. Another key aim of neural models is to ensure that risk variables affect user behaviors in real-time (Pittoli *et al.*, 2018). Cardiovascular disease is the world's leading cause of mortality, and an electrocardiogram (ECG) is a major diagnostic tool (Zoni-Berisso *et al.*, 2014). The detection of heart failure by determining whether or not electrocardiography is normal is more complex. The typical examination and categorization of the ECG signal rely on the guidance of trained physicians, which is long and labor-intensive. Consequently , the requirement for fully automated ECG analyses is on the rise (J. Zhang *et al.*, 2019).

Cardiovascular Disease (CVD) is the major cause of morbidity and mortality, accounting for almost one-third of yearly deaths, despite much progress in diagnosis and treatment. Acute types of a cardiovascular disasters such as thrombosis, plaque atherosclerosis are 15-20 years old. These extended durations of quiet symptoms have made early screening challenging for medical practitioners (Escárcega *et al.*, 2018). Most patients, such as ischemic cardiomyopathy and acute coronary syndrome, during the initial visit, reached advanced stages of the illness. In the meanwhile, other CVDs may have similar symptoms, such as chest discomfort, irregular heartbeat, breathing shortness, discomfort in the neck, mouth, throat, upper or back abdomen, and addiction, increasing the risks of doctors diagnosing the error. The normal practice of cardiovascular medicine needs circumstances as complicated as reduced- or preserved-heart failure, multivessel coronary arteries, complicated arrhythmias, abrupt heart arrest, cardiovascular (CVD) disorder during pregnancy, or congenital heart disease. Despite progress in each of these areas, major clinical concerns remain.

Such post-determined symptoms and silent cardiovascular disease signals may be calculated and evaluated utilizing deep learning because of its capacity to automate the interpretation of medical images, boost clinical decision-making, find new phenotypes, and pick better treatment routes for complicated disorders. It may be suitable for cardiovascular medicine in which hemodynamic and electrophysiological parameters are more and more continuously recorded by wearable devices and by cardiac imaging segmentation.

To yet, DL's cardiovascular outcomes are encouraging but still small and many obstacles need to be addressed. In the therapeutic environment, first and foremost, DL is frequently criticized and cannot be clearly explained. Inputs may be rigorously censored using different techniques to determine those that affect categorization the most. Meta-analyzes of different DL methods that are applied to the same data might boost trust. Several strategies may allow 'model agnostic measures to analyze complicated models. Thus, insights into human cognition may give theoretical insights into the interpretation of DL models.

Second, if data is insufficient and/or methods complicated, any ML may suffer from overfitting. DL in several clinical trials. This suggest that other analyses are suitable for statistical models (e.g. logistic regression). Future investigations may merge statistical classification with DL.

Third, DL confronts new ethical criticism if partial or bad data lead to partial predictions or, worse, make manipulation of the findings easier. Adverse instances, in which little changes to the input data lead to big changes in DL categorization, are a key problem for DL with potentially substantial medical Predicts. Although certain approaches have been presented to avoid adverse instances (e.g. reactive techniques), they do not work.

Deep learning is a technology method in which computers access knowledge in two distinct ways: first analyzing brain wave patterns and then analyzing speech patterns to get a sense of its context. Such a pyramid of concepts helps a program to grasp complicated (complex and multifaceted) concepts by Construct ing them out of easier ones (Goodfellow *et al.*, 2016; Lai, 2015; Pham *et al.*, 2017).

Polson and Sokolov (2014) defined deep learning as "Deep learning (DL) is a high dimensional data reduction technique for Constructing high-dimensional predictors in input-output models". Machine learning (ML), a term invented in the 1950s by Samuel , deals with innovative design and creation of teaching processes that allow computers to learn to solve problems autonomously without being directly programmed (Taylor *et al.*, 2010). In specific, ML is a method aimed at specifically selecting, researching and gaining information from an abundance of data, creating a short pattern capable of explaining unexplained trends or relationship and addressing difficult problems in turn. This learning phase is typically carried out by Repeat exposure to the defined issue, enabling the model to continually refine itself and develop its capacity for solving similar problems in the future. Primary discrepancies between the statistics and ML approaches include: statistics use a strict math methodology, whereas ML methods permit the partial use of heuristics for issue resolution , Stats only enable computational data processing, while ML approaches often allow for many types of data to be processed concurrently (for example numerical or categorical), and (3) statistics are hypothesized (Yoo *et al.*, 2018). Within the clinical category, for example, Supervised learning algorithms discriminate against better patients and are a general collection of ML approaches used to make this predictive modeling possible. Classification is an externally supplied ML task that motivates classified documents contexts (i.e., explanations Consisting of an object's observer/measurement values and the desired output value) to build a hypothesis model that can predict potential (unseen) instances (i.e. allocate the output value). A variety of managed learning algorithms exist and their Efficient implementation to various types of real-world problems attracts Considerable attention; two novel supervised learning algorithms created are mentioned in this thesis.

2.3 **Neural Artificial Network**

ANN is some kind of ML model that McCulloch and Pitts first proposed in 1943. (Ingre & Yadav, 2015; Landahl *et al.*, 1943; McCulloch & Pitts, 1943). This is influenced by neuronal processes in the brain and is able to conduct multiple functions, such as Regression and grouping. It is made up of linked artificial neurons that first acknowledge input data and second measure the output value on the basis of the input values given (W. G. J. A. o. i. m. Baxt, 1991). A major benefit of ANN over traditional mathematical approaches is the potential of ANN to model dynamic non-linear interactions. When modeling non-trivial functions, this gives ANN the strategic advantage; helping it to produce successful success when applied to different complex problems in science and engineering. However, ANN has many drawbacks: (1) it is extremely responsive to the importance of its parameters; (2) the design and sophistication of the designed network plays a major role in its performance; (3) it has a large computational training cost; and (4) it may be difficult for humans to understand the resulting induction models (Bellazzi & Zupan, 2008).

2.4 DT-Decision Trees

DT is a relevant for decision process that combines a guided acyclic graph to carry out classification, built from training data (Ben-Haim & Tom-Tov, 2010; Brijain *et al.*, 2014). Each non-leaf node is liable for checking a function within the tree layout, which Quinlan created in 1986, is one of the leading DTs (Quinlan, 1986). C4.5 (successor of ID3), See5 (successor of C4.5)

(Quinlan, 1992) and CART (Classification And Regression Tree) are some of the most common DT algorithms (Y. Wang & Witten, 1996). One major benefit of DT is its low computational complexity, while the main downside is that since the evaluated dataset includes several attributes, the built tree will become very complex (Y. Wang & Witten, 1996).

2.5 Naïve Bayesian

The Bayesian Naïve is an Efficient probabilistic classifier based on the Bayesian theorem. It predicts multiple probabilities of the input data which implies that the input features vary from one another, i.e. the existence of one function is not related to the absence of another. Since it is a reasonably simple classifier that assumes unreasonable freedom compared with other more sophisticated algorithms, it can work equally well (Bellazzi & Zupan, 2008), And one of the most common classifications used for drug evaluation is (Rish, 2001; Rish *et al.*, 2001). However, the performance of the Naïve Bayesian classifier can be surpassed by advanced algorithms such as ANN and SVM, with non-linear biomarkers (Bellazzi & Zupan, 2008; Frank *et al.*, 2000; Webb, 2010).

2.6 Multilayer Perceptron Neural Network (MLP)

A multilayer perceptron (MLP) is a form of deep neural network that proposed to fix complex problems with additional perceptron's, stacked in many layers (Bishop, 1995). MLP is one of the most popular neural network architectures used in support structures for medical decision making. And it refers to the subset of neural networks which are supervised.

H. Yan *et al.* (2006) explored decision making multilayer perceptron for heart diseases diagnosis. A fluid and fuzzy cognitive method is the medical diagnosis by design, and soft computational strategies. In the advancement of medical decision support structures, such as neural networks, immense capacity has been shown to be applied (MDSS). The researchers have used a multiplayer-based policy support system for the detection of cardiovascular diseases. In the process input layer, forty input variables are used, grouped into four classes, and then coded using the suggested coding schemes. For the cascading learning process, the number of nodes in the hidden layer is determined. Each of the five nodes in the output layer correlates to a severe heart condition. The missing patient data is handled using the substitution medium type. In addition, the computer is trained using an improved back propagation algorithm. Figure 2.1 shows a multilayer perceptron model used for early prediction of CVDs using multiple symptoms. Symptoms of the disease are used as input layer that in the hidden layer are analyzed and given as a given in the output layer of the model.

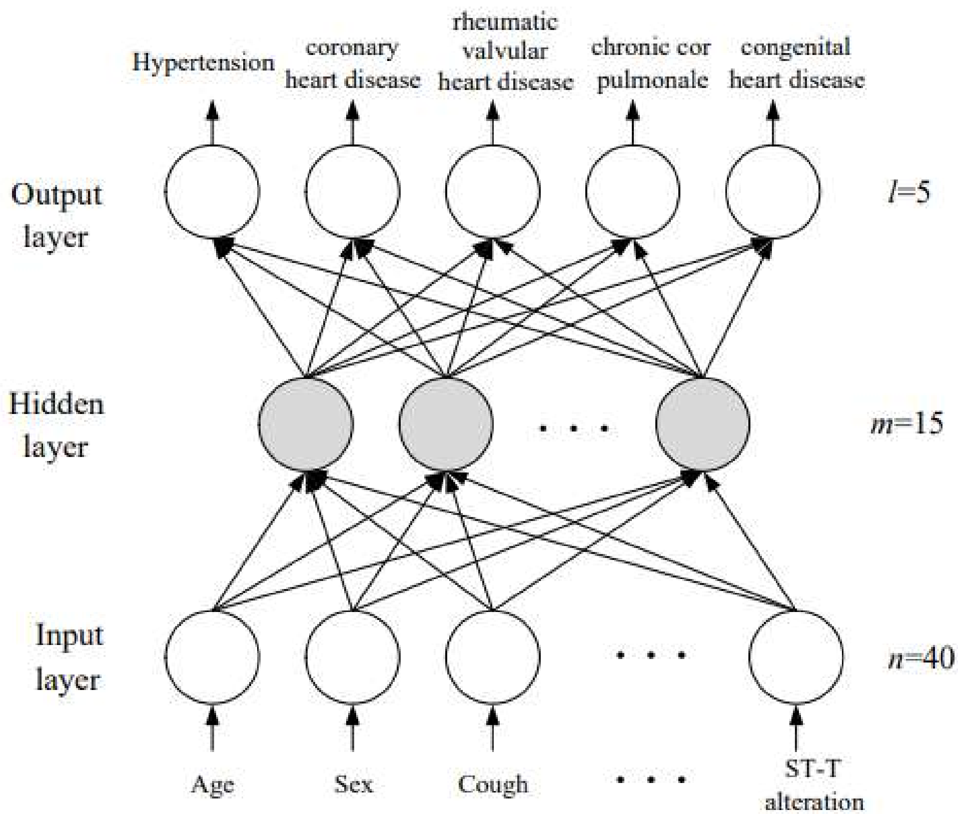


Figure 2.1: Source: H. Yan *et al.* (2006)

For the preparation and development of the program, a total of 168 medical reports obtained from patients with five cardiac disorders is used. In specific, in order to test the program generalizability, three measurement techniques, cross validation, holdout and bootstrapping, are implemented. The findings indicate that the proposed predictive analytics framework based on MLP will achieve very high diagnostic precision (> 90 percent) and comparably low intervals (< 5 percent), showing its utility in assisting the cardiac disease clinical decision-making method.

H. Yan *et al.* (2006) uses following statistics in order to represent their results.

a. Precision:

In comparison with the actual right outcomes, it is the percentage of the real positives that is measured as:

Precision $=\frac{\text{No.ofTruePositives}}{\text{No.ofTruePositives+NooffalsePositives}}$

b. Sensitivity:

In comparison to the total right outcomes, it is the percentage of the real positives that is measured as:

Sensitivity= $\frac{\text{No.ofTruePositives}}{\text{No.ofTruePositives+Nooffalsenegatives}}$

c. Accuracy:

It is the proportion of test tuples that are correctly identified by every algorithm.

Accuracy = $\frac{\text{NoofTruepositives+NoofTruenegatives}}{\text{No.ofTruePositives+Nooffalsenegatives+No.offalsePositives++Nooftruenegatives}}$

2.7 Deep Neural Networks (DNN)

The current model is aimed on both textual and visual outbrings of data analysis. It uses certain Denoising auto encoders and skip gram models. In order to explore and analyze textual structured sentiments CBOW model is used.

The major of developing these models were to evaluate the similarities between documentary data evolved from social media such as twitter. (Yanagimoto *et al.*, 2013) used T&C News as a data set documentary to perform the analysis of sentiments.

2.8 Convolutional Neural Networks (CNN)

Convolutional neural networks took sentiments into pooling layers for analysis. The emotions are being mapped as sentence length and converted into corresponding scattered vectors of fixed size. The technique is more popular in visual representation of emotions, opinions and sentiments. CNN is expressed using Caffe and Pythons on linux based devices such as android smartphones. GoogLeNet proposed a 22 layered deep CNN which then best express sentiments, emotions and notions based on its varying size and depth. Word2vec is another seven layered convolutional neural network developed by Google itself which uses words to express them as vectors of specific shape and size.

CNN has proved to be very Productive in solving image recognition challenges. Analysis work based on CNN substantially increased the best performance for many image datasets, including the MNIST, CIFAR10, and the NORB database. It's also very useful for learning from picture data regarding local and global systems. General picture artifacts such as handwritten numbers or human faces have apparent local and global forms, but it is possible to incorporate simple local characteristics such as edges and curves to become more complicated characteristics such as corners and forms and ultimately objects. CNN has also increasingly been introduced into diagnostic imaging research, such as the segmentation of knee cartilage (Prasoon *et al.*, 2013)

2.9 Deep Recurrent Neural Networks

Recurrent Neural Networks are based not on fixed sized context rather than based on hierarchical bidirectional recurrent neural network which is being used evaluate patients reviews about healthcare in the history. The huge data set in the form of text mining; challenge was gathered to evaluate the longs short term memory of patients' reviews about hospitality.

The model is focused on the temporal actions and opinions of user experiences as well as a permanent emotional product. Models give approaches on the product review of users in context of long- and short-term memory.

2.10 Deep Belief Networks (DBN)

RBM-based deep belief networks (DBNs) have a few shrouded layers. Include portrayal has been shown to be Productive using DBN. It makes use of unlabeled data to fill in the gaps left by marked examination problems. The models used in this methodology are Poorly Shared Deep Neural

Networks, which support natural language by exchanging sentimental labels. This method, which employs back propagation, allows for the planned work to be shortened. The suggested method is more accurate and Efficient than the previous studies in terms of cross-lingual emotion classification, according to the experimental results (Ruangkanokmas *et al.*, 2016).

2.11 Cardiovascular Diseases

The category of illnesses connected with the heart and/or blood vessels is cardiovascular disease (CVD). This involves diseases that involve [1] Blood vessel restriction that brings blood to the heart, such as in coronary heart disease, Cerebrovascular disorder in the head and peripheral arterial disease in the limbs. Second, cardiac and heart valve tissue damage induced by rheumatic fever such as rheumatic heart attack and heart muscle failure in order to pump more blood into the blood vessels. (Organization, 2013).

Acute myocardial infarction (MI) - generally referred to as a cardiac attack - is an acute occurrence of special significance. This is because people across the globe are facing a deleterious health crisis that induces significant mortality. (Go *et al.*, 2013; Wilson *et al.*, 2016; Wilson & Izmailov, 2020). Atherosclerosis - the buildup of plaque in the walls of the arteries, diminished them and raised the blood challenge. MI cases typically arise when myocardial ischemia persists over a prolonged amount of time, overwhelming the structures of myocardial cellular recovery intended to support the regular functioning process and Cardiovascular function homeostasis. If this imbalanced requirement and blood supply reaches a critical threshold and persists for an extended time, it will result in permanent loss or necrosis of myocardial cells. Such an occurrence is sometimes induced in a coronary artery by plaque breakup with the forming of a thrombus, and in the most tragic situation, it can contribute to the death of an individual.

Several epidemiological experiments have been carried out to further recognize and classify the disorder, Considering the adverse influence of MI on culture. Such study has also established essential risk factors for CVD, including age, race, Saturated fat, high blood pressure, overweight, asthma, tobacco, drink, psychosocial causes, and poor and morbidly obese eating patterns (Anand *et al.*, 2008; Hubert *et al.*, 1983; Hung *et al.*, 2015; Levin & Stokes, 1989; Psaty *et al.*, 2001; Rosengren *et al.*, 2004). However, when evaluating risk factors, causation is important because the extent of their Predicts on individual health will vary over one generation. The mortality rate may also be decreased by diligent tracking, updating and regulating certain risk factors.

Includes, emerging approaches, socio-economic cost control criteria and escalating requirements for customized treatment (Olier & Vellido, 2008), new projections for the technologies able to deliver diagnosis, estimates and suggestions for the patient. This was part of a predictive, preventive and tailored Medicine strategy (Snyderman & Williams, 2003). These are some of the goals of the idea of "3P" in medicine was to provide medical practitioners with sophistized, reliable and productive risk management approaches as well as early, precise and tailored diagnoses for patients who might delay the onset of MI.

Coronary Artery Disease

The prevalence of CAD is growing worldwide, and the cost to government and other health stakeholders is huge (Kuulaasmaa, et al., 2000). In addition to the financial pressures it imposes, CAD is often deadly and is one of the most Common causes of death worldwide (WHO, 2017 ; Gendeirs, et al., 2012).

CAD is caused by the formation of plaque on the walls of the arteries that supply the heart with blood (coronary arteries) (BBC, 2013). This plaque is made of cholesterol and other chemicals placed on the wall of the artery (National Heart, 2016). CAD accounts for 7 million deaths worldwide every year.

The prevalence of CAD is on the rise worldwide, and disease management costs government and other health workers a lot of money (Kuulasmaa, et al., 2000). In addition to the financial pressures imposed, CAD is often fatal and one of the most Common deaths causes in the world (WHO, 2016 ; Genders, et al., 2012). The contrast between the normal coronary artery and a CAD artery is seen in Figure below.

Over time, CAD may damage the heart muscle and progress to heart failure, a disease which is often acute where the heart cannot pump blood the way it should. An first symptom of this is an irregular heartbeat/cardiac rhythm termed arrhythmia BBC (2016).

The diagnosis of CAD uses several variables including blood pressure, cholesterol, sugar, high BMI (overweight/obesity), physical inactivity, poor diet and smoking, etc (National Heart, 2016).

Other variables, including as age, sex and family history, are also likely to be CAD risk factors (Foundation 2015) CAD risk factors (National Heart, 2016).

Moreover, a doctor, usually a highly-trained cardiologist, conducts various tests to diagnose CAD and suggest a suitable treatment regimen if a patient shows symptoms or is at high risk of heart (NHS, 2015). This procedure is both resource-intensive and labour demanding and makes it extremely costly to diagnose and cure.

"Coronary artery disease starts throughout infancy and by the time of teenage years, there is evidence that plaques are created in most individuals that will remain with us for life," said Fisher, past editor of ATVB, the American Heart Association journal. "Early-established preventive interventions are expected to provide higher lifetime benefits. Healthy living can postpone CAD development and it is hoped that CAD would be rectified before it may cause CHD."

A balanced lifestyle with excellent diet, weight control and lots of physical exercise may play a major part in preventing CAD.

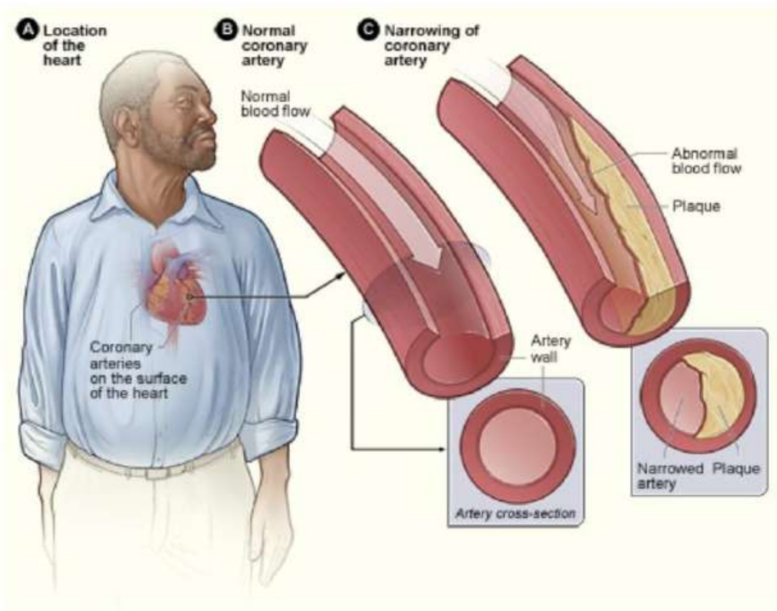


Figure 2.2 (Source: National Heart, Lung and Blood Institute. License: Public Domain)

2.12 Symptoms of CAD

When it comes to coronary artery disease, individuals may be completely unaware they have it since they have no symptoms at all at first. Plaque formation in your arteries may take anywhere from several years to many decades. Even minor symptoms may suggest your heart is working harder to carry oxygen-rich blood to your body when your arteries tighten. Chest discomfort and shortness of breath are the most frequent symptoms, particularly after mild physical activity such as going up stairs, although they may occur even while you're lying-in bed at night.

Coronary artery disease may be undetected until a heart attack occurs. Chest pain (angina) symptoms include: heaviness, tightness, pressure, hurting, burning, numbness, heaviness, squeezing or a dull ache. Angina may also include: difficulty breathing. Discomfort may also be felt in your left shoulder, arms, neck, back, or jaw, or it can extend throughout your whole body.

- I'm worn out.
- Feeling dizzy or lightheaded.
- Nausea.
- Weakness.
- Women may have distinct symptoms of a heart attack, such as discomfort or pain in the shoulders, neck, abdominal (belly), and/or back.
- Constipation or a feeling of unease in the stomach.
- Anxiety that doesn't seem to have a cause.
- Sweat that feels like ice.

2.13 Diagnosis

The cardiologist (heart doctor) will inquire about your symptoms, examine your medical history, go through your risk factors, and conduct a physical exam unless you're experiencing an emergency (such as a heart attack or stroke).

The following types of diagnostic tests may be used:

These examinations capture the electrical activity of the heart via the use of an electrocardiograph (EKG). Tests for heart attacks, ischemia, and irregular heartbeats.

This is a treadmill test to see how well your heart works while it's under the most stress possible. Angina and coronary artery blockages may be detected with this test.

Pharmacologic stress test: Medication is administered to raise your heart rate and imitate exercise instead of utilizing exercise to test your heart while it's working its hardest. Angina and coronary artery blockages may be detected with this test.

Atherosclerosis (hardening of the arteries) may be detected by a test that detects calcium deposits in the coronary arteries.

It utilizes sound waves to examine how well your heart's structures operate and how well your heart is functioning as a whole.

There are a variety of blood tests performed to check for conditions that may damage the arteries, such as high triglycerides, low HDL (good) cholesterol, high lipoprotein (bad) cholesterol, high C-reactive protein (CRP), high glucose, high hemoglobin (HbA1c), and other conditions.

It involves the insertion of tiny tubes into the heart's blood arteries to assess heart function, which includes the existence of coronary artery disease. Cardiac catheterization

Other types of imaging examinations for diagnosing health issues include:

A radioactive tracer is administered prior to the nuclear imaging test, and pictures of the heart are produced.

Computerized tomography angiography: CT and contrast dye are used to examine 3D images of the heart in motion and identify blockages in the coronary arteries.

2.14 Factors of risk

According to the research performed by the American Heart Association, the following are probable risks for CAD:

- Age

The majority of individuals who die of heart disease are 65 years of age or older. At 65 years of age, women who suffer heart attacks are more likely to die in a few weeks than males.

- Gender

Men are more likely than women to suffer heart attacks and they experience attacks earlier in life. Even after menopause, the mortality rate of women from cardiac disease is not as high as males.

- Inheritance (Including Race)

If children have parents with heart disease, they will acquire the illness more often. Most individuals with a significant family history of heart disease are likely to produce one or more additional risk factors.

- Smoke of tobacco

The chance of a smoker developing CHD for non-smokers is Considerably greater. Cigarette smoking is a strong independent risk factor for sudden heart mortality in CHD patients. Cigarette smoking also works to significantly raise the risk of CHD with other risk factors. Even for non-smokers, exposure to smoke of other individuals raises the risk of heart disease.

- High cholesterol in the blood

The risk of CHD increases as blood cholesterol increases. This risk rises further if additional risk factors (such as high blood pressure and cigarette smoking) are present. Cholesterol levels in a person are also influenced by age, sex, inheritance and nutrition.

- Blood pressure higher

High blood pressure increases the effort in the heart, thickening and strengthening the heart muscle. This cardiac muscle strengthening is not natural and inhibits the heart from functioning correctly. The risk of stroke, heart attack, renal failure and heart failure is also increased.

- Inactivity of the physical

Inactive lifestyles are a risk factor for heart disease. Regular physical exercise, moderate to vigorous, helps to decrease the risk of heart or blood vessel disease. Even modest activity is beneficial, if done on a regular and long-term basis. Physical exercise may help manage blood cholesterol, obesity and diabetes, and decrease blood pressure in certain individuals.

- Obesity and excess weight

People who have extra body fat — particularly in their tail — are more prone to have heart and stroke even if there are no other risk factors. Overweight and obese people with risk factors for cardiovascular disorders, e.g. hypertension, high cholesterol, or elevated blood sugar, may alter their lifestyles and reduce triglycerides, the blood glucose, HbA1c, and the risk of Type 2 diabetes clinically. Although many individuals may have difficulties reducing weight, a sustained decrease in weight of 3% to 5% may lead to clinically significant reductions in some risk factors. Weight reduction may decrease over 5 percent heart rate, cholesterol, and blood glucose.

- Mellitus diabetes

  Diabetes significantly raises the risk of cardiovascular disease. Much if glucose levels are managed, diabetes raises the risk of heart disease and stroke, but if blood sugar is not properly monitored the dangers are even higher. At least 68% of individuals over 65 years old with diabetes die from heart disease and 16% die from stroke. People with obesity or overweight diabetes should alter their lifestyle (e.g. eat healthier, do regular physical exercise, reduce weight) to help control blood sugar.

Arrhythmia

Arrhythmia is an issue with the heartbeat rate or rhythm. It implies that perhaps the heart beats too fast, too slowly, or irregularly. Whenever the heart beats quicker than usual, tachycardia is termed. If the heart beats too slowly, bradycardia is termed. Atrium fibrillation is the most frequent form of arrhythmia, which produces irregular and rapid heartbeat.

Many things may alter the rhythm of the heart, such as heart attack, smoking, cardiac abnormalities and stress. Some chemicals or medications may also induce rhythmic conditions.

Arrhythmic symptoms include quick or sluggish heartbeat, skip beats, light-headedness or dizziness, tachycardia, breathlessness and perspiration (Medicine, 2016).

There are many kinds of rhythms, and each kind is connected with a pattern and may thus be identified and classified. The rhythms may be categorized into two main groups. The first group comprises of arrhythmias made of a single irregular heartbeat known as morphological arrhythmias. The other group is made up of rhythms produced by the so called rhythmic arrhythmic a series of irregular heartbeats. Both kinds of arrhythmias lead to morphological changes in heartbeat wave frequency, which may be detected via the ECG test. The most frequent kinds of rhythms are shown in Figure 2.2 below.

Figure 2.3 Source: Lemmer, B. (2006)

The procedure of detecting and categorizing arrhythmias may be extremely problematic for a human person, because it is often required to analyze every heartbeat of the ECG data collected over many hours, or even days by a patient wearing a Holter monitor. Furthermore, due to tiredness, there is a potential of human mistake by the individual doing ECG data analysis. An option is to utilize automated categorization computer methods (Luz, et al., 2015).

Arrhythmias Causes

Arrhythmia is caused by a cardiac electrical system issue. Some arythmia causes include:

- Irritable cells of the heart

  Heart cells may begin to fail and give out aberrant electrical impulses. Signals from these dysfunctional cardiac cells interfere with the correct signals from the heart's normal pacemaker. This 'defuses' the heart that causes an uneven pulse

- Signals blocked

  The electronic impulses telling the heart to beat may be 'blocked.' This slowly causes the heart to beat.

- Abnormal trajectory

  Electrical impulses may begin in the correct location, but are stopped and diverted in order not to follow the correct route through the heart and create an arrhythmia.

- Drugs and stimulants in certain instances, arrhythmia may be caused by drugs and other substances, such as coffee, nicotine and alcohol.

Arrhythmias Types

- Bradiocardial symptoms (slow heartbeat)

  This word is used when the heart beats too slowly, usually fewer than 60 beats per minute. When the heart beats so slowly, it's significant that it can't pump enough blood to fulfil the body's requirements. Untreated bradycardia may lead to extreme fatigue, dizziness, lightheadedness or fainting, as insufficient blood reaches the brain. A sluggish heartbeat may be normal and may be linked to better fitness.

- Syndrome of the sick sinus

  This phrase explains when the natural cardiac pacemaker works too slowly and "fires" instruct the heart to beat slowly. It may be caused by the age or the fatty tissue of the heart's blood vessels.

- Block of the heart

- The heart block is termed the heart block when the signal from the receiving chambers (atria) to the chambers (ventricles) of the heart is delayed or blocked. It's unusual, but it may be severe. The symptoms may be minor or severe, depending on where and severity of the obstruction.

- Tachycardioid (a fast heartbeat)

  Tachycardia is usually above 100 beats per minute when the heart beats excessively quickly. Some types of tachycardia are easy to treat and not severe, while others may endanger life.

- Tachycardia super ventricular

  "Supraventricular tachycardia" is a fast pulse starting in the collecting chambers of the heart, atria or electric track in the atria (SVT). Common SVT forms include atrial and atrial fibrillation.

- Artrial Flutter

"atrial flutter" is an additional or early electrical signal that travels around the atria in a circle rather than following the usual signal route. This 'over-stimulation' causes the auricula to contract rapidly or 'flutter' Considerably faster than usual. Most of this fluttering is prevented from beating too quickly by an electrical route from the atria to inhibit the pumping of the heart, the ventricles. Atrial flutter does not typically endanger life, but may nevertheless induce chest discomfort, faintness or more severe cardiac issues.

- Fibrillation of the atrium

"Atrial fibrillation" is the most frequent type of SVT. This occurs when 'waves' of unchecked electrical impulses flow through the atria from the sinus node, instead of the usual controlled signals. The unregulated impulses force muscle fiber in the atria to contract out of time, such that the atria 'quiver.' Some of this electrical abnormality reaches the ventricles and causes a fast and erratic heart rate. If the heart is fibrous, it doesn't pump Consistently or function as it should. Atrial fibrillation may induce heartbeat, irregular pulsation, tightness or chest discomfort, faintness or vertigo. Atrial fibrillation may also raise the risk of stroke since blood in the atria may coagulate. These coagulations may break free from the heart, enter the circulation, and go into the brain causing a stroke.

- Supraventricular paroxysmal tachycardia

"Paroxysmal supraventricular tachycardia" is a "short circuit created by an additional electric connection or a heart-pathway which makes the heart susceptible to events of sudden frequent fast heartbeats which last minutes or even hours (PSVT). While these episodes may be scary, they are seldom harmful and may be handled quite successfully.

- White-Wolff-Parkinson syndrome

  The "Wolff-Parkinson-White Syndrome" is termed an additional or aberrant electric route which links the atria with the ventricles producing SVT episodes.

- Ventricular Tachycardia

  It may be extremely hazardous if the ventricles beat excessively quickly, termed "ventricular tachycardia." Tachycardia ventricular which is so severe that the ventricles cannot pump properly may lead to ventricular fibrillation. Ventricular fibrillation occurs when the electrical impulse that should cause heart beat divides around the ventricles into uncontrolled 'waves.' This life-threatening condition has to be promptly addressed.

Sleep Apnea

Tagluk et al. (2010) have developed a novel classification technique for Sleep Apnea Syndrome (SAS) utilizing wavelets and artificial neural network transformation (ANN). The network was pre - trained for various impulses. By multi resolution wavelet transformations, the abdominal respiration signals were split into spectral components. These spectral components were used for the artificial neural network inputs. The neural network was then designed to give three outputs to categories the patient's SAS condition. The suggested approach for this study is shown in Figure below.

A coefficient of a discrete wavelet transform applied to the raw specimens of the hypoxia in the abdominal stress signal Constituted the basis of the neural network. The experimental findings produced utilizing 360 apnea from 21 distinct patients showed the validity of the technique suggested. The highest overall accuracy was 78.85 per cent, which in comparison to manual grading was excellent enough.

Obstructive and central sleep apnea are the two forms of the disorder.

The more prevalent sleep disorder is obstructive sleep apnea. Obstructive sleep apnea is characterized by repeated episodes of partial or full obstruction of the upper airway while sleeping. Apneic episodes need more effort from your chest muscles and diaphragm since the pressure within your lungs is increasing. A sharp gasp or jolt of the body signals that breathing has resumed. These episodes may make it difficult to get a good night's sleep, decrease the amount of oxygen reaching critical organs, and even induce irregular heartbeat.

Because of unsteadiness in the breathing control center of patients with central sleep apnea, their airways are not closed while they sleep. Central apnea is linked to the nervous system's overall health.

Symptoms of Sleep Apnea

OSA is often detected for the first time by the patient's bed companion. There are a lot of people who are impacted by this who don't have any sleep issues. OSA is most often characterized by the following signs and symptoms:

- Snoring.
- Tiredness or drowsiness throughout the day.
- Frequent nocturnal awakenings due to restlessness during sleeping.
- Wakes up suddenly feeling like you're gasping or choked.
- In the morning, a painful throat or a dry mouth.
- Inability to concentrate, forgetfulness, or impatience are symptoms of cognitive impairment.
- Disturbances of mood (depression or anxiety).
- Sweating throughout the night.
- Urinating often in the middle of the night.
- Inability to have a sexual relationship.
- Headaches.

Those who suffer from central sleep apnea are more likely to have frequent awakenings or sleeplessness, as well as a choking or gasping feeling when they first wake up in the morning Children's symptoms may be more subtle and include:

- Inadequate grades at school.
- In the classroom, sluggishness or drowsiness is frequently misconstrued as laziness.
- The inability to properly breathe via the mouth and swallow food throughout the day.

- Breathing causes ribcage inward movement, or diaphragmatic breathing.
- Inconvenient sleeping arrangements, such as sleeping on your stomach or with your neck outstretched.
- Nighttime perspiration is excessive.
- diseases of cognition and behavior (hyperactivity, attention deficits).
- Bedwetting.

Consequences of obstructive sleep apnea on sleep quality

Sleep apnea, if ignored, may lead to a variety of health issues, such as hypertension, stroke, arrhythmias, cardiomyopathy, heart failure, diabetes, obesity, and heart attacks. Because people with sleep apnea have increased blood pressure, sleep apnea is prone to induce arrhythmias and heart failure. About half of those with heart problems or atrial fibrillation have sleep apnea.

The reason for this is that sleep apnea may lead to the following symptoms:

- Oxygen depletion that occurs often (hypoxia).
- Changes in the atmospheric concentration of carbon dioxide.
- Pressure changes in the chest have an immediate impact on the heart.
- Inflammation-related biomarkers are rising in the body.

Sleep apnea is common in cardiac arrhythmias including heart failure (it's a coin flip the whether patient has it or not), so you should see your doctor right away if you have any concerns.

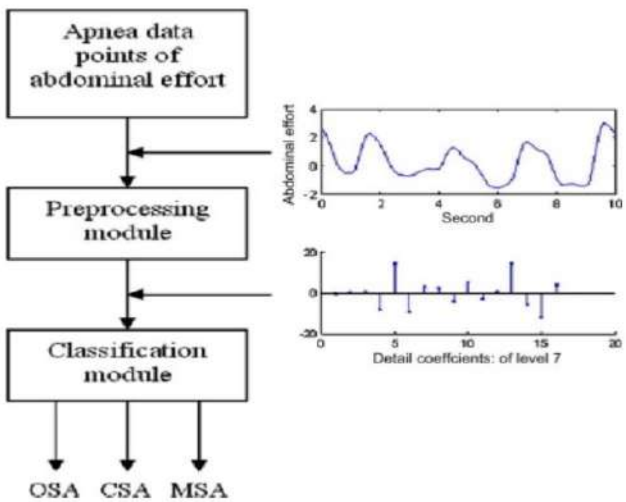


Figure 2.4 Methodology Proposed (Source: Tagluk et al., 2010)

Some Other Classification Methods for Heart Diseases

2.15 Heart General Disease

Tan & Teoh (2009) suggested a hybrid method Consisting of genetic algorithms and vector support machinery (SVMs). The grid search module selected the best characteristics in the data set. SVM then categorized the patterns into a smaller data set. By wrapping approach, they termed this method. The data sets utilized were acquired from the UCI study repository. When the unnecessary characteristics were eliminated, the GA- SVM hybrid was shown to be a decent classifier. The accuracy achieved for the method suggested was 76.20 percent. The suggested method also applies to multi-class domains with average precision of 84.07%.

Luukka & Lampinen (2010) used a grading approach based on pre-processing of data using Factor Analysis (PCA) and afterwards applying classification model to cardiac disease diagnostics. The traditional Electronic Medical Record (EMR) was utilized by the authors. Authors claimed that the key element of improvement of results was the use of an Efficient global optimizer and differential evolution in order to adapt the classification model rather than local optimization methods. They discovered that PCA pre-processing data produced better accuracy in categorization. The suggested method has averaged 82 percent accuracy.

Ansari & Gupta (2011) has created a Heart Disease Prediction Decision Support System utilising the Naïve Bayes method. The technology pulls valuable information from the heart disease database that was previously concealed. This model may respond to tough inquiries, each with its own power to facilitate model analysis, access to full information and accuracy. By integrating additional data mining methods, this model may be improved and extended further.

Shouman, et al. (2012) have conducted a study on KNN using a dataset of Cleveland Heart Disease to examine its Efficacy in heart disease prediction. The author also examined if the precision might be improved by combining voting with KNN. The findings indicated that KNN was 97.4 percent accurate. The findings also revealed that voting cannot improve the accuracy of the KNN in heart disease diagnosis.

Vijiyarani & Sudha (2013) presented a study analyzing data mining tree classification methods. The methods utilized and evaluated in the classification tree were Decision Stump, Random Forest and LMT Tree. This study was aimed at comparing the results of several categorization methods for a cardiovascular dataset. This study was done utilizing the Waikato knowledge analysis environment (WEKA). It is open source software Consisting of a set of algorithms for data mining. Amin et al. (2013) found that a significant quantity of data at medical institutions was accessible, however the data was not utilized correctly. This medical data lacked quality and comprehension since the development of a Productive decision support system needed very advanced data mining methods. The research showed that methods that are not only accurate and dependable but also decrease the cost of therapy should be developed and that patient care has to be increased. The systems should also be easily understood to improve human decision-making. In addition, because data mining techniques have shown significant success in prediction and diagnoses of diseases, and especially heart diseases, these techniques can thus also be implemented for treatment reasons, the author suggested that work should be done on proposing treatment plans for patients. The author also recommended that work should be done to put forth treatment plans for patients because data mining methods were successful in predicting and diagnosing heart illness and, in particular, cardiac disease, thus the use of these methods for treatment purposes.

2.16 Overlapping Symptoms

Depression diagnosis also relies on somatic symptoms that coincide with the overlapping of symptoms of certain medical conditions. (Ellis *et al.*, 2006); Milberger *et al.* (1995). Ellis *et al.* (2006) studied Disease signs correlate with depressive symptoms. The authors studies reviewed reported interviews with 46 of 61 qualifying populations residing among older adults with advanced disorders and a significant number of somatic depressive symptoms. Participants replied to an interactive query regarding emotions and formal queries about depressive symptoms. In the studies by Hsu *et al.* (2017) The overlapping general populace is very frequent with gastroesophageal reflux (GERD) and dyspepsia, although the relationship of each is little known. 107 participants of the population had "epigastric pain or burning" overlaps and 761 did not develop these symptoms. Subjects of GERD-D showed more serious GERD signs and were more frequently linked to GERD alone (IBS) syndrome (Hsu *et al.*, 2017).

Overlapping cardiovascular problems including palpitations, tightness in the chest and shortness of breath that arise in healthy individuals, like stress, suggests doctors and their patients have a very hard time assigning their causal or associated function to mental wellbeing. The management of signs and risk conditions is the priority of primary care clinicians and cardiologists, allowing less opportunity to cope with thoughts and emotions (Chaddha *et al.*, 2016).

General concern over everyday activities, though requirements for the formal diagnosis of generalized anxiety disorder are not fulfilled, has been found to encourage and accelerate coronary disease in psychological pain, including anguish and tension. The impact can also be progressive, indicating that further episode of anxiety, cold and fatigue, despite the usual coronary arteries or palpitations or heart beating, may be correlated with a greater incidence of cardiovascular disorders, as well as with the combination of symptoms or indicators of cardiovascular disease, such as chest pain act as overlapping symptoms of CVDs (Mensah & Collins, 2015; A. J. Thomas *et al.*, 2004).

Heart attack symptoms include the following:

- Discomfort or pressure in the left arm or chest
- Feelings of satiety, bloating, or choking (may feel like heartburn)
- Back, neck, throat, or arm pains are all possible symptoms.
- dizziness or sweating are symptoms of a more serious condition.
- Shortness of breath, dizziness, or trembling Extreme fatigue

Heart failure signs and symptoms include:

- a feeling of being out of breathe (often causes a hacking cough)
- Unhealthy weight gain occurs quickly (a weight gain of 2 or 3 pounds in a day is possible)
- Ankle, thigh, and abdominal swelling

- Dizziness
- Weakness and exhaustion
- An erratic or rapid pulse
- Nausea, heart palpitations, a racing heart, difficulty breathing when you wake up at night, and a shift in sleep patterns are all possible symptoms.
- Weight loss and a lack of appetite are two late signs.

The severity of your heart problems symptoms may or may not be linked to your heart's condition. Despite your symptoms, your heart function may only be slightly impaired.

The treatment for heart failure varies depending on the underlying reason, however it often involves medications to manage the symptoms, such as:

- To remove excess fluid from the body, use diuretics or water tablets.
- Beta-blockers are used to stop the effects of adrenaline.
- help regulate sodium levels with ACE inhibitors

Symptoms of an arrhythmia include:

- a racing pulse (experiencing "flip-flops" or "skip-beats," or feeling like your heart is "running away" is an example of this)
- your heart is pounding
- a sensation of faintness, lightheadedness, or dizziness

- a feeling of being out of breath
- pain in the sternum
- a feeling of weakness or exhaustion

depending on the kind of irregular heartbeat, treatment options include:

- heart-slowing medication
- Drugs that can help you get your heartbeat back to normal
- Antithrombotic drugs
- Cardioversion is a therapy that includes shocking your heart with a powerful electrical current to restore its normal rhythm.

Heart valve dysfunction may cause a variety of symptoms, including the following:

- Breathlessness or difficulty breathing after exertion
- fatigue, or a feeling of unsteadiness
- Fainting
- Chest discomfort when participating in a sport
- A fast pulse, irregular pulse, skipped pulses, or a flip-flop sensation in your chest may be felt as palpitations.
- Symptoms of heart failure caused by valve dysfunction include:

- Ankle, foot, or abdominal swelling
- gaining a lot of weight quickly

Adults with congenital cardiac disease may have the following signs and symptoms:

- a feeling of being out of breath
- Exercise is difficult because of a lack of time or resources.
- Heart failure and valve disease symptoms

Some signs of newborn congenital heart disease include:

- The skin, nails, and lips all have a pale blue tinge to them
- breathing that is too rapid, as well as inadequate nutrition
- Fat growth that isn't healthy
- a propensity towards bronchitis
- Absence of desire or capacity to work out

- Many individuals with cardiac muscle illness have no or mild symptoms and go about their daily lives as usual. Some people's symptoms increase over time as their heart function deteriorates.

Cardiomyopathy symptoms may occur at any age and include the following:

- a tightness or discomfort in the chest (typically after physical exertion, although it may also happen after rest or a meal)
- the signs and symptoms of cardiac arrest
- Reduced blood flow to the legs
- Fatigue\sFainting
- a racing pulse (chest flutters as a result of abnormal heart beats)
- Cardiomyopathy may cause sudden death in a tiny percentage of patients.

Pericarditis is characterized by the following signs and symptoms:

- A tightness in the chest. Unlike angina, this isn't a heart attack. In the middle of the chest, it may be a stab wound. In certain cases, the discomfort may extend to the neck, limbs, or back. Coughing, swallowing, or taking a big breath makes it worse; sitting forward makes it better.
- Fever of a low grade
- Heart rate has risen.
- Pericarditis usually goes away on its own, but in certain cases, doctors may prescribe medication to help manage it.
- Aspirin and other anti-inflammatory medications

- Steroids may be used in extreme instances.

2.17 Framework for Promoting Clinical Judgment

CDSS applies to any electronic device built and established to aid with Critically, clinical decision-making. An area that has been of particular importance that has been in recent years the capacity to evaluate the attributes of different individuals to create patient-specific reviews or guidelines, which are subsequently provided to physicians for Consideration (Bright *et al.*, 2012). Due to its ability of drawing on the abundance of daily clinical knowledge, which often is not exploited, the CDSS has become one of the most critical elements in future health care, including data-driven clinical procedures like diagnosis and prognosis as well as the exploration of new medical insights (e.g., the underlying mechanisms of a disease). Furthermore, the functionality of different programmed may be mixed and given, making it a dynamic tool whose usefulness and Efficacy in the clinical sense cannot be underestimated. (Bright *et al.*, 2012).

In professional decisions, the CDSS not only supports the need to bridge the gaps between practitioners, having them adhere to the same level of practice as their best practice. In spite of this benefit, CDSS has been highly appealing in the healthcare market, with many interesting works from the Artificial Intelligence Research community (W. G. J. A. o. i. m. Baxt, 1991; Brennan *et al.*, 2013; Chawla & Davis, 2013; Green *et al.*, 1995; Grotzinger *et al.*, 2012) - postulating methods that incorporate both knowledge-driven and data-driven principles for medical Through the continuing implementation of CDSS, it is intended that it will ultimately encourage doctors to concentrate on activities when they are most needed, leaving CDSS with the role of remembering, seeking and evaluating the "encyclopedic" component of medicine.

2.17.1 Management of CVD diseases.

2.17.1.1 Deep learning

Deep learning is a technique in which computers access information in two different ways: first, analyze brain wave patterns and then analyze language patterns to understand their context. Such a pyramid of notions assists a program to understand difficult and multifarious things by making them easier (Goodfellow *et al.*, 2016).

The establishment of typical machine learning systems requires rigorous engineering and large expertise to create extractors that can turn raw data into adequate categorization representations. In addition, the engineering process takes time and the characteristics are generally poor since previous knowledge is manufactured by hand. Deep learning has been the main technology for computer vision and image problems in recent years. It is a set of techniques for machine learning using supervised and non-supervised techniques to learn features automatically via the deployment of multi-layered classification hierarchies (Krittanawong *et al.*, 2019). It can revolutionize the modeling of CADx systems compared with previous machine learning approaches. With deep learning, characteristics may be found immediately without the need to explicitly define them.

These revealed aspects of deep learning can overcome those uncovered by traditional approaches. In addition, feature interactions and hierarchy may be maintained concurrently inside the deep neural network design, which would simplify the selection of the feature. Finally, features may be extracted, selected, and classified inside the same architecture collaboratively optimized. Following are different models that can be used in deep learning techniques.

2.17.1.2 Artificial neural network (ANN):

It is an essential component of deep learning techniques (ANN). It is a system of information processing Consisting of several linked components that collaborate in the concurrent processing of a given issue. ANNs have achieved a high degree of success in visual tasks where raw features cannot be interpreted separately because they are capable of learning hierarchical representation.

ANN is a kind of ML model initially introduced by McCulloch and Pitts in 1943 (Ingre & Yadav, 2015). This is affected by neural processes in the brain and may perform many roles, such as regression and grouping. It Consists of artificial neurons which first accept input data and then measure the output value based on the provided input values. The capacity of ANN to describe non-linear dynamic interactions is a key advantage of ANN over conventional mathematical techniques. This offers ANN the strategic edge when modeling non-trivial functions; helps to succeed if it is used to various complicated challenges in science and engineering. ANN has, however: (1) a high degree of reception to the significance of its parameters; (2) the design and sophistication of the designed network plays an important role in its performance; (3) a high level of computational training cost; and (4) the resulting induction models can be difficult for humans to understand (Bellazzi & Zupan, 2008).

2.17.1.3 Convolutional Neural Networks (CNN)

A CNN is a neural network branch that includes a stack of layers executing a particular WFATation, e.g., convolution, pooling, loss computation, etc. CNN, has generated several achievements in image identification, segmentation, and reconnaissance for objects and areas (Hesamian *et al.*, 2019). A CNN Consists of many neuron layers processing sections of an input picture. The neuron outputs are tiled to generate an overlap and provide a filtered image. This is done on each layer until the final result is the class probability usually predicted. CNN training includes several rounds for network parameters optimization. During each iteration, several samples are randomly picked from the input training and are distributed among the network layers. Network settings are changed by back-propagation to minimize a cost function for optimum results. Fresh or unknown data may be utilized to predict once trained. Features may automatically be taught without the knowledge or hard coding via a training package. In addition, the retrieved characteristics are reasonably resilient to picture alterations or changes. Research finally showed that CNNs outperform conventional techniques of picture categorization and can obtain state-of-the-art outcomes. Different academics have examined the use of deep learning methods for general and health objectives. CNN's have largely been used for detection, segmentation, and classification in the area of medical imaging. These responsibilities are part of the CADx process, as previously stated (FEVEandeur *et al.*, 2018).

2.17.1.4 Fully Convolutional Network (FCN)

In Long's complete convolutionary network (FCN) Long et al., the final completely linked layer has been replaced by a completely convolutionary layer. This significant increase enables the network to have a dense pixel forecast. To improve the location performance, high-resolution activation maps are merged with samples Outputs are fed to convolution layers for more precise output assembly. This innovation makes it possible for the FCN to have full-size picture pixel-wise predictions instead of a patch-wise prediction and also allows it to forecast the complete picture in one forward pass. Nie et al. did an identical experiment with the use of the FCN. The result indicated the advantage of FCN over CNN by reaching an average coEffecient of 0.885 compared to 0.864, although both tests employed the same methods and dataset (Hesamian *et al.*, 2019).

2.17.1.5 Deep Recurrent Neural Networks

Recurrent neural networks are not built on a fixed context rather on a hierarchical bidirectional recurrent neural network that evaluates patients' historical healthcare reviews. The vast data in the form of text mining was collected to analyze the long short-term memory of patients' hospitality evaluations.

The approach focuses both on user experience' time-related behaviors and views and on a persistent emotional impact. Models provide ways in the long-term and short-term memory product assessment of CYANumers (Hesamian *et al.*, 2019).

2.18 Research gap and Future directions:

Deep learning offers better integration of medical data sources, addresses patient disease type heterogeneity, bridges the gap between omics and bedside phenotypes and finally enables individualized medication. Scientific advancement may require that current limits be overcome, including limited theoretical design and testing, limited interpretability, and overfit strategies. Cardiovascular medicine, in particular, is good at smart analysis of continuous and massive data streams in this new era of wearable sensors and the integration of traditional data. This integration would form the foundation for a medical web of things between medical devices and analytical systems if data protection and security concerns were met. Seamless integration of various data sources could allow continuous monitoring of diseases, risk stratification, and early warnings on potential decompensation.

The literature research showed that the suggested technique might also cover additional classification issues using data sets of the same kind employed in this investigation. However, there is still more to be done to examine their potential and use in studying clusters, noise reduction, and confusing rules-based techniques for detecting illnesses. In the future, the data sets for the identification and prediction of illnesses using deep learning algorithms must be more focused. Additional data sets and in particular huge data sets must be examined to demonstrate the Emptysis of the time technique of computation for huge data. It also analyses how the reFEVEended technique might be used to incorporate different sorts of medical data sets. However, the literature on overlapping symptoms and overlap prediction provides research need to be addressed. Our study focuses on the early prediction in CVDs of overlapping symptoms.

2.19 Theoretical Reviews

Cao *et al.* (2019) studied deep learning models for cardiovascular disease to improve the medical diagnosis and screening of diseases. It is challenging for the clinician to scan and diagnose the CVDs in the early stage since they have the same signs and separate triggers. Machine learning may provide a clearer way to differentiate them both. Though, the authors used the medical image recognition type of deep learning to screen and diagnose various diseases in the present Research. For a refresher, picture detection, distinction, and pattern recognition are important, and it is going to be really popular with loads of research scholars. As a component, picture segmentation, grouping, and other factors are used to think about in-depth cardiovascular disease. CVDS are becoming the main Constituent of improving mortality rates in recent years, owing to the lack of information regarding the early treatment of the disease. The machine learning techniques helped the machine to work better in certain areas, which the author(s) define as computational biomedical. As well, the study is looking forward to creating a patient portal integrated with deep learning technologies to simplify the care of the patient and to include remote evaluation and tracking.

Kording *et al.* (2018) explore the overall role of machine learning in biomedical science. The overarching aim of the thesis is to develop and use machine learning models focused on studies to assess the threats, disease control, and enhancements in understanding the human physiological state patterns depending upon several attributes. Or the programmers and physicists are trying to understand the machine as an algorithm, to understand which algorithms the brain uses to remember. Or the programmers and physicists are trying to understand the machine as an algorithm, to understand which algorithms the brains to remember. The research study briefly explains the benchmarking based on machine learning, which can provide a scale measurement of what is being concluded through the input data. Benchmarking gives standardized values between the model prediction and actual, which can be useful to eradicate errors and missing attributes in the model. Neural encoding is the examination of brain waves such that they can be affected by external attributes, for instance, curve analysis. In comparison, neural decoding is the study of participants' intentions depending on their feelings. Moreover, the necessity of machine learning in today's wide life aspects is discussed by the researcher in the present article.

Bakator *et al.* (2018) did the implementation of deep learning for medical diagnosis in their study. A detailed review of numerous research papers in the area of the use of deep neural networks in the medical field has been carried out. More than 300 research papers were investigated by the authors, and 46 articles were presented in more depth after many selection measures. The findings show that when it comes to deep learning and medical picture processing, convolutional neural networks (CNN) are the most frequently portrayed. Furthermore, MRI also was Commonly used as training details. Segmentation is the most Commonly represented when it comes to the particular use. It is necessary to remember that the study and interpretation of the paper are weighted against more current papers and articles in the title that contained "deep learning." It can be shown that the form of data that is used to train and implement deep neural networks has a wide range of data. For expert-level diagnostics, CT scan images, MRIs, fundus photography, and other forms of details may be used.

The descriptive structure of this analysis can add to the current body of literature on a moderate basis. The goal was to include an article that was objective, clear, and succinct. The individual study findings provide ample knowledge and insight into deep learning applications for identifying, recognizing, segmentation, and diagnosing different diseases and anomalies in particular anatomical regions of concern (ROI). Without even a question, the use of deep learning in the medical sector can continue to grow since it has already produced promising results in medical image processing and, more specifically, in the identification and diagnosis of image-based cancer. In the long term, this will improve healthcare reliability and Cyanosis, thus reducing the likelihood of chronic illnesses being detected late. Though, as stated earlier, there will still be a fair journey to go until neural networks of ideas associated can be Commercially important. Finally, artificial intelligence is supposed to "rise" by the combination of learning regarding the interpretation and abstract thinking.

Brunese *et al.* (2020) explores the deep learning approaches for heart diseases through cardiac sounds. Machine learning models were selected to recognize cardiac sound patterns to evaluate the symptoms and risk predictions. Many factors of mortality are linked with cardiovascular disease. In practice, the heart rhythm is disrupted by many irregularities, such as a heart murmur or artifact. The investigators suggest a system for predicting heart problems. The research interprets this function vector as an input for a deep neural network by accumulating a collection of features obtainable directly from cardiac sounds to distinguish whether a cardiac sound belongs to a healthy individual or to a patient with a cardiac condition.

One person loses his or her life every 37 seconds because of cardiovascular diseases according to the Centre for Disease Control and Prevention (Ulbricht & Southgate, 1991). The authors chose two staged evaluations in their study design. Descriptive feature of the samples were explored using Orange frameworks, a collection of machine learning applications that is largely used for empirical analysis in data mining (Demšar *et al.*, 2013). Secondly, the model was created using Keras, a high-level API for neural networks, written in Python and able to WFATate on TensorFlow2, a Google research and development open-source data visualization library. This paper aims to provide a first stage cardiac pathology screening method. The experiment this research undertook shows the feasibility of the method suggested in the real world.

Karimi-Bidhendi *et al.* (2020) explored the completely automatic segmentation model for deep learning for cardiovascular magnetic resonance. Improving clinical workflow, diagnostic precision and analysis Efficacy are known to be unmet clinical needs for the increasing patient FEVEunity of congenital heart disease (CHD). Cardiovascular visualization includes non-invasive and non-ionizing tests for CHD patients. While CMR data allows for precise heart function analysis and anatomy, the clinical workflow relies mostly on time-Consuming CMR images manual analysis. . Therefore, as the present work aims to create, an integrated and reliable segmentation tool specifically dedicated to pediatric CMR images will greatly enhance the clinical workflow.

Large, annotated datasets are needed to train artificial intelligence algorithms for CMR research, which are not readily accessible for pediatric content, especially in patients with CHD. The authors built a novel approach, to mitigate this issue, a genetic Adversarial Network (GAN) is used to synthesize the training data collection. In addition, the authors trained and validated a large, completely convolutionary network (FCN), which the authors made accessible to the public. The findings of the chambers' segmentation from our completely automated system demonstrated good Cyanosis with manual segmentation, and two separate statistical tests did not notice a substantial statistical discrepancy.

Kansagara *et al.* (2011) presented a systematic review on the risk prediction models for hospital readmission. It is of Considerable importance to forecast hospital readmission danger to assess which patients will benefit more from treatment change measures, as well as to risk-adjust readmission rates for hospital comparative purposes. The goal of their Research was to summarize established models for the Prediction of readmission risk, explain their Chest Pain, and determine suitability for clinical or administrative usage. Fourteen frameworks are focused on institutional retrospective knowledge which may theoretically be utilized for comparative purposes in hospitals. To classify high-risk individuals in real time in order to potentially promote tailored treatments, three administrative data-based models were developed.

To sum up, the estimation of readmission danger is a dynamic undertaking with several inherent limitations. The majority of models built to date have low predictive potential, whether for hospital comparison or therapeutic reasons. While these models could prove valuable in some environments, better methods are required to measure hospital success in discharging patients, as well as to classify patients at higher risk of preventable readmission.

Peili *et al.* (2018) estimated the deep learning models on the risk factors of coronary artery disease. One of the prevalent diseases that endanger the health and existence of individuals is Heart Disease (CHD).

The standard form of diagnosis depends largely on the technical expertise of the physicians and the experience of the clinic. In recent years, precision medical therapies focused on big data and deep learning have been a science hotspot. (Litjens *et al.*, 2017; Shen *et al.*, 2017). In comparison to undertaking algorithms, Machine Learning is Part of a broader class of artificial intelligence techniques that are based on data representation learning (Nature, 2015). This is a neural artificial network with many unknown layers between the input layer and the output layer known as the Deep Neural Network this same machine learning algorithm (Goodfellow *et al.*, 2016; LeCun *et al.*, 1998; Schmidhuber, 2015).

The literature, however, focuses mainly on how the CHD early warning models can be designed and customized, while missing the lifecycle management simulation Consequences of data-model-experimental outcomes training.

The algorithm of Tracking-Ancestor and The Find-Specified-Ancestor algorithms are programmed to navigate the family of the deep neural model. The results of the Research suggest that would include an Productive automated data processing system for CHD early warning researchers.

Srivastava *et al.* (2020) has introduced a new method of evaluating disease using a dataset of Cleveland Heart Disease, integrating computing capacity with separate ML and DM algorithms and has concluded that K-Nearest Neighbors provides the maximum Accuracy of all algorithms by 87 percent. In addition, and therefore not enough in the medical sector, a web app is built using a python flask that enables the CYANumer to insert attributes and forecast heart failure. Another H-studies.

David (2018) has addresses and uses a predictive method to evaluate and forecast the potential of cardiovascular disease in utilizing three data mining classification algorithms such as Random Forecast, Decision Tree and Naïve Bayes. The main purpose of this essential work is to find the best classification algorithm to ensure optimum Cyanosis in classification of ordinary and abnormal individuals, which takes longer to settle on a better classification and achieve the results needed. Prevention of loss of life is also necessary at an earlier point. The experimental setup was developed to test the Chest Pain of algorithms with the help of the UCI machine learning repository's dataset for heart disease. The Random Forest Algorithm is found to be most Productive with 81 percent relative to other algorithms for Prediction of cardiac disease, and this finding in the medical sector is known to be incomplete as it needs stronger and productive performance.

Schirrmeister *et al.* (2017) It provides a technique that uses selection, segmentation, characteristic extraction, and certain learning algorithms to diagnose Chronic Heart disease, including boosting, supported k-Nearest neighbors, vector machines, Naïve Bayes grouping, J48 and random tree. In the experimental level, the LOSO cross-validation calculation is used, and the model is 96 percent accurate.

Q. Zhang *et al.* (2017) have built a Cardiac Health Monitoring hardware framework using the Help Vector Machine algorithm to classify heartbeat, an unattended learning technique for heartbeat purification, and a chest ECG regression tool.

The IOT technology for Prediction and diagnosis of cardiac disease is used by Rajkumar *et al.* (2019) using Java on Amazon Cloud. van den Tempel *et al.* (2018) proposed to use the Multilayer Feed Forward Neural Network with Levenberg Marquards Learning Model for Classification of Diabetes and In combination with the Naïve Bayesian Network, coronary disease obtained a precision for asthma.

Kwon *et al.* (2019) predicted in-hospital mortality rates using deep network models among the patients of heart diseases through echocardiographic techniques. The leading cause of global death is heart disease (HD); HD has many mortality forecast models for recognizing chronically sick patients and directing decision-making. However, current templates cannot be included in the process of initial therapy or screening. The purpose of this Research was to extract and test an HD echocardiography-based mortality prediction.

Usage of derivative data from a clinic, the authors built a prediction model focused on deep learning. And researchers also carried out external confirmation using hospital echocardiography study. The authors carried out a subgroup study of hospital's patients with coronary heart disease and heart failure and associated deep learning with the statistical models Commonly used, such as GRACE score, TIMI, and GWTG-HF ratings. Study conclusions have explained that the DL models focused on echocardiography forecast hospital mortality.

Bernard *et al.* (2018) explored MRI prediction using the deep neural networks, and deep learning techniques to diagnose (members *et al.*, 2014; Norris *et al.*, 1992; Silberberg *et al.*, 1989). Over the past decades, the automation of the related functions has therefore been the focus of extensive study. The dataset includes data from 150 CMRI multi-equipment recordings with comparison and description measurements from two medical professionals. The ultimate aim of this paper is to determine how much state-of-the-art techniques of deep learning will go in evaluating CMRI, such as segmenting the myocardium and the two ventricles,

The findings provided so far show that we are on the eve of fully automated CMRI analysis to crack the nut. This will cause the time spent on processing raw data to be minimized such that the patient could be presented with the results of the test before visiting the radiology clinic. The new systems have pre-filled radiological reports with an advanced automated speech recognition technology in today's clinical procedures, so that clinicians can dictate the different physiological and technological criteria. An automated software for CMRI research may also easil (Isin & Ozdalili, 2017)y be implemented into this system. That said, until such software is accepted by accreditation agencies and incorporated into MRI, further investigations are still important.

Isin and Ozdalili (2017) suggested the deep learning models for detection of arrhythmias. The electrocardiogram is an important diagnostic instrument in the clinical protocol for assessing cardiac arrhythmias. In this Research, by classifying patient ECGs into corresponding cardiac disorders, a deep learning algorithm previously trained on a general picture data set is transferred to conduct automated ECG arrhythmia diagnostics. As a function extractor, the transferred deep coevolutionary neural network is used and the extracted characteristics are fed into a basic neural network of back propagation to conduct the final classification. In order to test the suggested system, three separate ECG waveform conditions were chosen from the MIT-BIH arrhythmia database. The findings obtained showed that the transferred deep learning function extractor cascaded with a traditional neural network for back propagation could attain very high output rates. The maximum accurate perception score obtained is 98.51 percent, although the Cyanosis of the examination is about 92 percent. On the basis of these observations, transferred deep learning proved to be a successful form of automated identification of cardiac arrhythmias thus removing the strain of training a deep coevolutionary neural network from scratch, offering a readily accessible technique.

Research Gap

From the literature review, it has been indicated that the proposed solution could also refer to other classification problems involving data sets of the same type used in this analysis. Yet study into clustering, noise reduction and ambiguous rules-based approaches for the detection of diseases remains a lot to be done to explore both their ability and usefulness. In future, more focus needs to be given to the data sets for the detection and Prediction of diseases utilizing gradual deep learning approaches. This approach also needs to be tested on additional data sets and in particular on large data sets, in order to illustrate the usefulness of the calculation time method on large data.

Furthermore, it explores how the approach suggested can be applied to include other forms of medical data sets. Yet there is very less literature regarding the overlapping of symptoms and prediction of overlapping which creates a research gap to be filled. Our research is aimed on finding the early prediction of overlapping symptoms in the CVDs.

Chapter III Methodology

3.1 Introduction

This chapter provides the reasoning for the approach and the description of the approaches used. The option/development of questionnaires or techniques used in data collection is given in this segment. It describes explicitly the mechanism involved in developing/selecting the tools and the size of the compilation of primary data. It also determines the psychological EMPTct assessment method of the instrument. The methods used to gather data, including the survey procedure, is also addressed.

3.2 Research Strategies

There are a number of techniques for recognizing the environment in which testing is performed by researchers in market research. Scientists follow two study strategies in particular: quantitative strategies focused on empirical measurements and numerical data analysis, and qualitative strategies which emphasize words rather than quantity in data collection and analysis (Bell, Bryman, & Harley, 2018).

The nature of the sample may be qualitative, quantitative or a combination of the two based on the research issue (Yin, 2000). Due to the complexity of the research and the need to include as many participants as possible a quantitative approach is used in this situation.

3.3 Research Design

The study design is designed to find answers to main questionnaires and to gather the data needed to address our research questions (Lee & Lings, 2008). The core elements of study architecture are analytical unit methods, research problems and data processing, categorization and statistical analysis. However, this analysis approach harmonizes the empirical data to be gathered with the previous research issues of the report and ultimately with its conclusions (Yin, 2000). The study design applies to the requirements: accuracy, quality and validity utilized in the test evaluation. (Saunders, Lewis, & Thornhill, 2009). The survey questionnaire was, nevertheless, a critical instrument.

3.4 Research Approach

The research approach is a plan and method which involves the general assumptions of detailed data collection, analysis and interpretation processes. The research approach It is thus dependent on the essence of the research issue. It is crucial to choose the most appropriate study approach since it demonstrates how best to answer or at least discuss research questions. For each sample, the deductive, inductive or combined methods are chosen. The deductive method was introduced because of the nature of this research.

3.5 Sampling

The sampling strategies may typically be separated into two forms: likelihood or random sampling and impossible or un-random sampling (J. Wilson, 2014). Sampling technique means that any object in the community can be included in the sample fairly. In the case of the impossible sampling, the likelihood of the variable being chosen from the survey is not understood, because there can be no inferential statistics with regard to the population. The convenience sampling would be used for our test study, which is the kind of unlikely sample. It is crucial to choose the most Effecient study approach since it demonstrates how best to answer or at least pose research questions. For each sample, the deductive, inductive or mixture of all methods is chosen. The deductive method was followed because of the nature of this research.

3.5.1 Deductive approach

The deductive approach starts with the idea of the subject matter hypothesis being accepted and refined into more concrete, testable hypotheses. Eventually, this would result in the researcher being able to check the data and validate the original research hypotheses. Saunders, Lewis, and Thornhill (2009) indicated that an existing theory should be used to Construct an adopted method when beginning work from a deductive position.

3.6 Population

In our research study, the research study population or participants will Consist of the eligible physicians registered in the UAE Hospitals. The participants include those who have no expected experience in ambulatory practices.

3.7 Dataset

To evaluate the study's objectives the population for sampling will have Consisted of UAE hospitals and a dataset Consisting on cvd risk assessment tools in UAE by Oulhaj A (2019) will be used.

3.8 Data description

There are 3 types of input features:

Objective: factual information.

Examination: results of medical examination;

Subjective: information given by the patient.

Cardiovascular Variable Selection

Following clinic pathological variables will be chosen for sampling of dataset, extracting experimentally on many patient cases.

Table 3.1 shows the list of variables which are to be used in conducting this study, categorized into four groups i.e., Basic Information, Symptoms, Inducement and Medical History, Physical signs and Assistant Examination. Variables selected for the study are given in the following table which include the symptoms and their abbreviations used in the software, which are calculated on 3 level scale, -1 equals to none, 0.5 equals to normal, which 1 equals to higher intensity of symptoms.

Table 3.1 Variables for Cardiovascular Diseases in the Selected Dataset

Variable name		**Variable description**	Designation
Basic Information	id	Patient ID	
	gender	Age	[0, 1]
	age	Age years	[0, 1]
	cgh	Cough	[-1, 0.5, 1]
Symptom	emp	Emptysis/Expectoration	[-1, 0.5, 1]
	dys	Dyspnea	[-1, 0.5, 1]
	gas	Gasping/Panting	[-1, 0.5, 1]
	nau	Nausea/vomiting	[-1, 0.5, 1]
	dizz	Dizziness	[-1, 0.5, 1]
	head	Headache	[-1, 0.5, 1]
	fev	Fever	[-1, 0.5, 1]
	cyan	Cyanosis	[-1, 0.5, 1]
	pal	Palpitations	[-1, 0.5, 1]

	weak	Weakness or fatigue	[-1, 0.5, 1]
	press	Discomfort, pressure, heaviness in the chest	[-1, 0.5, 1]
	cp	Chest pain (precordial region, posterior sternal)	[-1, 0.5, 1]
	ell	Edema of lower limb	[-1, 0.5, 1]
Inducement and history	kfoi	Known factors of inducement	[-1,0,1]
	uri	Upper respiratory infection	[-1, 0.5, 1]
	cpd_his	Chronic pulmonary diseased history	[-1, 0.5, 1]
	hyp_his	Hypertention family history	[-1, 0.5, 1]
	CHD_his	Coronary heart diseases family history	[-1, 0.5, 1]
Physical sign and assistant examination	bp	Blood pressure	[0,1]
	cve	Cervical venous engorgement	[-1, 0.5, 1]
	bar_che	Barrel chest	[-1, 0.5, 1]

	sound_b	Sound of breath in pulmonary	[-1, 0.5, 1]
	Moi	Moist rales	[-1, 0.5, 1]
	sonant	Boundary of heart sonant	[-1, 0.5, 1]
	sm	Systolic murmur	[-1, 0.5, 1]
	dm	Diastolic murmur	[-1, 0.5, 1]
	s_thri	Systolic thrill	[-1, 0.5, 1]
	SHS	Second heart sound	[-1, 0.5, 1]
	LK_tend	Liver and kidney tenderness	[-1, 0.5, 1]
	Hyp_note	Hyperresonant note	[-1, 0.5, 1]
	EPR	Eminence in precordial region	[-1, 0.5, 1]
	CRO	Cardiac rhythm in good order or not	[-1, 0.5, 1]
	P_wave	Pulmaonic P-wave	[-1, 0.5, 1]
	Neck_vr	Neck venous return	[0,1]
	C_enlar	Cardiac enlargement	[-1, 0.5, 1]
	ECG	Electrocardiogram	[-1, 0.5, 1]
	STT_alter	ST-T alteration	[-1, 0.5, 1]

3.9 Sampling Techniques

Sampling is an method of selecting data from the overall population, the present figure 3.1 below explains the different kinds of sampling methods used in the research methodologies.

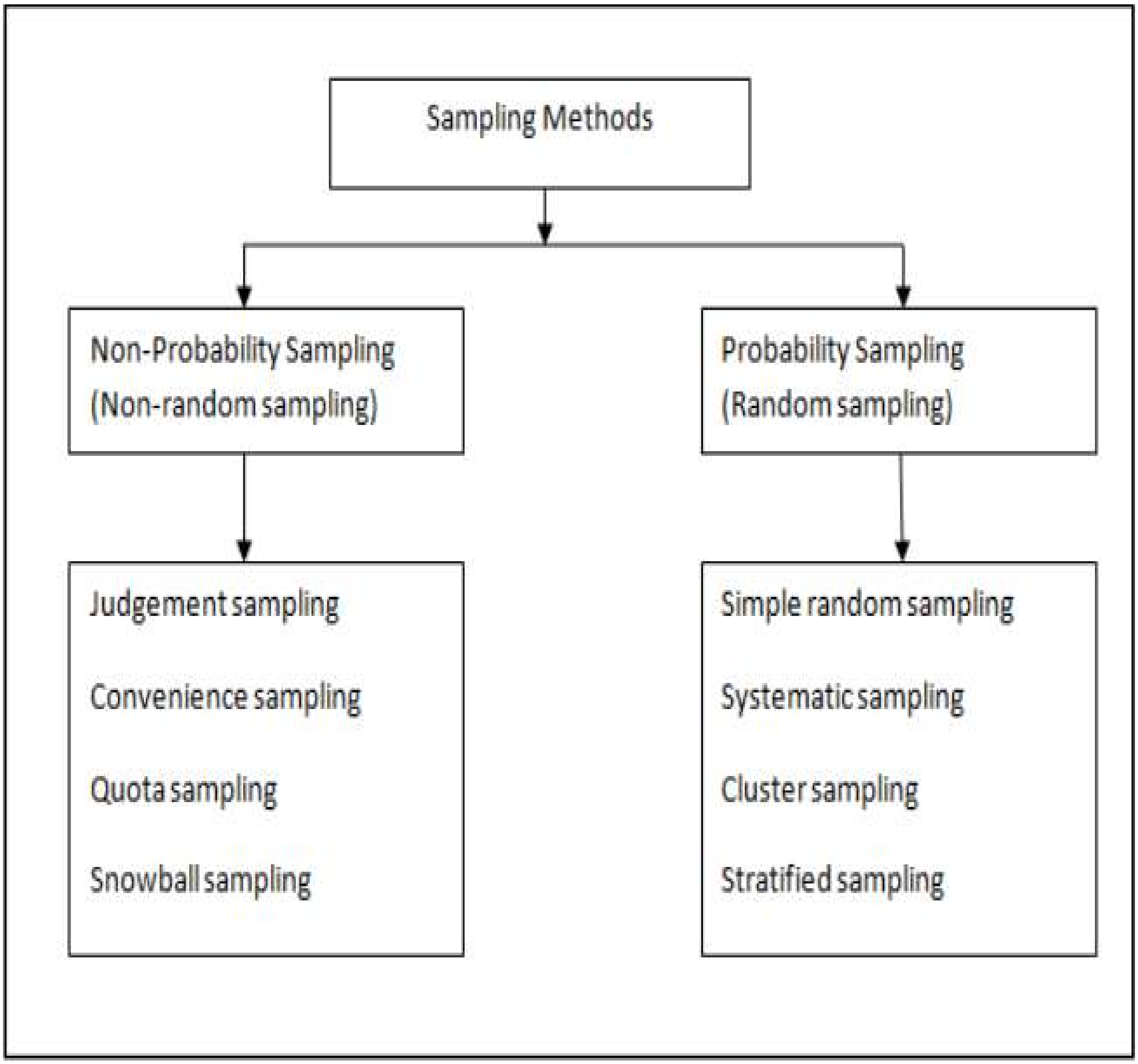


Fig 3.1Sampling Methods

We used the comfort sampling technique in this study. Convenience sampling technology is primarily used to pick samples for primary data processing and is part of the non-likely sampling design group. A convenience sample is a form of unlikely sampling procedure, where a community of people can be contacted or reached with the sample easily.

3.10 Analysis of Data

Descriptive studies will assess age, race, and medical history descriptive data and include them as frequencies, numbers, mediums (M), medium and normal difference (SD). Further work will include utilising a prediction model and a multi-layer perceptron with a modern Google framework named Tensorflow and Python.

Validation measures

Reliability and validity are Considered as two crucial parameters which are mostly used to quantify the nature of research. The research makes utilization of the acceptance procedures, for example, reliability and validity keeping in mind the end goal to make the research more honest. Reliability and validity are the essential worries in quantitative research. Furthermore, it is most critical in quantitative study to utilize these parameters to make research more honest to goodness and in the meantime, they do not old any huge spot in the subjective research. Moreover, there are four parameters, for example, transferability, believability, reliability and comparability which are most imperative to discover the qualities in the subjective research. The validity of a Construct provides agreement between the concept and the instrument or device used to measure it. There are two sub-categories of Construct validity measure namely "convergent validity" and "discriminant validity".

The general agreement among responses collected without the influence of each other in situations where the measures are theoretically related is known as convergent validity or in other words to establish convergent validity, one needs to show that measures that should be related are in reality related. The lack of relation between measures which should not be related in theory is known as discriminant validity (Carmines & Zeller, 1979).

Implementation Methodology

A-Analysis of Samples using Machine Learning

The data set was comprised of several combinations based of machine learning permutations. Suppose we has Eight Sample from N =1 to N = 8, Then there will be 276 Machine Learning-(ML) Permutations. All these ML-Combinations are regressed using SPSS against all instances in which the model was predictoried (eight different usability factors). The main cause of the multi linear approach for stepping regression is that the distance between predictor responses is significantly reduced. This approach builds will help us out to check which one is the best sample of water tested for arsenic in different ways by integrating single and many independent variables with the dependent variable, such as the two factors IV, three factors IV, four factors IV etc. The R2 value is determined using all possible combinations of statistically significant predictors with a 0.000 value. MLR results are shown in below tables in the following section for the various combinations of predictors greater the value of R^2 means a better model.

B-Assessment Using Neural Network

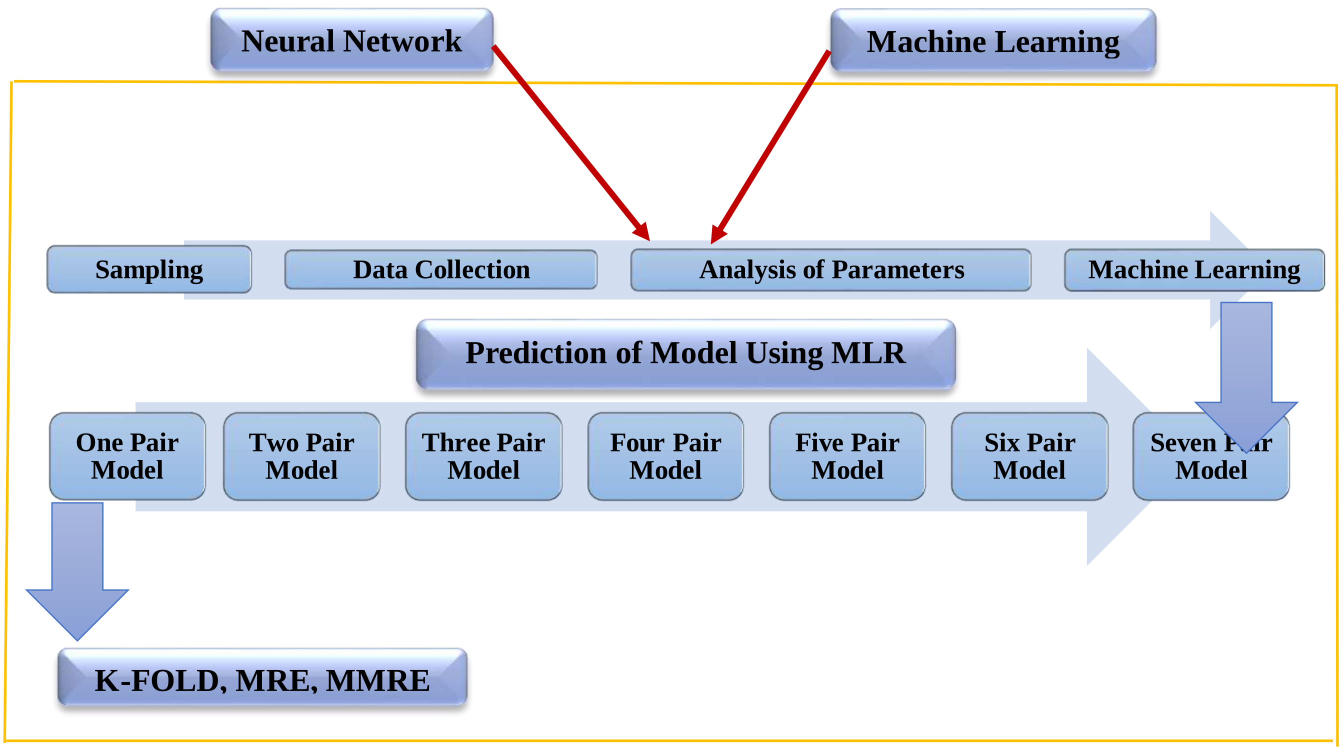
De facto normal prediction accuracy metrics are used to identify the arsenics in water. MMRE and PRED(x) are the techniques of machine learning. In the literature. PRED value (0.25) is greater or equal to 0.75. The value of MRE which is greater than 0.25 will be Considered as Pred(X) and will be rejected. It was found that the MMRE value was 0.0515.

B-1 Validation Process

Cross-validation K-fold (Rodríguez, 2010) is a non-exhaustive model validation technique. This technique uses the performance of the predicted model on an autonomous data set. The dataset is divided into the same number of folds depending on the data size. Data calibration and validation doubles their data points through k-fold cross-validation. The training segment contains (k-1) and the test section contains (k-1) for each interaction data set (1). It was predetermined the sequence of the answers in the folds. In each iteration, eight folds were used to calibrate the model, and the rest were used to validate the model.

B-2 K-Fold Cross Validation

The data values in all folds are divided into ten fixed groups. Suppose we have 100 data sets against each sample of ML, we will be able to have 10 folds each containing 1-10 sets. For fold K = 1 to K= 10. even each of its value in the K fold prediction we identified all data sets are significant values. We found all six predictors to be significant if the value after training is 0.05. It should be noted that PRED (0.25) is calculated in all folds. All the values of MMRE and R2 show the validation of the proposed" model.



Instrumentation of Water Sampling in SPSS

A quantitative study has been undertaken, and I've chosen an above detection method instrument in which I've selected a quantity of 20 water sample persons, only a handful of whom are containing arsenic and numerous people have been using this water. All these results have been instrumented in SPSS to generate some results.

Fig. 3.2 Validity Measurements

3.11 Research Model

Now time series forecasting, or predictive modeling can be done using any framework; TensorFlow provides us with a few different models for like as Convolution Neural Network (CNN), Recurrent Neural Networks (RNN), dataset forecast will be done and make all predictions. The current study evaluates the early Prediction of overlapping symptoms of CVDs, to evaluate the study objective following model will be used.

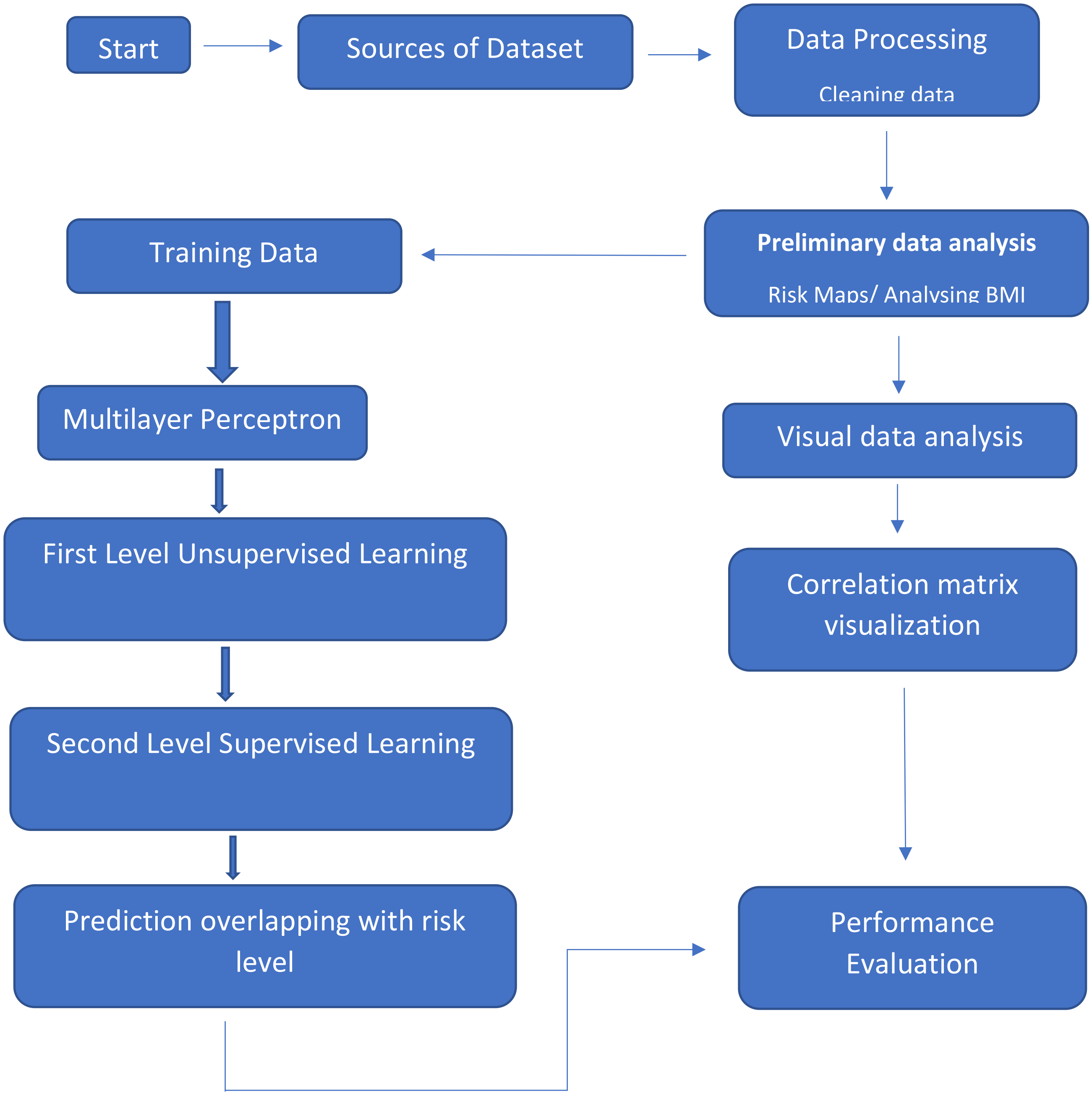


Figure 3.3 Research Model

Table 3.1 shows the framework of our study, starting from the collection of datasets to the deep layer model performance in predicting overlapping. Multilayer perceptron will be used to predict the overlapping in symptoms. Symptoms along with specified disease, and demographics like age will used as input layer to prediction of overlapped symptoms.

The research model explains the process of research which starts from the source of data, the data is downloaded online from the database, Consists on the heart symptoms. Second step in the process is processing and cleaning of the data, the sheets then be treated to remove missing values from it. In the next step the data will be loaded to the study model, and training of the model is done. Unsupervised learning, and supervised learning of the deep learning model is performed, and in the end the evaluation of the overlapping of the symptoms is calculated. In the next step the results from the model are graphically represented and correlated. In the last step the performance is evaluated using the results from the model.

3.12 Deep Learning Model

The deep learning model Consists of three layers, input to which data is loaded, as given in figure 3.4 below, the hidden layer of the model, which is processing unit of the model. It involves the processing of the given data, and present the results in the end in output layer. The output layer shows the best matches in the given data and solves the mystery. Input in the model in the present study is CVD disease, their demographics and the symptoms, which are being processed in the hidden layers, and in the end the model gives the best matched overlapped symptoms of the CVD disease. After the training process, the model is used to predict the overlapping in the symptoms to predict that specific disease.

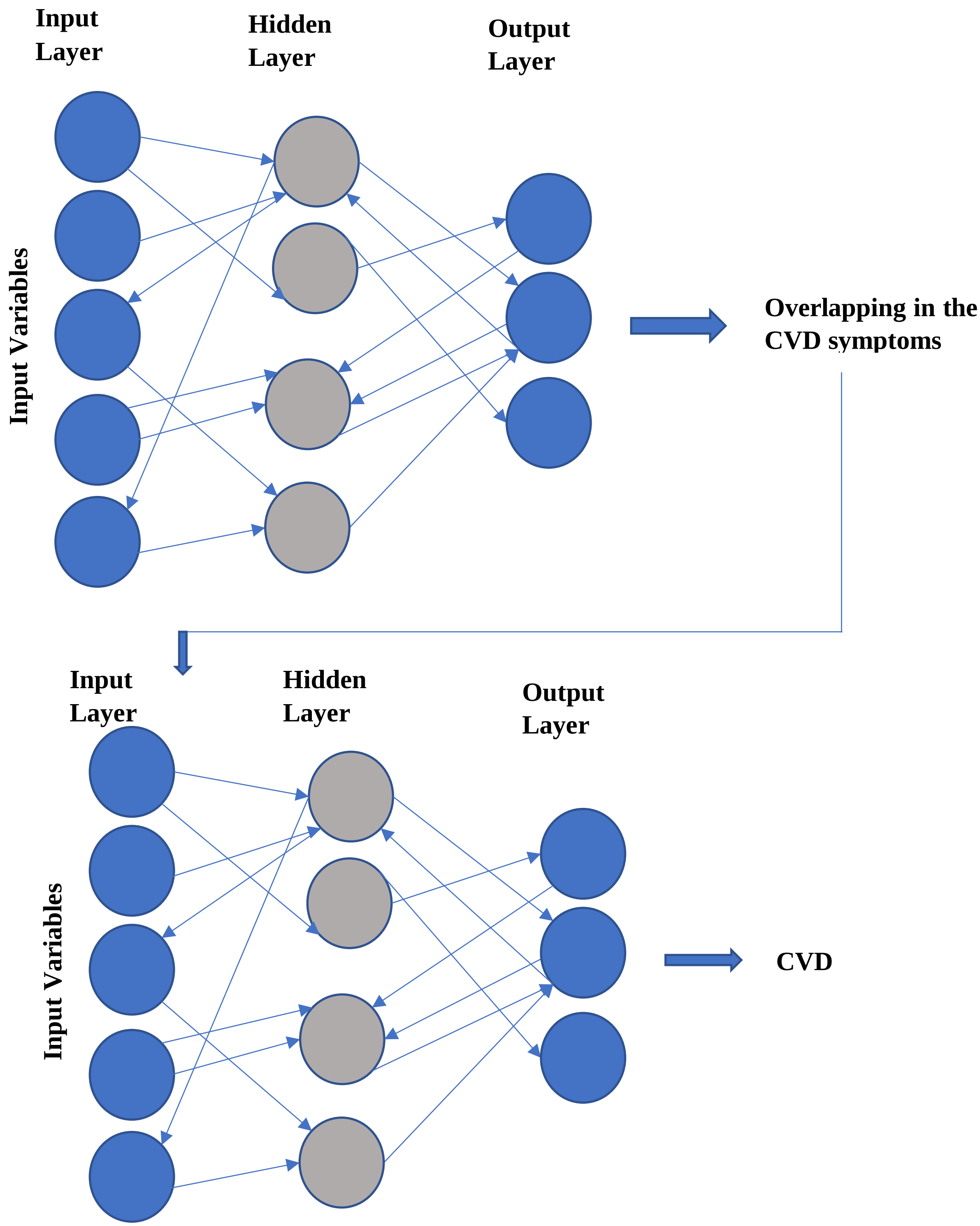


Figure 3.4 Multilayer Perceptron progress in the proposed Model

Figure 3.2 shows a multilayer perceptron model used in the prediction of overlapping symptoms of the CVDs. Model uses three layer, (1) input layer in which data will be entered, (2) hidden layer where model uses that input data to give output, (3) output layer gives the results of the analysis.

3.13 Chapter Summary

The present research is designed, and methodology is extracted from the huge amount of literature review which provides for the techniques and frameworks in order to conduct such research. The quantitative research design is selected for this study. the chapter discusses all the details and variables selected for the heart disease prediction. Variables are categorized into three categories including demographics (age, sex), symptoms, inducement and history physical sign and assistant examination.

Different software quality models for predicting symptoms

MCCALL'S MODEL

Jim McCall presented a software quality model used for deep learning in detection of symptoms for cardiovascular disease (Malhotra, 2012), which is one of the most famous predecessors of current quality models to protect patients from severe heart cases. A variety of software quality models have been developed. Some of which have been standardized. McCall developed the model for the US Army, UU in 1977. McCall's quality model Consists of the following accuracy factors:

- Correction: the functionality conforms to the specific diseases.

- Chest Pain: use of detecting resources such as hospitals and different medications.
- Integrity: protect a system of unauthorized access.
- Reliability: the ability of the system to perform well.
- Usability: the ease of applying the software.

According to McCall, usability comprises of two symptoms namely (i) discomfort in chest (ii) shortness of breath

FUYS SOFTWARE QUALITY MODEL (Suman. & Wadhwa, 2014)

Robert Grady and Hewlett Packard presented the FUYS model. This model is based on quality to build a secure platform for users to maintain their confidentiality concerns about different diseases. They built the FUYS model for Rational Software Company. FUYS model comprises the following non-functional requirements.

QUALITY MODEL PROTECTS USERS:

It involves human factors, general aesthetics, Cyanosis and documentation. Human factors are appropriately Considered throughout development. General aesthetics is the paradox that people perceive more aesthetic designs. Cyanosis refers to the principle that related things should be presented similarly while non-related things should be shown distinctively. Documentation is an insight into the actual user experience.

Below were the qualities of accuracy level of early predictive deep learning model.

Reliability: "frequency and severity of failure, resilience, predictability, accuracy and average time between failures (MTBF).

Performance: "Constitutes conditions on functional necessities such as speed, Chest Pain, availability, accuracy, performance, response time, recovery time and use of resources".

Compatibility: "Consist of test capacity, extensibility, and adaptability, relief of maintenance, compatibility, configurability, service capacity, installation capacity and location".

NIELSEN MODEL

(Nielsen, 1994)) As indicated by ISO-9241 that is the extended version of ISO 9126 (UAE Hospital requirements for treatment of heart patients with visual showcase terminals of symptoms) (ISO, 1998) standard, we have the accompanying definition: Usability of early predictive deep learning system and its ability to function Effectively and Efficiently while giving emotional fulfilment to its patients. The usability of an interface is typically connected with five parameters associated with associated with deep learning.

According to Nielsen, there are mainly five symptoms that must be Considered in each deep learning application to satisfy patients requirements. These are learnability, Chest Pain, memorability, mistakes and Discomfort Pressure in Chest.

USER DEEP LEARNABILITY TOWARD HEART ATTACK:

The application must be easy to learn for the heart attack using deep learning so that the patients can easily perform their activities to enhance functionality level of heart.

Chest Pain of early prediction: The application must be easy to use and there must be an understanding of the objective associated with deep learning and the Common cardiovascular diseases. Chest Pain refers to the speed with which the patient can use the medication to complete the treatment once the patient has cure the disease.

Memorability: The improvement of the patients from the symptoms to take the treatment of the disease, when the patient does not take the treatment for a while and then return to it and how easily the patient becomes healthy. Measuring the time to complete the treatment after a while using deep learning technique. Also, when Considering the number of clicks, steps and deep learning analysis that is required for the patient's treatment.

Mistakes in deep learning

The deep learning procedure have a low error rate making in the UAE hospitals management of his devices as well as the platform patients are using, but if errors occur, how many are and how fast can the patients recover from them? This process can be verified by counting the number of errors that the patients will make while taking their treatment.

Overlapping:

This is measured by recognizing the attitude of patients after taking the treatment. Listen to the patient to gather information about the disease whether it is legitimated or not, what he likes and does not like, and the difficulty level of the symptoms and treatment carried out for cardiovascular disease.

SQUARE’S MODEL

(Sivaji, 2014) Early predictive deep learning square’s model carried out with standards to provide an overview of the contents of the Systems and Software Quality Requirements and Evaluation (Square), Common reference models and definitions. The ISO / IEC 9126-1: 2001 standard has been revised by ISO / IEC 25010: 2011. They identified eight quality characteristics: Like adding techniques like treatment, regular activities and performance of the patients.

Functional suitability: "ability of the patients to perform activities that attain the declared and implicit necessities".

Performance Chest Pain: "performance linked to the number of resources applied under the Constituted conditions".

Compatibility: "Patients performance and their participation in regular activities, system or component to alter information with other patients, systems or components, and perform their daily activities, while sharing the same hardware or software environment".

Reliability: "degree of patients to perform specific functions under specific conditions for a specific period".

Security: "degree of a patients to fend for information and data".

Maintainability: "degree of fluctuations and Chest Pain of a patients that will be altered by the expected maintainers".

Portability: "degree of consciousness and Chest Pain of a system, product or Constituent that will be transferred from one hospital to another".

Usability: "the degree of a patients that peculiar patients must use to achieve specific objectives with Emptysis, Chest Pain and Discomfort Pressure in Chest. The attributes of square model involve in ISO 25000 will be used.

These Requirements and Evaluation (SQuaRE) – Systems and Software Quality Models are very important because a low quality less compatible will easily be lose the patient's data of their treatments; which supplanted ISO 9126 in which Product Quality, utilized for three distinctive quality models for software products: Quality being used model, Product quality model, and Data quality model. The extended work of ISO 25010 in the aspect of usability shown in table 3. (Ravanello, 2014)

BERTOA MODEL

The Quality Model Bertoa depends on the ISO 9126 Model. It characterizes a lot of quality properties for the Productive evaluation of COTS (Commercial-off-the-shelf). The COTS are utilized by software development organizations to make increasingly complex software to handle user's data saved in systems as well as at social media platforms to avoid link disclosure. According to Bertoa, usability comprises of factors namely: learnability the mechanism by which system will recognize what sort of thing you're afterwards, understandability of users can recognize how to select a software product that is appropriate for their intended use and how it can be used for specific tasks, and Weakness and Fatigue is the ability of the software product to allow the user to control it. (Spiekermann, 2010)

KUROSU-3

Kurosu proposed his latest model as in some concepts of ISO/IEC25010. According to Kurosu-3, usability comprises of factors namely: recognizability of patients toward treatment can be used by specified patients to achieve specified treatments to secure his sensitive attributes with Emptysis Chest Pain and Discomfort Pressure in Chest toward social media platform in a specified context of use, learnability of a product or system empowers the client to figure out how to utilize it with Emptysis, Chest Pain in critical circumstances, memorability is Degree to which patients can recall how to use the provided treatment , patients error protection is also the Degree in which a patient is anything but difficult to work, control and fitting to utilize, Weakness and Fatigue is the ability of the software product to allow the patients to WFATate and treat it and accessibility is Degree in which a patient can be utilized by individuals with the broadest scope of qualities and abilities to accomplish a predetermined symptoms in a predefined set of utilization. (Kurosu, 2014)

Hartmut Hoehle (et al) researched in a paper on the usability of different treatments of cardiovascular diseases. In this paper, the researcher has examined different cultural qualities; manliness independence/, power separation, vulnerability evasion, and long haul direction that can cause. These cultural attributes are utilized as moderators to test a model that to which extent they affect square's model of usability that fulfils the needs of patients with different requirements. The model included information gathered from 1844 patients from 4 hospitals. The conclusions presented in this model clarified 38% of the change in if it is aimed to cure them in terms of their treatment. This model provides multidimensional research by looking at all five mentioned national cultural qualities as possible factors with regards to deep learning social media applications. (Hoehle H. Z., 2015).

Ching-Wen Hsu et al make a research which is going to help to work on basic elements of usability for the Emptysis of square's model on cardiovascular patients, where data has been leaked. Patient's treatments have Consistently been analyzed on the technology acceptance model (TAM) which is accomplished by using multiple conditions and different treatments. The reason for this research was to discover basic influencing symptoms of cardiovascular diseases, which would impact the patient's concerns towards their recovery.

This analysis utilizes the DEMATEL strategy to recognize those symptoms that which is affecting to which extent. DEMATEL is a 5 stage process, to be specific; generating, normalizing and achieving the direct impact framework method.

The critical symptoms that are found to be influencing the model more were perceived ease of using them, perceived usefulness of cardiovascular treatments, patient's performance and their recovery phase. The Consequences of this investigation are going to explain that patients performance level and their treatments which encouraging the advancement in their treatment. Next, the assessment elements are utilized in the relevant writing on fractional TAM factors, which was going to exclude all those factors which were giving negative correlations toward M-business. (Hsu C. W., 2018)

Hartmut Hoehle et al introduced his research paper on cardiovascular disease symptoms and policies that guide toward their difficulty in problem. This study conceptualizes deep learning model creates and approves the treatment to validate their measurement that to which level it is measured to be the best. The researcher explains that predictive deep learning model has been gaining a lot of attention from individuals across the world when we Consider patient's interactions with PC. (Hoehle H. A., 2016)

To conceptualize deep learning model, Hartmut researched Microsoft's deep learning rules that they defined in the latest square's model development in the hospitals and emphasize better enhancement from the perspective of treatment. After that researcher has been gone through the survey of multiple hospitals about the cardiovascular diseases and their treatments used the SPSS technique in putting all content gathered from multiple hospitals by this survey. When doing statistical analysis this researcher exploratory factor investigation technique on the German patients that what symptoms influences them and make the changes in their functions or daily tasks. The results showed that square's model is predicting the behaviour of German patients this paper can be utilized to direct future research in patients to PC interaction and will help in the feasible structure of deep learning model.

Kim et al present a paper, which is going to elaborate on the relation of deep learning model and patient's recovery from cardiovascular diseases. The objective of this research study was to create a questionnaire for patients and find out what could be the relation between influencing symptoms and time period of patient's treatment. Increase in approaching intentions of the patients towards their treatment of the problem is also including deep learning model that was analyzed to determine if they are carrying positively correlation with each other or not.

With multiple linear regression analysis MLR, six main symptoms have been evaluated as that may affect patient's performances and their improvement in recovery. They are designed in such a way that meets patient's requirements, Discomfort Pressure in Chest, latest techniques which were newly introduced, feedback of the patient is integrated into that as well as the Chest Pain of the treatment. The survey was conducted among a total of 219 candidates and involved 13 severe symptoms and 8 mild symptoms. The only limitation of this study is that it was not brand or model-oriented. (Kim, 2012).

D. Lee et al were working on finding out the relationship between the symptoms with patient's irregularities. In this paper, research was conducted that how patients interacting with treatments and how to get recovery easily. Consequences say that for deep learning model on Discomfort Pressure in Chest, trust and brand consciousness are researched to keep up a long term patient's relationship. 310 patients from Korea participated in this research. The technique that was used to conduct research was utilizing the Partial Least Squares (PSL) technique as it is more reasonable than the covariance-based methodology.

(Lee, Antecedents and consequences of mobile phone usability: Linking simplicity and interactivity to SATS, trust, and brand loyalty. Information & Management, 2015) Simplicity factor and interaction factor were taken to be two variables defined in this research that need to be analyzed in the research.

The reliability symptoms for both of the variables was higher than 0.80 and the Average security was higher than 0.50, which is predicting the strong reliability and validity of the data as well as in variables.

Karima Moumane et al processed an experimental analysis dependent on a lot of measures to assess the of deep learning procedures running on various hospitals that which one is the better to reduce the symptoms. In this analysis usability of deep learning applications is assessed on multiple Operating systems; IOS, Android, Symbian. A model is created on software quality standards of the ISO 9126 which is utilized to assess that which one of the Operating systems is better. ISO 25062 and ISO 9241 models have been utilized in this research and Consist of information collected from 32 clients, which 7.0 questionnaires.

Two applications were investigated; google applications and maps. Multiple difficulties were recognized while utilizing applications by the users and the flaws have been identified one of them was screen size, the resolution of the screen and the memory of the deep learning phone, approve the discoveries of our system with some software issues not compatible with the user. (Moumane, 2016)

Ali Balapour et al published a research paper Meta-regression study on the usability of applications. Fundamentally absence of usability is a significant Common issue in PC sites and deep learning applications. This article was going to investigate the correlation between usability perception and a factor influencing usability.(Balapour, 2017)

CHAPTER NUMBER FOUR PREDICTION OF DISEASE

The methods and procedures the researcher will use to analyse the early disease forecasters related to their sensitive attributes during social media usability will be discussed in this chapter. The regression model is used to simulate, and the outcomes are then compared using a hybrid model. Using K-Fold, MRE, which includes the MMRE technique, for the evaluation and validation of the proposed model.

4.1. ANALYSIS OF PREDICTORS

The simple linear reverse was initially used to dignify each of the eight possible predictors' that causes insecurity of data leaked (SLR). After that, a technique used for extracting usability variables predictions was to be used by the researcher gradually multiple linear regressions. This model will be used to assess the usability factors and determine them (Kellar, 2013). The SPSS tool was used in both regression analyses (version 25.0). Table 5 shows the results of SLR. Now as per questionnaire we have evaluated data breaching in below terms that platform’s security should have Emptysis, learnability, Fever, Human Factor, Cyanosis, Weakness or Fatigue, Discomfort Pressure in Chest and Chest Pain that how user rated them in terms of Heart Issues. These are abbreviated as CHEP is the best predictor of individual deep learning application usability factors and Headache is the weakest. The definition of Chest Pain is CHEP, the definition of lifelong learning is DYSP, Fever is defined as FEVE, the definition of Headache as HEADACHE, Cyanosis defined like CYAN, Weakness and Fatigue as WFAT, fulfilment as DPCH and the definition of success is CHEP.

Table 4.1: SLR Results

Predictor	**R-Square**	**Standardized Beta**	**Significance**
EMPT	0.643	0.802	0.000
DYSP	0.699	0.836	0.000
FEVE	0.149	-0.386	0.000
HEADACHE	0.029	0.171	0.000
CYAN	0.406	-0.637	0.000
WFAT	0.054	0.232	0.002
DPCH	0.299	0.547	0.000
CHEP	0.715	0.846	0.000

The SLR equation of the strongest predictor is provided as: $\overline{Y} = 0.347 + (0.846*CHEP)$

The next section presents the prediction model obtained using MLR.

Disease prediction: abnormal heart Rhythm has been predicted with 84.6% accuracy level.

4.2. MLR ANALYSIS OF SYMPTOMS

The data set was comprised of 276 regression instances in which the model was predictoried (eight different usability factors). The main cause of the multi linear approach for stepping regression is that the distance between predictor responses is significantly reduced.

This approach builds up the model in different ways by integrating single and many independent variables with the dependent variable, such as the two factors IV, three factors IV, four factors IV etc. The R2 value is determined using all possible combinations of statistically significant predictors with a 0.000 value. MLR results are shown in below tables in the following section for the various combinations of predictors greater the value of R^2 means a better model.

4.2.1. MLR WITH TWO PREDICTORS

Table 4.2: Withdraws MLR scores most of them are statistically significant combinations only. There were 45 combinations in total out of which 34 provided significant results of Neural Combinations. Table 6 signifies the MLR Consequences with two predictors.

Table 4.2: MLR Results with Two Predictors

Dependent Variable	**Predictors (In Pair)**	**R-Square**	**Standardized Beta**	**Significance**
1	FEVE	0.643	-0.002	0.965
	EMPT		0.801	0.000
2	FEVE	0.751	-0.232	0.000
	DYSP		0.791	0.000
3	FEVE	0.157	-0.366	0.000
	HEADACHE		0.095	0.195
4	FEVE	0.407	-0.040	0.000
	CYAN		-0.615	0.000
5	FEVE	0.298	-0.525	0.000
	WFAT		-0.410	0.000
6	FEVE	0.393	-0.310	0.000
	DPCH		0.500	0.000
7	FEVE	0.722	-0.086	0.000

	CHEP		0.814	0.000
8	CYAN	0.672	-0.220	0.000
	EMPT		0.663	0.000
	CYAN	0.774	-0.311	0.000
9	DYSP		0.689	0.000
	CYAN	0.413	-0.625	0.000
10	CHEP		0.084	0.164
	CYAN	0.532	-0.703	0.000
11	WFAT		0.361	0.000
	CYAN	0.541	-0.518	0.000
12	DPCH		0.387	0.000
	CYAN	0.413	-0.625	0.000
13	HEADACHE		0.084	0.164
	CYAN	0.759	-0.250	0.000

14	CHEP		0.709	0.000
	CYAN	0.672	-0.220	0.000
15	EMPT	0.763	0.356	0.000
	CHEP		0.565	0.000
16	EMPT	0.834	0.464	0.000
	DYSP		0.552	0.000
17	EMPT	0.677	0.791	0.000
	WFAT		0.185	0.000
18	EMPT	0.705	0.694	0.000
	DPCH		0.271	0.000
19	EMPT	0.643	0.802	0.000
	HEADACHE		0.000	0.996
20	CHEP	0.844	0.517	0.000
	DYSP		0.487	0.000

21	CHEP	0.753	0.837	0.000
	WFAT		0.195	0.000
22	CHEP	0.747	0.753	0.000
	DPCH		0.202	0.000
23	CHEP	0.719	0.838	0.000
	HEADACHE		0.061	0.147
24	CHEP	0.844	0.517	0.000
	DYSP		0.487	0.000
25	DYSP	0.700	0.829	0.000
	WFAT		0.030	0.492
26	DYSP	0.724	0.747	0.000
	DPCH		0.182	0.000
27	WFAT	0.089	0.246	0.001
	HEADACHE		0.189	0.012

28	WFAT	0.343	0.212	0.001
	DPCH		0.539	0.000
29	HEADACHE	0.312	0.535	0.000
	DPCH		0.117	0.074

It is observed that DYSP is carrying the highest value of R-Square 0.844 and provides the following regression equation: ***Y = -0.248+ (0.487* DYSP) + (0.517*CHEP)***

Disease prediction: Aorta Disease has been predicted with 84.4% accuracy level.

4.2.2. MLR WITH THREE PREDICTORS

This creates "the model by combining five independent variables of usability factors with a dependent variable of user rating. The R Square value is calculated using all possible combinations of predictors, with the majority of them statistically relevant at 0.000. Only statistically relevant combinations are included in MLR findings in Table 9. There were a total of four variations, four of which yielded no statistically significant results. The MLR results with five predictors are presented in" Table 4.3.

Table 4.3: MLR Results with Three Predictors

Dependent Variable	**Predictors (In Pair)**	**R-Square**	**Standardized Beta**	**Significance**
1	EMPT	0.838	0.449	.000
	DYSP		0.655	.001
	FEVE		-0.069	.000
2	EMPT	0.835	0.487	.000
	DYSP		0.644	.000
	HEADACHE		0.022	.408
3	EMPT	0.846	0.413	.000
	DYSP		0.618	.000
	CYAN		-0.113	.003
4	EMPT	0.839	.506	.000
	DYSP		.613	.000
	WFAT		.079	.022
5	EMPT	0.846	.474	.000

	DYSP		.585	.000
	DPCH		.139	.001
6	EMPT	0.846	.280	.000
	DYSP		.522	.000
	CHEP		.377	.000
7	EMPT	0.643	.853	.000
	FEVE		-.002	.964
	HEADACHE		.000	.991
8	EMPT	0.677	.725	.000
	FEVE		.079	.122
	CYAN		-.205	.000
9	EMPT	0.685	.736	.000
	FEVE		-.110	.047
	WFAT		.226	.000

10	EMPT	0.705	.686	.000
	FEVE		-.016	.736
	DPCH		.271	.000
11	EMPT	0.763	.351	.000
	FEVE		-.010	.818
	CHEP		.565	.000
12	EMPT	0.672	0.664	.000
	HEADACHE		-0.001	.975
	CYAN		-0.220	.000
13	EMPT	0.677	.839	.000
	HEADACHE		.013	.723
	WFAT		.195	.000
14	EMPT	0.705	.741	.000
	HEADACHE		-.004	.904

	DPCH		.304	.000
15	EMPT	0.763	.350	.000
	HEADACHE		.022	.579
	CHEP		.567	.000
16	EMPT	0.731	.590	.000
	CYAN		-.313	.000
	WFAT		.254	.000
17	EMPT	0.727	.577	.000
	CYAN		-.195	.000
	DPCH		.257	.000
18	EMPT	0.781	.264	.000
	CYAN		-.175	.000
	CHEP		.541	.000
19	EMPT	0.737	.685	.000

	WFAT		.181	.000
	DPCH		.268	.000
20	EMPT	0.797	.685	.000
	WFAT		.181	.000
	CHEP		.268	.000
21	EMPT	0.79	.338	.000
	DPCH		.186	.000
	CHEP		.493	.000
22	DYSP	0.754	.788	.000
	FEVE		-.220	.000
	HEADACHE		.059	.137
23	DYSP	0.783	.699	.000
	FEVE		-.114	.011
	CYAN		-.242	.000

24	DYSP	0.769	.743	.000
	FEVE		-.293	.000
	WFAT		.151	.000
25	DYSP	0.772	.712	.000
	FEVE		-.223	.000
	DPCH		.165	.000
26	DYSP	0.856	.499	.000
	FEVE		-.118	.000
	CHEP		.466	.000
27	DYSP	0.779	.687	.000
	HEADACHE		.072	.055
	CYAN		-.302	.000
28	DYSP	0.711	.817	.000
	HEADACHE		.106	.013

	WFAT		.041	.352
29	DYSP	0.732	.743	.000
	HEADACHE		.091	.026
	DPCH		.174	.000
30	DYSP	0.848	.488	.000
	HEADACHE		.063	.041
	CHEP		.508	.000
31	DYSP	0.792	.626	.000
	CYAN		-.368	.000
	WFAT		.147	.000
32	DYSP	0.791	.622	.000
	CYAN		-.296	.000
	DPCH		.152	.000
33	DYSP	0.867	.452	.000

	CYAN		-.182	.000
	CHEP		.441	.000
34	DYSP	0.726	.734	.000
	WFAT		.046	.275
	DPCH		.187	.000
35	DYSP	0.853	.448	.000
	WFAT		.099	.002
	CHEP		.539	.000
36	DYSP	0.851	.454	.000
	DPCH		.099	.006
	CHEP		.494	.000
37	FEVE	0.413	-.024	.739
	HEADACHE		.081	.188
	CYAN		-.612	.000

38	FEVE	0.315	-.504	.000
	HEADACHE		.111	.097
	WFAT		.419	.000
39	FEVE	0.396	-.299	.000
	HEADACHE		.058	.352
	DPCH		.496	.000
40	FEVE	0.724	-.078	.086
	HEADACHE		.048	.255
	CHEP		.811	.000
41	FEVE	0.559	-.182	.006
	CYAN		-.611	.000
	WFAT		.413	.000
42	FEVE	0.543	-.053	.407
	CYAN		-.487	.000

	DPCH		.388	.000
43	FEVE	0.759	.023	.623
	CYAN		-.261	.000
	CHEP		.711	.000
44	FEVE	0.511	-.442	.000
	WFAT		.371	.000
	DPCH		.462	.000
45	FEVE	0.781	-.199	.000
	WFAT		.271	.000
	CHEP		.757	.000
46	FEVE	0.754	-.091	.031
	DPCH		.204	.000
	CHEP		.719	.000
47	HEADACHE	0.551	.115	.032

	CYAN		-.689	.000
	WFAT		.374	.000
48	HEADACHE	0.545	.061	.255
	CYAN		-.510	.000
	DPCH		.383	.000
49	HEADACHE	0.761	.044	.258
	CYAN		-.245	.000
	CHEP		.706	.000
50	HEADACHE	0.364	.147	.021
	WFAT		.230	.000
	DPCH		.518	.000
51	HEADACHE	0.758	.085	.031
	WFAT		.206	.000
	CHEP		.821	.000

52	HEADACHE	0.750	0.052	.188
	DPCH		0.199	.000
	CHEP		0.748	.000
53	CYAN	0.647	-.592	.000
	WFAT		.334	.000
	DPCH		.348	.000
54	CYAN	0.825	-.333	.000
	WFAT		.269	.000
	CHEP		.649	.000
55	CYAN	0.786	-0.234	.000
	DPCH		0.184	.000
	CHEP		0.633	.000
56	WFAT	0.782	.196	.000
	DPCH		.198	.000

	CHEP		.745	.000

DYSP, CYAN and CHEP is the regression model which is carrying the highest value of R-Square 0.867. $\overline{Y}$ ***= 0.498+ (0.452*DYSP) + (-0.182*CYANIS) + (0.441*CHEP)***

From the above symptoms of Dyspnea, Cyanosis and Chest Pain which predict congenital heart disease prediction: has been predicted with 88.7% accuracy level.

4.2.3. MLR WITH FOUR PREDICTORS

This is going to build the model in which four usability factors are taken three IV with one DV. The value of R^2 is planned with all possible combinations of IVs which are usability factors and researcher have come to know that all of them are statistically significant at the value of 0.000. Table 7 provides Multiple Linear Regression outcomes with all of them are statistically significant. We have a total 70 combinations in total and we have 39 combinations were non-significant. Table 7 represents the results of regression which is based on four value combinations.

Table 4.4: MLR Results with Four Predictors

Dependent Variable	**Predictors (In Pair)**	**R-Square**	**Standardized Beta**	**Significance**
1	EMPT	0.835	0.418	0.000
	DYSP		0.565	0.000
	FEVE		-0.072	0.051
	HEADACHE		0.020	0.549
2	EMPT	0.846	0.379	0.000
	DYSP		0.538	0.000
	FEVE		-0.027	0.481
	CYAN		-0.129	0.004
3	EMPT	0.850	0.408	0.000
	DYSP		0.532	0.000
	FEVE		-0.128	0.001
	WFAT		0.122	0.001
4	EMPT	0.850	0.402	0.000

	DYSP		0.516	0.000
	FEVE		-0.075	0.034
	DPCH		0.124	0.001
5	EMPT	0.873	0.228	0.000
	DYSP		0.461	0.000
	FEVE		-0.066	0.043
	CHEP		0.330	0.000
6	EMPT	0.847	0.382	0.000
	DYSP		0.534	0.000
	HEADACHE		0.025	0.423
	CYAN		-0.141	0.001
7	EMPT	0.840	0.467	0.000
	DYSP		0.529	0.000
	HEADACHE		0.033	0.312

	WFAT		0.078	0.018
8	EMPT	0.846	0.439	0.000
	DYSP		0.506	0.000
	HEADACHE		0.022	0.480
	DPCH		0.123	0.001
9	EMPT	0.871	0.253	0.000
	DYSP		0.451	0.000
	HEADACHE		0.035	0.228
	CHEP		0.337	0.000
10	EMPT	0.859	0.377	0.000
	DYSP		0.482	0.000
	CYAN		-0.196	0.000
	WFAT		0.128	0.000
11	EMPT	0.857	0.372	0.000

	DYSP		0.486	0.000
	CYAN		-0.137	0.001
	DPCH		0.119	0.001
12	EMPT	0.879	0.199	0.000
	DYSP		0.434	0.000
	CYAN		-0.129	0.000
	CHEP		0.325	0.000
13	EMPT	0.852	0.456	0.000
	DYSP		0.473	0.000
	WFAT		0.085	0.008
	DPCH		0.131	0.000
14	EMPT	0.879	0.263	0.000
	DYSP		0.413	0.000
	WFAT		0.104	0.000

	CHEP		0.353	0.000
15	EMPT	0.876	0.261	0.000
	DYSP		0.419	0.000
	DPCH		0.095	0.004
	CHEP		0.314	0.000
16	EMPT	0.677	0.680	0.000
	FEVE		0.086	0.121
	HEADACHE		0.008	0.862
	CYAN		-0.257	0.000
17	EMPT	0.685	0.735	0.000
	FEVE		-0.109	0.051
	HEADACHE		0.008	0.869
	WFAT		0.226	0.000
18	EMPT	0.705	0.687	0.000

	FEVE		-0.017	0.723
	HEADACHE		-0.007	0.870
	DPCH		0.272	0.000
19	EMPT	0.763	0.346	0.000
	FEVE		-0.007	0.871
	HEADACHE		0.021	0.597
	CHEP		0.567	0.000
20	EMPT	0.732	0.583	0.000
	FEVE		-0.023	0.664
	CYAN		-0.305	0.000
	WFAT		0.261	0.000
21	EMPT	0.730	0.591	0.000
	FEVE		0.060	0.237
	CYAN		-0.221	0.000

	DPCH		0.252	0.000
22	EMPT	0.784	0.280	0.000
	FEVE		0.059	0.194
	CYAN		-0.201	0.000
	CHEP		0.536	0.000
23	EMPT	0.747	0.620	0.000
	FEVE		-0.125	0.013
	WFAT		0.227	0.000
	DPCH		0.273	0.000
24	EMPT	0.807	0.277	0.000
	FEVE		-0.125	0.005
	WFAT		0.237	0.000
	CHEP		0.568	0.000
25	EMPT	0.790	0.329	0.000

	FEVE		-0.019	0.648
	DPCH		0.187	0.000
	CHEP		0.494	0.000
26	EMPT	0.732	0.585	0.000
	HEADACHE		0.021	0.620
	CYAN		-0.314	0.000
	WFAT		0.256	0.000
27	EMPT	0.727	0.578	0.000
	HEADACHE		-0.006	0.886
	CYAN		-0.195	0.000
	DPCH		0.257	0.000
28	EMPT	0.782	0.258	0.000
	HEADACHE		0.020	0.598
	CYAN		-0.175	0.000

	CHEP		0.543	0.000
29	EMPT	0.737	0.682	0.000
	HEADACHE		0.011	0.792
	WFAT		0.182	0.000
	DPCH		0.267	0.000
30	EMPT	0.799	0.332	0.000
	HEADACHE		0.039	0.289
	WFAT		0.190	0.000
	CHEP		0.570	0.000
31	EMPT	0.790	0.334	0.000
	HEADACHE		0.015	0.675
	DPCH		0.186	0.000
	CHEP		0.495	0.000
32	EMPT	0.782	0.510	0.000

	CYAN		-0.285	0.000
	WFAT		0.245	0.000
	DPCH		0.246	0.000
33	EMPT	0.837	0.201	0.000
	CYAN		-0.266	0.000
	WFAT		0.245	0.000
	CHEP		0.531	0.000
34	EMPT	0.806	0.253	0.000
	CYAN		-0.164	0.000
	DPCH		0.178	0.000
	CHEP		0.475	0.000
35	EMPT	0.824	0.327	0.000
	WFAT		0.183	0.000
	DPCH		0.183	0.000

	CHEP		0.496	0.000
36	DYSP	0.786	0.697	0.000
	FEVE		-0.103	0.023
	HEADACHE		0.058	0.121
	CYAN		-0.241	0.000
37	DYSP	0.777	0.739	0.000
	FEVE		-0.281	0.000
	HEADACHE		0.062	0.109
	WFAT		0.152	0.000
38	DYSP	0.774	0.711	0.000
	FEVE		-0.213	0.000
	HEADACHE		0.051	0.186
	DPCH		0.162	0.000
39	DYSP	0.858	0.498	0.000

	FEVE		-0.109	0.001
	HEADACHE		0.046	0.133
	CHEP		0.463	0.000
40	DYSP	0.810	0.624	0.000
	FEVE		-0.171	0.000
	CYAN		-0.280	0.000
	WFAT		0.190	0.000
41	DYSP	0.800	0.633	0.000
	FEVE		-0.112	0.009
	CYAN		-0.228	0.000
	DPCH		0.150	0.000
42	DYSP	0.869	0.462	0.000
	FEVE		-0.051	0.149
	CYAN		-0.154	0.000

	CHEP		0.430	0.000
43	DYSP	0.793	0.653	0.000
	FEVE		-0.288	0.000
	WFAT		0.164	0.000
	DPCH		0.178	0.000
44	DYSP	0.878	0.440	0.000
	FEVE		-0.182	0.000
	WFAT		0.165	0.000
	CHEP		0.474	0.000
45	DYSP	0.863	0.466	0.000
	FEVE		-0.118	0.000
	DPCH		0.099	0.004
	CHEP		0.442	0.000
46	DYSP	0.786	0.697	0.000

	HEADACHE		-0.103	0.023
	CYAN		0.058	0.121
	WFAT		-0.241	0.000
47	DYSP	0.795	0.623	0.000
	HEADACHE		0.064	0.077
	CYAN		-0.288	0.000
	DPCH		0.147	0.000
48	DYSP	0.869	0.453	0.000
	HEADACHE		0.051	0.077
	CYAN		-0.177	0.000
	CHEP		0.436	0.000
49	DYSP	0.735	0.727	0.000
	HEADACHE		0.096	0.020
	WFAT		0.055	0.190

	DPCH		0.180	0.000
50	DYSP	0.858	0.447	0.000
	HEADACHE		0.071	0.018
	WFAT		0.105	0.001
	CHEP		0.530	0.000
51	DYSP	0.855	0.456	0.000
	HEADACHE		0.059	0.052
	DPCH		0.095	0.007
	CHEP		0.486	0.000
52	DYSP	0.815	0.551	0.000
	CYAN		-0.355	0.000
	WFAT		0.157	0.000
	DPCH		0.162	0.000
53	DYSP	0.889	0.376	0.000

	CYAN		-0.242	0.000
	WFAT		0.165	0.000
	CHEP		0.452	0.000
54	DYSP	0.873	0.422	0.000
	CYAN		-0.179	0.000
	DPCH		0.093	0.005
	CHEP		0.420	0.000
55	DYSP	0.861	0.411	0.000
	WFAT		0.105	0.001
	DPCH		0.106	0.002
	CHEP		0.515	0.000
56	FEVE	0.558	-0.164	0.015
	HEADACHE		0.081	0.129
	CYAN		-0.608	0.000

	WFAT		0.405	0.000
57	FEVE	0.546	-0.042	0.513
	HEADACHE		0.055	0.310
	CYAN		-0.487	0.000
	DPCH		0.384	0.000
58	FEVE	0.761	0.032	0.500
	HEADACHE		0.048	0.223
	CYAN		-0.261	0.000
	CHEP		0.708	0.000
59	FEVE	0.512	-0.427	0.000
	HEADACHE		0.061	0.280
	WFAT		0.364	0.000
	DPCH		0.462	0.000
60	FEVE	0.784	-0.186	0.000

	HEADACHE		0.051	0.172
	WFAT		0.265	0.000
	CHEP		0.759	0.000
61	FEVE	0.756	-0.083	0.050
	HEADACHE		0.038	0.334
	DPCH		0.202	0.000
	CHEP		0.718	0.000
62	FEVE	0.663	-0.180	0.002
	CYAN		-0.495	0.000
	WFAT		0.371	0.000
	DPCH		0.353	0.000
63	FEVE	0.828	-0.081	0.052
	CYAN		-0.292	0.000
	WFAT		0.284	0.000

	CHEP		0.644	0.000
64	FEVE	0.786	0.010	0.823
	CYAN		-0.239	0.000
	DPCH		0.184	0.000
	CHEP		0.635	0.000
65	FEVE	0.813	-0.198	0.000
	WFAT		0.262	0.000
	DPCH		0.201	0.000
	CHEP		0.669	0.000
66	HEADACHE	0.649	0.079	0.097
	CYAN		-0.580	0.000
	WFAT		0.331	0.000
	DPCH		0.347	0.000
67	HEADACHE	0.827	0.060	0.073

	CYAN		-0.323	0.000
	WFAT		0.266	0.000
	CHEP		0.650	0.000
68	HEADACHE	0.787	0.037	0.313
	CYAN		-0.231	0.000
	DPCH		0.183	0.000
	CHEP		0.631	0.000
69	HEADACHE	0.788	0.068	0.065
	WFAT		0.196	0.000
	DPCH		0.194	0.000
	CHEP		0.739	0.000
70	CYAN	0.847	-0.311	0.000
	WFAT		0.256	0.000
	DPCH		0.173	0.000

	CHEP		0.585	0.000

It has “been observed that result is carrying he best regression model as the previous values obtained in the 3 usability factors DYSP, CYAN and CHEP whereas WFAT is added into it as fourth value and giving the best R-Square here 0.889 even greater than the previous one it means R-Square has been increased by adding WFAT.

Provides the following regression equation:

***Y = 0.344+ (0.376*DYSP) + (-0.242** **CYAN*) + (0.165** **WFAT*) + (0.452** **CHEP)**

Dyspnea, Cyanosis and Chest Pain with Weakness and Fatigue are the symptoms has been predicted with disease of pulmonary embolism.

4.2.4. MLR WITH FIVE PREDICTORS

This creates the model by combining five independent variables of usability factors with a dependent variable of user rating. The R Square value is calculated using all possible combinations of predictors, with the majority of them statistically relevant at 0.000. Only statistically relevant combinations are included in MLR findings in Table 9. There were a total of four variations, four of which yielded no statistically significant results. The MLR results with five predictors are presented in” Table 4.5.

Table 4.5: MLR Results with Five Predictors

Dependent Variable	**Predictors (In Pair)**	**R-Square**	**Standardized Beta**	**Significance**
1	EMPT	0.847	.374	.000
	DYSP		.539	.000
	FEVE		-.024	.541
	HEADACHE		.023	.472
	CYAN		-.130	.004
2	EMPT	0.850	.404	.000
	DYSP		.533	.000
	FEVE		-.126	.001
	HEADACHE		.023	.470
	WFAT		.122	.000
3	EMPT	0.850	.399	.000
	DYSP		.517	.000
	FEVE		-.073	.041

	HEADACHE		.015	.639
	DPCH		.123	.001
4	EMPT	0.874	.221	.000
	DYSP		.462	.000
	FEVE		-.062	.058
	HEADACHE		.028	.327
	CHEP		.332	.000
5	EMPT	0.863	.349	.000
	DYSP		.492	.000
	FEVE		-.079	.041
	CYAN		-.168	.000
	WFAT		.149	.000
6	EMPT	0.857	.362	.000
	DYSP		.493	.000

	FEVE		-.030	.429
	CYAN		-.123	.004
	DPCH		.120	.001
7	EMPT	0.880	.192	.000
	DYSP		.439	.000
	FEVE		-.023	.514
	CYAN		-.119	.003
	CHEP		.324	.000
8	EMPT	0.864	.385	.000
	DYSP		.476	.000
	FEVE		-.134	.000
	WFAT		.134	.000
	DPCH		.136	.000
9	EMPT	0.890	.196	.000

	DYSP		.414	.000
	FEVE		-.131	.000
	WFAT		.148	.000
	CHEP		.357	.000
10	EMPT	0.879	.225	.000
	DYSP		.430	.000
	FEVE		-.066	.036
	DPCH		.096	.003
	CHEP		.309	.000
11	EMPT	0.861	.368	.000
	DYSP		.484	.000
	HEADACHE		.034	.261
	CYAN		-.196	.000
	WFAT		.131	.000

12	EMPT	0.857	.367	.000
	DYSP		.488	.000
	HEADACHE		.021	.496
	CYAN		-.136	.001
	DPCH		.118	.001
13	EMPT	0.880	.189	.000
	DYSP		.436	.000
	HEADACHE		.033	.236
	CYAN		-.128	.000
	CHEP		.327	.000
14	EMPT	0.853	.449	.000
	DYSP		.475	.000
	HEADACHE		.028	.362
	WFAT		.087	.006

	DPCH		.130	.000
15	EMPT	0.880	.252	.000
	DYSP		.411	.000
	HEADACHE		.043	.126
	WFAT		.104	.000
	CHEP		.359	.000
16	EMPT	0.877	.358	.000
	DYSP		.428	.000
	HEADACHE		-.194	.000
	DPCH		.137	.000
	CHEP		.130	.000
17	EMPT	0.872	.352	.000
	DYSP		.430	.000
	CYAN		-.200	.000

	WFAT		.143	.000
	DPCH		.129	.000
18	EMPT	0.898	.170	.000
	DYSP		.366	.000
	CYAN		-.193	.000
	WFAT		.152	.000
	CHEP		.352	.000
19	EMPT	0.886	.198	.000
	DYSP		.404	.000
	CYAN		-.126	.000
	DPCH		.092	.004
	CHEP		.305	.000
20	EMPT	0.886	.262	.000
	DYSP		.374	.000

	WFAT		.107	.000
	DPCH		.103	.001
	CHEP		.334	.000
21	EMPT	0.732	.580	.000
	FEVE		-.021	.702
	HEADACHE		.019	.653
	CYAN		-.307	.000
	WFAT		.262	.000
22	EMPT	0.730	.591	.000
	FEVE		.060	.241
	HEADACHE		.001	.989
	CYAN		-.221	.000
	DPCH		.252	.000
23	EMPT	0.784	.274	.000

	FEVE		.063	.169
	HEADACHE		.027	.483
	CYAN		-.203	.000
	CHEP		.539	.000
24	EMPT	0.747	.620	.000
	FEVE		-.125	.013
	HEADACHE		.001	.983
	WFAT		.227	.000
	DPCH		.273	.000
25	EMPT	0.807	.274	.000
	FEVE		-.117	.008
	HEADACHE		.029	.412
	WFAT		.232	.000
	CHEP		.572	.000

26	EMPT	0.791	.326	.000
	FEVE		-.017	.685
	HEADACHE		.014	.715
	DPCH		.187	.000
	CHEP		.495	.000
27	EMPT	0.783	.495	.000
	FEVE		-.047	.333
	CYAN		-.270	.000
	WFAT		.259	.000
	DPCH		.250	.000
28	EMPT	0.838	.184	.002
	FEVE		-.049	.246
	CYAN		-.250	.000
	WFAT		.259	.000

	CHEP		.534	.000
29	EMPT	0.807	.265	.000
	FEVE		.045	.299
	CYAN		-.183	.000
	DPCH		.175	.000
	CHEP		.472	.000
30	EMPT	0.834	.258	.000
	FEVE		-.129	.002
	WFAT		.231	.000
	DPCH		.188	.000
	CHEP		.498	.000
31	EMPT	0.782	.506	.000
	HEADACHE		.015	.683
	CYAN		-.286	.000

	WFAT		.246	.000
	DPCH		.246	.000
32	EMPT	0.838	.189	.001
	HEADACHE		.041	.210
	CYAN		-.266	.000
	WFAT		.249	.000
	CHEP		.535	.000
33	EMPT	0.806	.249	.000
	HEADACHE		.014	.693
	CYAN		-.163	.000
	DPCH		.178	.000
	CHEP		.476	.000
34	EMPT	0.825	.317	.000
	HEADACHE		.032	.344

	WFAT		.186	.000
	DPCH		.182	.000
	CHEP		.500	.000
35	EMPT	0.859	.192	.000
	CYAN		-.252	.000
	WFAT		.240	.000
	DPCH		.169	.000
	CHEP		.468	.000
36	DYSP	0.814	.621	.000
	FEVE		-.160	.000
	HEADACHE		.061	.083
	CYAN		-.279	.000
	WFAT		.191	.000
37	DYSP	0.802	.632	.000

	FEVE		-.102	.019
	HEADACHE		.050	.164
	CYAN		-.228	.000
	DPCH		.147	.000
38	DYSP	0.870	.462	.000
	FEVE		-.042	.233
	HEADACHE		.046	.116
	CYAN		-.155	.000
	CHEP		.428	.000
39	DYSP	0.795	.652	.000
	FEVE		-.278	.000
	HEADACHE		.053	.152
	WFAT		.165	.000
	DPCH		.175	.000

40	DYSP	0.880	.440	.000
	FEVE		-.174	.000
	HEADACHE		.048	.088
	WFAT		.166	.000
	CHEP		.471	.000
41	DYSP	0.865	.467	.000
	FEVE		-.110	.001
	HEADACHE		.041	.167
	DPCH		.096	.005
	CHEP		.440	.000
42	DYSP	0.830	.548	.000
	FEVE		-.173	.000
	CYAN		-.267	.000
	WFAT		.200	.000

	DPCH		.163	.000
43	DYSP	0.896	.386	.000
	FEVE		-.109	.001
	CYAN		-.193	.000
	WFAT		.191	.000
	CHEP		.431	.000
44	DYSP	0.875	.433	.000
	FEVE		-.053	.126
	CYAN		-.150	.000
	DPCH		.094	.004
	CHEP		.409	.000
45	DYSP	0.887	.401	.000
	FEVE		-.185	.000
	WFAT		.173	.000

	DPCH		.111	.000
	CHEP		.448	.000
46	DYSP	0.817	.549	.000
	HEADACHE		.072	.036
	CYAN		-.348	.000
	WFAT		.161	.000
	DPCH		.158	.000
47	DYSP	0.893	.376	.000
	HEADACHE		.060	.023
	CYAN		-.238	.000
	WFAT		.168	.000
	CHEP		.447	.000
48	DYSP	0.875	.424	.000
	HEADACHE		.047	.095

	CYAN		-.174	.000
	DPCH		.090	.006
	CHEP		.416	.000
49	DYSP	0.866	.411	.000
	HEADACHE		.067	.022
	WFAT		.110	.000
	DPCH		.103	.003
	CHEP		.508	.000
50	DYSP	0.897	.340	.000
	CYAN		-.241	.000
	WFAT		.170	.000
	DPCH		.103	.001
	CHEP		.430	.000
51	FEVE	0.666	-.169	.004

	HEADACHE		.070	.134
	CYAN		-.497	.000
	WFAT		.379	.000
	DPCH		.343	.000
52	FEVE	0.830	-.072	.087
	HEADACHE		.051	.123
	CYAN		-.292	.000
	WFAT		.285	.000
	CHEP		.640	.000
53	FEVE	0.787	.017	.699
	HEADACHE		.039	.292
	CYAN		-.239	.000
	DPCH		.182	.000
	CHEP		.633	.000

54	FEVE	0.814	-.191	.000
	HEADACHE		.042	.231
	WFAT		.262	.000
	DPCH		.198	.000
	CHEP		.668	.000
55	FEVE	0.852	-.093	.018
	CYAN		-.270	.000
	WFAT		.281	.000
	DPCH		.178	.000
	CHEP		.570	.000
56	HEADACHE	0.850	.053	.090
	CYAN		-.307	.000
	WFAT		.260	.000
	DPCH		.170	.000

EMPT, DYSP, “CYAN, WFAT and CHEP are the five attributes model also needs a single computation. It has an R^2 value of 0.898 and uses five predictors namely. Table 15 gives brief statements of these selected attributes.”

$$\bar{Y} = 0.113 + (0.170*EMPT) + (0.366*DYSP) + (-0.193*CYAN) + (0.152*WFAT) + (0.352*CHEP)$$

Dyspnea, Cyanosis and Chest Pain with weakness and Fatigue and Emptysis are the symptoms leading to Heart Valve and Pericardial diseases.

4.2.5. MLR WITH SIX PREDICTORS

The model is created by combining seven separate variables with one dependent variable. R2 is determined using all possible predictor combinations, most of which are not statistically significant in the 0.05 stage. In Table 11, there are no statistically significant results from a combination of seven predictors. Just one statistically significant combination has been found.

Table 4.6: MLR Results with Six Predictors

Dependent Variable	Predictors (In Pair)	R-Square	Standardized Beta	Significance
1	EMPT	0.864	.343	.000
	DYSP		.492	.000
	FEVE		-.076	.053

	HEADACHE		.028	.355
	CYAN		-.169	.000
	WFAT		.150	.000
2	EMPT	0.857	.358	.000
	DYSP		.494	.000
	FEVE		-.027	.477
	HEADACHE		.018	.556
	CYAN		-.124	.004
	DPCH		.119	.001
3	EMPT	0.881	.184	.000
	DYSP		.440	.000
	FEVE		-.018	.609
	HEADACHE		.031	.267
	CYAN		-.120	.002

	CHEP		.327	.000
4	EMPT	0.864	.343	.000
	DYSP		.492	.000
	FEVE		-.076	.053
	HEADACHE		.028	.355
	WFAT		-.169	.000
	DPCH		.150	.000
5	EMPT	0.891	.188	.000
	DYSP		.415	.000
	FEVE		-.127	.000
	HEADACHE		.033	.222
	WFAT		.149	.000
	CHEP		.360	.000
6	EMPT	0.880	.219	.000

	DYSP		.431	.000
	FEVE		-.063	.048
	HEADACHE		.024	.393
	DPCH		.094	.004
	CHEP		.312	.000
7	EMPT	0.876	.328	.000
	DYSP		.437	.000
	FEVE		-.086	.021
	CYAN		-.164	.000
	WFAT		.160	.000
	DPCH		.133	.000
8	EMPT	0.902	.140	.002
	DYSP		.376	.000
	FEVE		-.083	.012

	CYAN		-.163	.000
	WFAT		.175	.000
	CHEP		.354	.000
9	EMPT	0.886	.190	.000
	DYSP		.410	.000
	FEVE		-.025	.465
	CYAN		-.115	.003
	DPCH		.092	.003
	CHEP		.305	.000
10	EMPT	0.898	.190	.000
	DYSP		.377	.000
	FEVE		-.135	.000
	WFAT		.156	.000
	DPCH		.107	.000

	CHEP		.335	.000
11	EMPT	0.873	.351	.000
	DYSP		.430	.000
	HEADACHE		.030	.305
	CYAN		-.195	.000
	WFAT		.139	.000
	DPCH		.129	.000
12	EMPT	0.900	.156	.001
	DYSP		.367	.000
	HEADACHE		.044	.086
	CYAN		-.193	.000
	WFAT		.156	.000
	CHEP		.356	.000
13	EMPT	0.886	.189	.000

	DYSP		.406	.000
	HEADACHE		.029	.285
	CYAN		-.126	.000
	DPCH		.090	.004
	CHEP		.308	.000
14	EMPT	0.888	.250	.000
	DYSP		.376	.000
	HEADACHE		.039	.153
	WFAT		.110	.000
	DPCH		.101	.001
	CHEP		.338	.000
15	EMPT	0.906	.168	.000
	DYSP		.331	.000
	CYAN		-.192	.000

	WFAT		.158	.000
	DPCH		.101	.000
	CHEP		.332	.000
16	EMPT	0.784	.493	.000
	FEVE		-.045	.354
	HEADACHE		.012	.762
	CYAN		-.271	.000
	WFAT		.259	.000
	DPCH		.249	.000
17	EMPT	0.839	0.174	.004
	FEVE		-0.044	.300
	HEADACHE		0.037	.255
	CYAN		-0.252	.000
	WFAT		0.261	.000

	CHEP		0.538	.000
18	EMPT	0.808	.261	.000
	FEVE		.048	.273
	HEADACHE		.019	.592
	CYAN		-.184	.000
	DPCH		.174	.000
	CHEP		.474	.000
19	EMPT	0.835	.253	.000
	FEVE		-.126	.002
	HEADACHE		.022	.508
	WFAT		.232	.000
	DPCH		.187	.000
	CHEP		.500	.000
20	EMPT	0.861	.171	.002

	FEVE		-.062	.113
	CYAN		-.232	.000
	WFAT		.258	.000
	DPCH		.173	.000
	CHEP		.471	.000
21	EMPT	0.860	.182	.001
	HEADACHE		.035	.252
	CYAN		-.253	.000
	WFAT		.243	.000
	DPCH		.168	.000
	CHEP		.472	.000
22	DYSP	0.827	0.547	.000
	FEVE		-0.163	.000
	HEADACHE		0.052	.116

	CYAN		-0.267	.000
	WFAT		0.201	.000
	DPCH		0.16	.000
23	DYSP	0.899	.385	.000
	FEVE		-.100	.002
	HEADACHE		.048	.062
	CYAN		-.193	.000
	WFAT		.192	.000
	CHEP		.428	.000
24	DYSP	0.877	.433	.000
	FEVE		-.045	.196
	HEADACHE		.042	.146
	CYAN		-.150	.000
	DPCH		.091	.005

	CHEP		.407	.000
25	DYSP	0.888	.401	.000
	FEVE		-.177	.000
	HEADACHE		.043	.114
	WFAT		.173	.000
	DPCH		.109	.001
	CHEP		.446	.000
26	DYSP	0.905	.349	.000
	FEVE		-.113	.000
	CYAN		-.189	.000
	WFAT		.198	.000
	DPCH		.107	.000
	CHEP		0.407	.000
27	DYSP	0.900	.341	.000

	HEADACHE		.056	.029
	CYAN		-.236	.000
	WFAT		.174	.000
	DPCH		.100	.001
	CHEP		.425	.000
28	FEVE	0.854	-.085	.031
	HEADACHE		.043	.166
	CYAN		-.270	.000
	WFAT		.281	.000

From above tables summarize the results of applying forward stepwise MLR on our dataset. Six attributes model also needs a single computation. It has an R^2 value of 0.906 and uses six predictors which are EMPT, DYSP, CYAN, WFAT, DPCH and" CHEP.

Y= -0.024+ (0.168** EMPT**) + (0.331**+ DYSP**) + (-0.192**+ CYAN**) + (0.158**+ WFAT**) +

(0.101** DPCH**) + (0.332** CHEP**)

Dyspnea, Cyanosis and Chest Pain, Weakness and Fatigue, Emptysis and Discomfort with chest pain has been overlapping symptoms which are the symptoms leading to Heart Valve and Pericardial diseases.

4.2.6 MLR WITH SEVEN PREDICTORS

The model is created by combining seven separate variables with one dependent variable. R^2 is determined using all possible predictor combinations, most of which are not statistically significant in the 0.05 stage. In Table 11, there are no statistically significant results from a combination of seven predictors. Just one statistically significant combination has been found.

Table 4.7: MLR Results with Seven Predictors

Dependent Variable	Predictors (In Pair)	R-Square	Standardized Beta	Significance
1	EMPT	0.877	.324	.000
	DYSP		.439	.000
	FEVE		-.083	.027
	HEADACHE		.023	.425
	CYAN		-.165	.000
	WFAT		.161	.000

	DPCH		.132	.000
2	EMPT	0.903	.131	.005
	DYSP		.376	.000
	FEVE		-.078	.019
	HEADACHE		.038	.137
	CYAN		-.165	.000
	WFAT		.176	.000
	CHEP		.357	.000
3	EMPT	0.887	.184	.000
	DYSP		.411	.000
	FEVE		-.020	.546
	HEADACHE		.027	.324
	CYAN		-.116	.003
	DPCH		.091	.004

	CHEP		.307	.000
4	EMPT	0.899	.184	.000
	DYSP		.378	.000
	FEVE		-.131	.000
	HEADACHE		.029	.274
	WFAT		.157	.000
	DPCH		.106	.000
	CHEP		.338	.000
5	EMPT	0.910	.136	.002
	DYSP		.340	.000
	FEVE		-.088	.006
	CYAN		-.160	.000
	WFAT		.182	.000
	DPCH		.105	.000

	CHEP		.333	.000
6	EMPT	0.907	.155	.001
	DYSP		.332	.000
	HEADACHE		.040	.105
	CYAN		-.192	.000
	WFAT		.161	.000
	DPCH		.099	.001
	CHEP		.336	.000
7	EMPT	0.862	.163	.003
	FEVE		-.058	.141
	HEADACHE		.030	.324
	CYAN		-.234	.000
	WFAT		.259	.000
	DPCH		.171	.000

	CHEP		.474	.000
8	DYSP	0.906	.349	.000
	FEVE		-.105	.001
	HEADACHE		.044	.080
	CYAN		-.189	.000
	WFAT		.198	.000
	DPCH		.104	.000
	CHEP		.405	.000

The equation is given below for the suggested model with R-Square 0.910

$$\mathbf{Y = 0.078+ (0.136* EMPT) + (0.340+ DYSP) + (-0.088+ FEVE)}$$

$$\mathbf{+ (-0.160+ CYAN) + (0.182* WFAT) + (0.105* DPCH) + (0.333* CHEP)}$$

Through deep learning the symptoms predicted are Fever at 8 times in reverse way, Dyspnea 34 times, Cyanosis 16 at 0.160 times and Chest Pain 33 times, Weakness and Fatigue 18.2 times, Emptysis 13.6 times and Discomfort Pressure with Chest Pain 10.5 times, again chest pain and fever has been overlapping symptoms with has been overlapping symptoms leading to the Heart Attack disease.

4.2.6 MLR WITH EIGHT PREDICTORS

When we applied the regression test with all usability factors as an independent variables and user rating and it is found that results are non-significant even R-Square is increased 0.911. Which is Consequently implying that headache is making this non-significant.

Table 4.8: MLR Results with Eight Predictor

Dependent Variable	Predictors (In Pair)	R-Square	Standardized Beta	Significance
	EMPT	0.911	.128	.004
	DYSP		.341	.000
User Rating	FEVE		-.083	.009
	HEADACHE		.034	.172
	CYAN		-.163	.000
	WFAT		.183	.000
	DPCH		.103	.000

	CHEP		.336	.000

Y = -3.34*10'-5+ (0.128** **EMPT*)** ***+ (0.341+ **DYSP*)*** ***+ (-0.083+*** **FEVE*)***

+ *(0.034 HEADACHE) + *(-0.163*+ CYAN*)* + *(0.183** WFAT*)* + *(0.103** DPCH*)* + *(0.336** CHEP*)***

4.3 SUGGESTED MODEL FOR UAE HOSPITALS

Researcher obtained results for all possible combinations of 2, 3, 4, 5, 6, and 7 predictor variables after using MLR. By this generated suggested a secure model where data breaching will not be possible. Steadily increase the number of variables until we achieve the best possible model. Table 12 summarizes all of the best regression models that generated important results.

Table 4.9: Summary of MLR Based Models

Sr. No	**Predictors**	**Prediction Model**	**R-Square**
1	CHEP	$\overline{Y}$ = 0.347 + (0.846*CHEP)	O.715
2	CHEP, DYSP	Y = -0.248+ (0.487* DYSP) + (0.517*CHEP)	0.844
3	DYSP, CYAN and CHEP	$\overline{Y}$ = 0.498+ (0.452*DYSP) + (-0.182*CYANIS) + (0.441*CHEP)	0.867
4	DYSP, CYAN, CHEP and WFAT	*Y = 0.344+ (0.376*DYSP) + (-0.242** CYAN*) +* *(0.165** WFAT*) + (0.452** CHEP)	0.889
5	EMPT, DYSP, CYAN, WFAT and CHEP	$\overline{Y}$ = 0.113 + (0.170*EMPT) + (0.366*DYSP) + (-0.193*CYAN) + (0.152*WFAT) + (0.352*CHEP)	0.898
6	EMPT, DYSP, CYAN, WFAT, DPCH and CHEP	Y= -0.024+ (0.168* EMPT) + (0.331+ DYSP) + (-0.192+ CYAN) + (0.158+ WFAT) + (0.101* DPCH) + (0.332* CHEP)	0.906
7	EMPT, DYSP, FEVE, CYAN, WFAT, DPCH and CHEP	Y = -3.34*10’-5+ (0.128* EMPT) + (0.341+ DYSP) + (-0.083+ FEVE) + (-0.163+ CYAN) + (0.183* WFAT) + (0.103* DPCH) + (0.336* CHEP)	0.910

MLR model with seven predictors as shown at Sr. No. 7 is which is showing the greater value of the R-Square is 0.911 not only this it is also significant on the other hand when regression is applied with the eight variables it is showing just 0.001 increase in the R-Square not only this it is also carrying the value non-significant whereas R-Square is showing greater change in previous models model 7 explains 91% of variation in determination of user rating prediction for usability factors. So the final model is 7 factors variables with the exception of headache.

$$\bar{\boldsymbol{Y}} = -0.078 + (0.145 * \text{EMPT}) + (0.395 + \text{DYSP}) + (-0.082 + \text{FEVE}) + (-0.128 + \text{CYAN}) + (0.190 * \text{WFAT}) + (0.118 * \text{DPCH}) + (0.376 * \text{CHEP})$$

4.4 COMPARISON OF SUGGESTED MODEL (HYBRID VS. RUF)

Hybrid Model in this research has finalized an ideal Hybrid model on the bases of utilizing factors filtered by Delphi techniques on which an ideal model with 8 usability factor has been finalized which are Emptysis, learnability, Fever, Cyanosis, Weakness or Fatigue, Discomfort Pressure in Chest and Chest Pain were the independent variables/factors of hybrid model affecting regressively the dependent variable rating. In this section, we provide comparison of our proposed RUF (Rating of Usability Factor) with HYBRID model. User Rating (UR), Hybrid Model Rating (with eight factors) and RUF Model which is finalized in the MLR and SLR Technique.

It was observed that Hybrid Model non-significantly predicts UR as evident from the value of R^2 or coefficient of determination is 0.911 which confirms that CHEP accounted for 71.5 percent variance in User Rating R prediction.

The regression equation is $\overline{\boldsymbol{Y}}$ = 0.347 + (0.846*CHEP)

Here, $\boldsymbol{Y}$ denotes predicted value of user rating (dependent variable) and OR represents rating given by Hybrid model (independent variable).

As shown by the value of the coefficient of determination, the RUF Model (which is based on 7 factors) performs better in predicting the value of Usability factors based on user rating applications in terms of usability factors, rating (R2 square). RUF explained 91 percent of the variance in rating based on the seven usability criteria (R2= 0.910), while Hybrid explained 91.1 percent of the variation (R2 Square= 0.911).

CHAPTER NUMBER FIVE

OVERLAPPING ASSESSMENT AND VALIDATION OF PROPOSED SCHEME

This chapter “provides for evaluating model values by using K fold cross validation with PRED(X) and MMRE, as well as summarized k-fold models with R-square values.

5.1 MODEL ASSESSMENT

De facto normal prediction accuracy metrics are used to achieve the extraordinary accuracy of the forecast model. MMRE and PRED(x) are typically used for accuracy checking. In the literature. PRED value (0.25) is greater or equal to 0.75. The value of MRE which is greater than 0.25 will be considered as Pred(X) and will be rejected. It was found that the MMRE value was 0.0515.

5.2 VALIDATION PROCESS

Cross-validation K-fold (Rodríguez, 2010) is a non-exhaustive model validation technique. This technique uses the performance of the predicted model on an autonomous data set. The dataset is divided into the same number of folds depending on the data size. Data calibration and validation doubles their data points through k-fold cross-validation. The training segment contains (k-1) and the test section contains (k-1) for each interaction data set (1). It was divided into 8 folds, each containing 21 answers, due to the large number of replies in our data collection. It was predetermined the sequence of the answers in the folds. In each iteration, eight folds were used to calibrate the model, and the rest were used to validate the model.

5.3 K-FOLD CROSS VALIDATION

The data values in all folds are divided into ten fixed groups. During each fold, each category comprises a total of 21 instances, i.e. 1–21 and 22–42. For fold K = 1 to K= 10. It has been observed that even after dividing data into 8 folds each fold has been found to be significant which proves that our dataset is correct and ideal

even each of it's value in the K fold prediction we identified all data sets are significant values. We found all six predictors to be significant if the value after training is 0.05. It should be noted that PRED (0.25) is calculated in all folds. The R^2 MMRE values and a validation summary for all folds are given in Table 4.9. All the values of MMRE and R2 show the validation of the proposed" model.

"Table 5.1: K-FOLD Validation Summary-Arranged K-FOLDs"

K=1

Data Point	**Predictor**	**Coefficient**	**Std.Error**	**Sig.**	**R2**
01 to 21	(Constant)	.121	.182	.508	0.914
	Emptysis	.128	.049	.010	
	Learnability	.408	.045	.000	
	Fever	-.097	.030	.001	
	Cyanosis	-.125	.030	.000	
	Weakness and Fatigue	.190	.030	.000	
	Discomfort Pressure in Chest	.111	.034	.001	

	Chest Pain	.385	.051	.000	

K=2

Data Point	Predictor	Coefficient	Std.Error	Sig.	R2
22 to 42	(Constant)	.079	.172	.648	0.915
	Emptysis	.102	.046	.027	
	Learnability	.433	.041	.000	
	Fever	-.073	.029	.013	
	Cyanosis	-.118	.027	.000	
	Weakness and Fatigue	.155	.030	.000	
	Discomfort Pressure in Chest	.140	.031	.000	
	Chest Pain	.373	.050	.000	

Data Point	Predictor	Coefficient	Std.Error	Sig.	R2
43 to 63	(Constant)	.212	.184	.250	0.908
	Emptysis	.103	.050	.041	
	Learnability	.372	.045	.000	

	Fever	-.086	.031	.007	
	Cyanosis	-.155	.030	.000	
	Weakness and Fatigue	.201	.031	.000	
	Discomfort Pressure in Chest	.123	.035	.001	
	Chest Pain	.404	.052	.000	

K=3

K=4

Data Point	**Predictor**	**Coefficient**	**Std.Error**	**Sig.**	**R2**
64 to 84	(Constant)	.050	.190	.793	0.905
	Emptysis	.131	.051	.011	
	Learnability	.419	.046	.000	
	Fever	-.084	.032	.010	
	Cyanosis	-.128	.030	.000	
	Weakness and Fatigue	.179	.032	.000	

	Discomfort Pressure in Chest	.112	.033	.001	
	Chest Pain	.390	.053	.000	

K=5

Data Point	Predictor	Coefficient	Std.Error	Sig.	R2
85 to 105	(Constant)	.089	.181	.624	0.911
	EMPT	.150	.049	.002	
	DYSP	.383	.046	.000	
	FEVE	-.087	.031	.005	
	CYAN	-.133	.030	.000	
	WFAT	.212	.032	.000	
	DPCH	.120	.035	.001	
	CHEP	.365	.052	.000	

K=6

Data Point	Predictor	Coefficient	Std.Error	Sig.	R2
106 to 126	(Constant)	-.001	.182	.995	0.914
	EMPT	.168	.052	.002	

	DYSP	.401	.047	.000	
	FEVE	-.067	.031	.030	
	CYAN	-.118	.029	.000	
	WFAT	.190	.031	.000	
	DPCH	.101	.033	.003	
	CHEP	.372	.051	.000	

K=7

Data Point	Predictor	Coefficient	Std.Error	Sig.	R2
127 to 147	(Constant)	-.004	.179	.984	0.909
	EMPT	.176	.052	.001	
	DYSP	.377	.046	.000	
	FEVE	-.079	.032	.014	
	CYAN	-.118	.030	.000	

	WFAT	.196	.033	.000	
	DPCH	.123	.034	.000	
	CHEP	.368	.052	.000	

K=8

Data Point	**Predictor**	**Coefficient**	**Std.Error**	**Sig.**	**R2**
148 to 168	(Constant)	.081	.180	.655	0.910
	EMPT	.206	.053	.000	
	DYSP	.361	.045	.000	
	FEVE	-.076	.038	.049	
	CYAN	-.131	.034	.000	
	WFAT	.194	.030	.000	
	DPCH	.118	.033	.001	
	CHEP	.343	.054	.000	

5.2 Summarized K-FOLD Predicted Model

Folds	Prediction Models	R^2	MMRE

1.	Y (K-1) = .121 + (0.119*EMPT) + (0.350*DYSP) + (-0.107*FEVE) + (-0.157*CYAN) + (0.186*WFAT) + (0.099*DPCH) + (0.339*CHEP)	0.914	0.1523
2.	Y (K-2) = .079 + (0.100*EMPT) + (0.388*DYSP) + (-0.084*FEVE) + (-0.160*CYAN) + (0.155*WFAT) + (0.132*DPCH) + (0.332*CHEP)	0.915	0.0705
3.	Y (K-3) = .212 + (0.097*EMPT) + (0.320*DYSP) + (-0.094*FEVE) + (-0.195*CYAN) + (0.197*WFAT) + (0.108*DPCH) + (0.374*CHEP)	0.908	0.0486
4.	Y (K-4) = .050 + (0.123*EMPT) + (0.360*DYSP) + (-0.089*FEVE) + (-0.160*CYAN) + (0.174*WFAT) + (0.101*DPCH) + (0.336*CHEP)	0.905	0.0471
5.	Y (K-5) = .089 + (0.141*EMPT) + (0.327*DYSP) + (-0.091*FEVE) + (-0.160*CYAN) + (0.193*WFAT) + (0.105*DPCH) + (0.321*CHEP)	0.911	0.0509

6.	Y (K-6) = -.001 + (0.155*EMPT) + (0.338*DYSP) + (-0.070*FEVE) + (-0.146*CYAN) + (0.173*WFAT) + (0.088*DPCH) + (0.326*CHEP)	0.914	0.0451
7.	Y (K-7) = -.004 + (0.160*EMPT) + (0.322*DYSP) + (-0.084*FEVE) + (-0.140*CYAN) + (0.178*WFAT) + (0.109*DPCH) + (0.326*CHEP)	0.909	0.0408
8.	Y (K-8) = .081 + (0.196*EMPT) + (0.311*DYSP) + (-0.079*FEVE) + (-0.165*CYAN) + (0.189*WFAT) + (0.103*DPCH) + (0.301*CHEP)”	0.910	0.0558

Table 5.3: K-FOLD Validation Summary-Random K-FOLDs

K=1

Data Point	**Predictor**	**Coefficient**	**Std.Error**	**Sig.**	**R2**
01 to 21	(Constant)	.105	0.184	.569	0.903
	EMPT	.112	0.052	.034	
	DYSP	.404	0.045	.000	
	FEVE	-.067	0.032	.042	

	CYAN	-.138	0.03	.000	
	WFAT	.181	0.031	.000	
	DPCH	.132	0.034	.000	
	CHEP	.382	0.051	.000	
K=2					
Data Point	**Predictor**	**Coefficient**	**Std.Error**	**Sig.**	**R2**
22 to 42	(Constant)	.091	.181	.616	0.914
	EMPT	.161	.049	.001	
	DYSP	.396	.044	.000	
	FEVE	-.084	.032	.009	
	CYAN	-.122	.029	.000	
	WFAT	.194	.030	.000	
	DPCH	.106	.033	.002	
	CHEP	.361	.052	.000	

K=3					
Data Point	**Predictor**	**CoEffecient**	**Std.Error**	**Sig.**	**R2**
	(Constant)	.059	.179	.742	0.914

43 to 63	EMPT	.151	.048	.002	
	DYSP	.401	.044	.000	
	FEVE	-.077	.030	.013	
	CYAN	-.146	.029	.000	
	WFAT	.215	.032	.000	
	DPCH	.134	.033	.000	
	CHEP	.338	.051	.000	

K=4

Data Point	**Predictor**	**Coefficient**	**Std.Error**	**Sig.**	**R2**
64 to 84	(Constant)	.016	.186	.932	0.909
	Emptysis	.156	.053	.004	
	Learnability	.418	.048	.000	
	Fever	-.076	.032	.021	
	Cyanosis	-.100	.031	.001	

	Weakness and Fatigue	.161	.031	.000	
	Discomfort Pressure in Chest	.089	.034	.009	
	Chest Pain	.392	.053	.000	

K=5

Data Point	Predictor	Coefficient	Std.Error	Sig.	R2
85 to 105	(Constant)	.121	.186	.516	0.907
	Emptysis	.151	.053	.005	
	Learnability	.356	.047	.000	
	Fever	-.079	.032	.015	

	Cyanosis	-.137	.030	.000	
	Weakness and Fatigue	.195	.032	.000	
	Discomfort Pressure in Chest	.104	.034	.002	
	Chest Pain	.408	.052	.000	

K=6

Data Point	Predictor	Coefficient	Std.Error	Sig.	R2
106 to 126	(Constant)	.077	.189	.682	0.903
	EMPT	.153	.050	.002	
	DYSP	.382	.046	.000	
	FEVE	-.096	.032	.003	
	CYAN	-.135	.031	.000	
	WFAT	.211	.033	.000	
	DPCH	.119	.035	.001	
	CHEP	.375	.051	.000	

K=7

Data Point	Predictor	Coefficient	Std.Error	Sig.	R2
127 to 147	(Constant)	.093	.173	.592	0.915
	EMPT	.138	.048	.005	
	DYSP	.385	.044	.000	
	FEVE	-.082	.029	.006	
	CYAN	-.135	.028	.000	
	WFAT	.184	.030	.000	
	DPCH	.131	.034	.000	
	CHEP	.385	.055	.000	

K=8

Data Point	Predictor	Coefficient	Std.Error	Sig.	R2
148 to 168	(Constant)	.060	.181	.741	0.910
	EMPT	.161	.049	.001	
	DYSP	.393	.045	.000	
	FEVE	-.091	.032	.005	
	CYAN	-.112	.030	.000	

	WFAT	.184	.032	.000	
	DPCH	.111	.034	.001	
	CHEP	.375	.051	.000	

5.4 “Random K-Fold Predicted Model”

Folds	Prediction Models	R^2
1.	Y (K-1) = .105 + (0.103*EMPT) + (0.353*DYSP) + (-0.072*FEVE) + (-0.175*CYAN) + (0.175*WFAT) + (0.119*DPCH) + (0.338*CHEP)	0.908
2.	Y (K-2) = .091 + (0.153*EMPT) + (0.341*DYSP) + (-0.091*FEVE) + (-0.155*CYAN) + (0.184*WFAT) + (0.094*DPCH) + (0.318*CHEP)	0.914
3.	Y (K-3) = .059 + (0.145*EMPT) + (0.344*DYSP) + (-0.083*FEVE) + (-0.180*CYAN) + (0.203*WFAT) + (0.117*DPCH) + (0.297*CHEP)	0.914
4.	Y (K-4) = .016 + (0.145*EMPT) + (0.353*DYSP) +	0.909

	(-0.080*FEVE) + (-0.126*CYAN) + (0.154*WFAT) + (0.079*DPCH) + (0.356*CHEP)	
5.	Y (K-5) = .121 + (0.140*EMPT) + (0.305*DYSP) + (-0.085*FEVE) + (-0.172*CYAN) + (0.190*WFAT) + (0.093*DPCH) + (0.363*CHEP)	0.907
6.	Y (K-6) = .077 + (0.143*EMPT) + (0.325*DYSP) + (-0.103*FEVE) + (-0.163*CYAN) + (0.195*WFAT) + (0.108*DPCH) + (0.338*CHEP)	0.903
7.	Y (K-1) = .093 + (0.133*EMPT) + (0.335*DYSP) + (-0.090*FEVE) + (-0.172*CYAN) + (0.179*WFAT) + (0.115*DPCH) + (0.332*CHEP)	0.915
8.	Y (K-1) = .060 + (0.150*EMPT) + (0.343*DYSP) + (-0.096*FEVE) + (-0.137*CYAN) + (0.172*WFAT) + (0.098*DPCH) + (0.328*CHEP)”	0.910

5.4 CONCLUSION

The analyst will break down the cardiovascular issues carried out from deep learning and which has been rated by early model prediction as above in terms of overlapping and disease prediction with accuracy level. according to the questionnaire provided against our factors/predictors, and all potential viewpoints will be assessed too. It has been tracked down that most of individuals' user of these applications in their regular daily existences have made a lot of mistakes from security point of view. The specialist surveyed that how data could be secured from breaching.

SLR represents Single Linear Regression up to 8 elements (i) CHEP (ii) DYSP (iii) DPCH (iv) Headache (v) FEVE (vi) EMPT (vii) WFAT (viii) CYAN) were applied to the Hybrid ideal model. Also, it was resolved that the entirety of the qualities was significant and have high R-squared values. In the mixture model, EMPT represents 64% of the change, with DYSP representing 69.9%, FEVE 14%, HEADACHE 02%, CYAN 40%, WFAT 5%, DPCH 29.9%, and CHEP 71.5 percent securing our sensitive attributes from Symptoms overlapping.

It has been found that these factors EMPT, DYSP, CYAN, and CHEP are the most Productive overlapping symptoms factors by individuals who have been using deep learning and were victim of heart attack or heart failure.

The scientist at that point decided to develop this by utilizing Multiple Linear Regression to make sets of these factors dependent on every single imaginable blend of secure model. Initial, a twofold pair was framed, and 21 out of 29 sets were discovered to be significant, with R-Square values in the great reach with sig values 0.000. DYSP and CHEP, again, have the most elevated R-Square of 0.844, representing 84.4 percent of the difference in results. Showing most valuable predictors in securing users.

On the crossover stage, triple pair MLR has now been presented. The pair of DYSP, CHEP, and CYAN currently clarify 86.7 percent of the fluctuation in this model. It has been discovered that CYAN was acquainted with improve the model's R Square. Four and five combined Multiple Linear Regressions have been utilized similarly. 0.889 is the R-Square in the fourth (Pair is DYSP, CHEP, CYAN, and WFAT) with the expansion of clarifying 88.9% of the equation, and 0.898 is the R-Square in the fifth (Pair is DYSP, CHEP and CYAN, WFAT and EMPT) with the expansion of clarifying 0.9 percent more than the fourth matched relapse. It was found that adding WFAT and Productive to the model improved the level of the model that could be explained. Since the specialist has utilized six matched relapses, just five of the 28 mixes have solid R-Square upsides of 0.906 and portray 90.6 percent of the model when DPCH is added to the above pair.

It has likewise been discovered that as the matching strategy is expanded, the quantity of significant blends diminishes. For instance, in the seventh combined various relapse, just one sets are critical, which is EMPT, DYSP, FEVE, CYAN, WFAT, DPCH, and CHEP. The R-Square is expanded to 0.910, which clarifies the model better compared to the past one.

Early Predictive Symptoms with Accuracy Level Number One:

DYSP and CHEP = 84.4%

Level Number Two:

DYSP, CHEP and CYAN is explaining 86.7%

Level Number Three:

DYSP, CHEP, CYAN and WFAT explaining 88.9%

Level Number Four:

DYSP, CHEP, CYAN, WFAT and EMPT 89.8%

Level Number Five:

DYSP, CHEP, CYAN, WFAT, EMPT and DPCH explaining 90.6%

Level Number Six: (Ideal Model)

DYSP, CHEP, CYAN, WFAT, EMPT, DPCH and FEVE explaining 91%.

Hybrid Model: (Rejected Model)

When the MLR is run on all eight elements, the R-Square is increased by just 0.1 percent due to the expansion of the final element, Headache, but the but condition becomes non-critical. As a result, when compared to the half breed model, the six model is the best model for the convenience of deep learning process to secure Patient from heart failure.

We isolated the information into a 0-21 arrangement of respondents and MRE was applied to the remainder of 21-147 with Constants of 0-21 K-FOLDs and the equivalent has been completed with irregular information K-FOLD and it was shown that all of the K-FOLDs are 0-21. While only one MRE esteem out of 336 qualities has a Pred(X) 0.25 or less, which isn't satisfactory, MMREs have suitable qualities for all of them, demonstrating the validity of our data. According to our data our arranged MMRE values are 0.1523, 0.0705, 0.0486, 0.0471, 0.0509, 0.0451, 0.0408 and 0.0558, some values are less than 0.05, we have applied grand MRRE and found 0.05 proving that our dataset is free of mean relative error. And those MRE values which are greater than 0.25 is counted as Pred(X) value is indicating that the RUF (Rating of Usability Factor) Model is correct and ideal model.

References

Al'Aref, S. J., Anchouche, K., Singh, G., Slomka, P. J., Kolli, K. K., Kumar, A., Pandey, M., Maliakal, G., Van Rosendael, A. R., & Beecy, A. N. J. E. h. j. (2019) Clinical applications of machine learning in cardiovascular disease and its relevance to cardiac imaging. *40*(24), 1975-1986.

Anand, P., Kunnumakara, A. B., Sundaram, C., Harikumar, K. B., Tharakan, S. T., Lai, O. S., Sung, B., & Aggarwal, B. B. J. P. r. (2008) Cancer is a preventable disease that requires major lifestyle changes. *25*(9), 2097-2116.

Bakator, M., Radosav, D. J. M. T., & Interaction. (2018) Deep learning and medical diagnosis: A review of literature. *2*(3), 47.

Baldi, P. J. A. r. o. b. d. s. (2018) Deep learning in biomedical data science. *1*, 181-205.

Baxt, W. G., & Skora, J. J. T. L. (1996) Prospective validation of artificial neural network trained to identify acute myocardial infarction. *347*(8993), 12-15.

Baxt, W. G. J. A. o. i. m. (1991) Use of an artificial neural network for the diagnosis of myocardial infarction. *115*(11), 843-848.

Bellazzi, R., & Zupan, B. J. I. j. o. m. i. (2008) Predictive data mining in clinical medicine: current issues and guidelines. *77*(2), 81-97.

Ben-Haim, Y., & Tom-Tov, E. J. J. o. M. L. R. (2010) A Streaming Parallel Decision Tree Algorithm. *11*(2).

Bernard, O., Lalande, A., Zotti, C., Cervenansky, F., Yang, X., Heng, P.-A., Cetin, I., Lekadir, K., Camara, O., & Ballester, M. A. G. J. I. t. o. m. i. (2018) Deep learning techniques for automatic MRI cardiac multi-structures segmentation and diagnosis: is the problem solved? *, 37*(11), 2514-2525.

Bishop, C. M. (1995). *Neural networks for pattern recognition*: Oxford university press.

Bishop, C. M. (2006). *Pattern recognition and machine learning*: springer.

Brennan, C. W., Verhaak, R. G., McKenna, A., Campos, B., Noushmehr, H., Salama, S. R., Zheng, S., Chakravarty, D., Sanborn, J. Z., & Berman, S. H. J. C. (2013) The somatic genomic landscape of glioblastoma. *155*(2), 462-477.

Bright, B., Hicke, J., & Hudak, A. J. E. R. L. (2012) Landscape-scale analysis of aboveground tree carbon stocks affected by mountain pine beetles in Idaho. *7*(4), 045702.

Brijain, M., Patel, R., Kushik, M., & Rana, K. (2014) A survey on decision tree algorithm for classification.

Brunese, L., Martinelli, F., Mercaldo, F., & Santone, A. J. P. C. S. (2020) Deep learning for heart disease detection through cardiac sounds. *176*, 2202-2211.

Cao, Y., Liu, Z., Zhang, P., Zheng, Y., Song, Y., Cui, L. J. J. o. A. I., & Systems. (2019) Deep learning methods for cardiovascular image. *1*(1), 96-109.

Chaddha, A., Robinson, E. A., Kline-Rogers, E., Alexandris-Souphis, T., & Rubenfire, M. J. T. A. j. o. m. (2016) Mental health and cardiovascular disease. *129*(11), 1145-1148.

Chawla, N. V., & Davis, D. A. J. J. o. g. i. m. (2013) Bringing big data to personalized healthcare: a patient-centered framework. *28*(3), 660-665.

Chen, R., Mias, G. I., Li-Pook-Than, J., Jiang, L., Lam, H. Y., Chen, R., Miriami, E., Karczewski, K. J., Hariharan, M., & Dewey, F. E. J. C. (2012) Personal omics profiling reveals dynamic molecular and medical phenotypes. *148*(6), 1293-1307.

Cheung, C. Y., Xu, D., Cheng, C.-Y., Sabanayagam, C., Tham, Y.-C., Yu, M., Rim, T. H., Chai, C. Y., Gopinath, B., & Mitchell, P. J. N. B. E. (2020) A deep-learning system for the assessment of cardiovascular disease risk via the measurement of retinal-vessel calibre. 1-11.

FEVEandeur, F., Goeller, M., Betancur, J., Cadet, S., Doris, M., Chen, X., Berman, D. S., Slomka, P. J., Tamarappoo, B. K., & Dey, D. J. I. t. o. m. i. (2018) Deep learning for quantification of epicardial and thoracic adipose tissue from non-contrast CT. *37*(8), 1835-1846.

David, H. B. F. IMPACT OF ENSEMBLE LEARNING ALGORITHMS TOWARDS ACCURATE HEART DISEASE PREDICTION.

Demšar, J., Curk, T., Erjavec, A., Gorup, Č., Hočevar, T., Milutinovič, M., Možina, M., Polajnar, M., Toplak, M., & Starič, A. J. t. J. o. m. L. r. (2013) Orange: data mining toolbox in Python. *14*(1), 2349-2353.

Ellis, G. K., Robinson, J. A., & Crawford, G. B. J. A. f. p. (2006) When symptoms of disease overlap with symptoms of depression. *35*(8).

Escárcega, R. O., Lipinski, M. J., Garcia-Carrasco, M., Mendoza-Pinto, C., Galvez-Romero, J. L., & Cervera, R. J. A. r. (2018) Inflammation and atherosclerosis: cardiovascular evaluation in patients with autoimmune diseases. *17*(7), 703-708.

Frank, E., Trigg, L., Holmes, G., & Witten, I. H. J. M. L. (2000) Naive Bayes for regression. *41*(1), 5-25.

Go, A. S., Mozaffarian, D., Roger, V. L., Benjamin, E. J., Berry, J. D., Borden, W. B., Bravata, D. M., Dai, S., Ford, E. S., & Fox, C. S. J. C. (2013) Heart disease and stroke statistics—2013 update: a report from the American Heart Association. *127*(1), e6-e245.

Goodfellow, I., Bengio, Y., Courville, A., & Bengio, Y. (2016). *Deep learning* (Vol. 1): MIT press Cambridge.

Green, R. C., Goldstein, F., Mirra, S., Alazraki, N., Baxt, J., Bakay, R. J. J. o. N., Neurosurgery, & Psychiatry. (1995) Slowly progressive apraxia in Alzheimer's disease. *59*(3), 312-315.

Grotzinger, J. P., Crisp, J., Vasavada, A. R., Anderson, R. C., Baker, C. J., Barry, R., Blake, D. F., Conrad, P., Edgett, K. S., & Ferdowski, B. J. S. s. r. (2012) Mars Science Laboratory mission and science investigation. *170*(1), 5-56.

He, K., Zhang, X., Ren, S., & Sun, J. (2015). *Delving deep into rectifiers: Surpassing human-level performance on imagenet classification.* Paper presented at the Proceedings of the IEEE international conference on computer vision.

Hesamian, M. H., Jia, W., He, X., & Kennedy, P. J. J. o. d. i. (2019) Deep learning techniques for medical image segmentation: achievements and challenges. *32*(4), 582-596.

Hsu, C.-S., Wen, S.-H., Hung, J.-S., Liu, T.-T., Yi, C.-H., Lei, W.-Y., Pace, F., Chen, C.-L. J. D. d., & sciences. (2017) Overlap of dyspepsia in patients with gastroesophageal reflux disease: impact of clinical, metabolic, and psychosocial characteristics. *62*(4), 994-1001.

Hubert, H. B., Feinleib, M., McNamara, P. M., & Castelli, W. P. J. C. (1983) Obesity as an independent risk factor for cardiovascular disease: a 26-year follow-up of participants in the Framingham Heart Study. *67*(5), 968-977.

Hung, D.-Z., Yang, H.-J., Li, Y.-F., Lin, C.-L., Chang, S.-Y., Sung, F.-C., & Tai, S. C. J. P. o. (2015) The long-term Predicts of organophosphates poisoning as a risk factor of CVDs: a nationwide population-based cohort study. *10*(9), e0137632.

Ingre, B., & Yadav, A. (2015). *Performance analysis of NSL-KDD dataset using ANN.* Paper presented at the 2015 international conference on signal processing and FEVEunication engineering systems.

Isin, A., & Ozdalili, S. J. P. c. s. (2017) Cardiac arrhythmia detection using deep learning. *120*, 268-275.

Jonas, E., & Kording, K. P. J. P. c. b. (2017) Could a neuroscientist understand a microprocessor? *, 13*(1), e1005268.

Kansagara, D., Englander, H., Salanitro, A., Kagen, D., Theobald, C., Freeman, M., & Kripalani, S. J. J. (2011) Risk prediction models for hospital readmission: a systematic review. *306*(15), 1688-1698.

Karimi-Bidhendi, S., Arafati, A., Cheng, A. L., Wu, Y., Kheradvar, A., & Jafarkhani, H. J. J. o. C. M. R. (2020) Fully-automated deep-learning segmentation of pediatric cardiovascular magnetic resonance of patients with complex congenital heart diseases. *22*(1), 1-24.

Kohane, I. S. J. N. R. G. (2011) Using electronic health records to drive discovery in disease genomics. *12*(6), 417-428.

Kording, K. P., Benjamin, A., Farhoodi, R., & Glaser, J. I. (2018). *The roles of machine learning in biomedical science.* Paper presented at the Frontiers of Engineering: Reports on Leading-Edge Engineering from the 2017 Symposium.

Krittanawong, C., Johnson, K. W., Rosenson, R. S., Wang, Z., Aydar, M., Baber, U., Min, J. K., Tang, W. W., Halperin, J. L., & Narayan, S. M. J. E. h. j. (2019) Deep learning for cardiovascular medicine: a practical primer. *40*(25), 2058-2073.

Krittanawong, C., Zhang, H., Wang, Z., Aydar, M., & Kitai, T. J. J. o. t. A. C. o. C. (2017) Artificial intelligence in precision cardiovascular medicine. *69*(21), 2657-2664.

Kwon, J. m., Kim, K. H., Jeon, K. H., & Park, J. J. E. (2019) Deep learning for predicting in-hospital mortality among heart disease patients based on echocardiography. *36*(2), 213-218.

Lai, M. J. a. p. a. (2015) Deep learning for medical image segmentation.

Landahl, H., McCulloch, W. S., & Pitts, W. J. T. b. o. m. b. (1943) A statistical Consequence of the logical calculus of nervous nets. *5*(4), 135-137.

LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. J. P. o. t. I. (1998) Gradient-based learning applied to document recognition. *86*(11), 2278-2324.

Levin, I., & Stokes, J. P. J. J. o. a. p. (1989) Dispositional approach to job Discomfort Pressure in Chest: Role of negative affectivity. *74*(5), 752.

Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., Van Der Laak, J. A., Van Ginneken, B., & Sánchez, C. I. J. M. i. a. (2017) A survey on deep learning in medical image analysis. *42*, 60-88.

McCulloch, W. S., & Pitts, W. J. T. b. o. m. b. (1943) A logical calculus of the ideas immanent in nervous activity. *5*(4), 115-133.

members, A. T. F., Elliott, P. M., Anastasakis, A., Borger, M. A., Borggrefe, M., Cecchi, F., Charron, P., Hagege, A. A., Lafont, A., & Limongelli, G. J. E. h. j. (2014) 2014 ESC Guidelines on diagnosis and management of hypertrophic cardiomyopathy: the Task Force for the Diagnosis and Management of Hypertrophic Cardiomyopathy of the European Society of Cardiology (ESC). *35*(39), 2733-2779.

Mensah, G. A., & Collins, P. Y. J. G. h. (2015) Understanding mental health for the prevention and control of cardiovascular diseases. *10*(3), 221.

Milberger, S., Biederman, J., Faraone, S. V., Murphy, J., & Tsuang, M. T. J. T. A. j. o. p. (1995) Attention deficit hyperactivity disorder and comorbid disorder: Issues of overlapping symptoms.

Mirnezami, R., Nicholson, J., & Darzi, A. J. N. E. J. M. (2012) Preparing for precision medicine. *366*(6), 489-491.

Nature, 摇. J. (2015) Y, BENGIO Y, HINTON G. Deep learning. *521*(7553), 436-444.

Norris, R. M., White, H. D., Cross, D. B., Wild, C. J., & Whitlock, R. M. J. E. h. j. (1992) Prognosis after recovery from myocardial infarction: the relative importance of cardiac dilatation and coronary stenoses. *13*(12), 1611-1618.

Olier, I., & Vellido, A. J. N. n. (2008) Advances in clustering and visualization of time series using GTM through time. *21*(7), 904-913.

Organization, W. H. (2013). *Transforming and scaling up health professionals' education and training: World Health Organization guidelines 2013*: World Health Organization.

Peili, Y., Xuezhen, Y., Jian, Y., Lingfeng, Y., Hui, Z., & Jimin, L. (2018). *Deep learning model management for coronary heart disease early warning research.* Paper presented at the 2018 IEEE 3rd International Conference on Cloud Computing and Big Data Analysis (ICCCBDA).

Pham, T., Tran, T., Phung, D., & Venkatesh, S. J. J. o. b. i. (2017) Predicting healthcare trajectories from medical records: A deep learning approach. *69*, 218-229.

Pittoli, F., Vianna, H. D., Barbosa, J. L. V., Butzen, E., Gaedke, M. Â., da Costa, J. S. D., dos Santos, R. B. S. J. T., & Informatics. (2018) An intelligent system for prognosis of nonCommunicable diseases' risk factors. *35*(5), 1222-1236.

Platform, P. M. (2021) American Heart Association.

Polson, N. G., & Sokolov, V. O. J. W. S. S. R. O. (2014) Deep learning. 1-12.

Poplin, R., Varadarajan, A. V., Blumer, K., Liu, Y., McConnell, M. V., Corrado, G. S., Peng, L., & Webster, D. R. J. N. B. E. (2018) Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning. *2*(3), 158-164.

Prasoon, A., Petersen, K., Igel, C., Lauze, F., Dam, E., & Nielsen, M. (2013). *Deep feature learning for knee cartilage segmentation using a triplanar convolutional neural network.* Paper presented at the International conference on medical image computing and computer-assisted intervention.

Psaty, B. M., Furberg, C. D., Kuller, L. H., Cushman, M., Savage, P. J., Levine, D., O'Leary, D. H., Bryan, R. N., Anderson, M., & Lumley, T. J. A. o. i. m. (2001) Association between blood pressure level and the risk of myocardial infarction, stroke, and total mortality: the cardiovascular health study. *161*(9), 1183-1192.

Quinlan, J. R. J. M. l. (1986) Induction of decision trees. *1*(1), 81-106.

Rajkumar, A., Ganesan, M., & Lavanya, R. (2019). *Arrhythmia classification on ECG using Deep Learning.* Paper presented at the 2019 5th International Conference on Advanced Computing & FEVEunication Systems (ICACCS).

Rish, I. (2001). *An empirical study of the naive Bayes classifier.* Paper presented at the IJCAI 2001 workshop on empirical methods in artificial intelligence.

Rish, I., Hellerstein, J., & Thathachar, J. J. I. T. W. R. C. (2001) An analysis of data characteristics that affect naive Bayes performance. *30*, 1-8.

Rogan, J., Franklin, J., Stow, D., Miller, J., Woodcock, C., & Roberts, D. J. R. S. o. E. (2008) Mapping land-cover modifications over large areas: A comparison of machine learning algorithms. *112*(5), 2272-2283.

Romiti, S., Vinciguerra, M., Saade, W., Anso Cortajarena, I., Greco, E. J. C. R., & Practice. (2020) Artificial Intelligence (AI) and Cardiovascular Diseases: An Unexpected Alliance. *2020*.

Rosengren, A., Hawken, S., Ôunpuu, S., Sliwa, K., Zubaid, M., Almahmeed, W. A., Blackett, K. N., Sitthi-Amorn, C., Sato, H., & Yusuf, S. J. T. L. (2004) Association of psychosocial risk factors with risk of acute myocardial infarction in 11 119 cases and 13 648 controls from 52 countries (the INTERHEART study): case-control study. *364*(9438), 953-962.

Ruangkanokmas, P., Achalakul, T., & Akkarajitsakul, K. (2016). *Deep belief networks with feature selection for sentiment classification.* Paper presented at the 2016 7th International Conference on Intelligent Systems, Modelling and Simulation (ISMS).

Schirrmeister, R. T., Springenberg, J. T., Fiederer, L. D. J., Glasstetter, M., Eggensperger, K., Tangermann, M., Hutter, F., Burgard, W., & Ball, T. J. H. b. m. (2017) Deep learning with convolutional neural networks for EEG decoding and visualization. *38*(11), 5391-5420.

Schlesinger, D. E., & Stultz, C. M. J. C. T. O. i. C. M. (2020) Deep learning for cardiovascular risk stratification. *22*(8), 1-14.

Schmidhuber, J. J. N. n. (2015) Deep learning in neural networks: An overview. *61*, 85-117.

Seetharam, K., Kagiyama, N., Sengupta, P. P. J. E. r., & practice. (2019) Application of deep learning health, telemedicine and artificial intelligence to echocardiography. *6*(2), R41-R52.

Shen, D., Wu, G., & Suk, H.-I. J. A. r. o. b. e. (2017) Deep learning in medical image analysis. *19*, 221-248.

Silberberg, J. S., Barre, P. E., Prichard, S. S., & Sniderman, A. D. J. K. i. (1989) Impact of left ventricular hypertrophy on survival in end-stage renal disease. *36*(2), 286-290.

Silver, D., Huang, A., Maddison, C. J., Guez, A., Sifre, L., Van Den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., & Lanctot, M. J. n. (2016) Mastering the game of Go with deep neural networks and tree search. *529*(7587), 484-489.

Snyderman, R., & Williams, R. S. J. A. M. (2003) Prospective medicine: the next health care transformation. *78*(11), 1079-1084.

Srivastava, K., Kumar Choubey, D., & Kumar, J. J. A. a. S. (2020) Implementation of Inventory Management System.

Taylor, A. J., Cerqueira, M., Hodgson, J. M., Mark, D., Min, J., O'Gara, P., & Rubin, G. D. J. J. o. t. A. C. o. C. (2010) ACCF/SCCT/ACR/AHA/ASE/ASNC/NASCI/SCAI/SCMR 2010 appropriate use criteria for cardiac computed tomography: a report of the American college of cardiology foundation appropriate use criteria task force, the society of cardiovascular computed tomography, the American college of radiology, the American heart association, the American society of echocardiography, the American society of nuclear cardiology, the north American society for cardiovascular imaging, the society for cardiovascular angiography and interventions, and the society for cardiovascular magnetic resonance. *56*(22), 1864-1894.

Thomas, A. J., Kalaria, R. N., & T O’Brien, J. J. J. o. a. d. (2004) Depression and vascular disease: what is the relationship? , *79*(1-3), 81-95.

Thomas, H., Diamond, J., Vieco, A., Chaudhuri, S., Shinnar, E., Cromer, S., Perel, P., Mensah, G. A., Narula, J., & Johnson, C. O. (2018). Global atlas of cardiovascular disease 2000-2016: the path to prevention and control.

Ulbricht, T., & Southgate, D. J. T. l. (1991) Coronary heart disease: seven dietary factors. *338*(8773), 985-992.

Usama, M., Ahmad, B., Wan, J., Hossain, M. S., Alhamid, M. F., & Hossain, M. A. J. I. A. (2018) Deep feature learning for disease risk assessment based on convolutional neural network with intra-layer recurrent connection by using hospital big data. *6*, 67927-67939.

van den Tempel, N., Odijk, H., van Holthe, N., Naipal, K., Raams, A., Eppink, B., van Gent, D. C., Hardillo, J., Verduijn, G. M., & Drooger, J. C. J. I. J. o. H. (2018) Heat-induced BRCA2 degradation in human tumours provides rationale for hyperthermia-PARP-inhibitor combination therapies. *34*(4), 407-414.

Wang, J., Ding, H., Bidgoli, F. A., Zhou, B., Iribarren, C., Molloi, S., & Baldi, P. J. I. t. o. m. i. (2017) Detecting cardiovascular disease from mammograms with deep learning. *36*(5), 1172-1181.

Wang, Y., & Witten, I. H. (1996) Induction of model trees for predicting continuous classes.

Webb, G. I. J. E. o. m. l. (2010) Naïve Bayes. *15*, 713-714.

Wilson, A. G., Hu, Z., Salakhutdinov, R., & Xing, E. P. (2016). *Deep kernel learning.* Paper presented at the Artificial intelligence and statistics.

Wilson, A. G., & Izmailov, P. J. a. p. a. (2020) Bayesian deep learning and a probabilistic perspective of generalization.

Wu, Y., Benjamin, E. J., & MacMahon, S. J. C. (2016) Prevention and control of cardiovascular disease in the rapidly changing economy of China. *133*(24), 2545-2560.

Yan, H., Jiang, Y., Zheng, J., Peng, C., & Li, Q. J. E. S. w. A. (2006) A multilayer perceptron-based medical decision support system for heart disease diagnosis. *30*(2), 272-281.

Yan, Y., Zhang, J.-W., Zang, G.-Y., & Pu, J. J. J. o. g. c. J. (2019) The primary use of artificial intelligence in cardiovascular diseases: what kind of potential role does artificial intelligence play in future medicine? *, 16*(8), 585.

Yanagimoto, H., Shimada, M., & Yoshimura, A. (2013). *Document similarity estimation for sentiment analysis using neural network.* Paper presented at the 2013 IEEE/ACIS 12th International Conference on Computer and Information Science (ICIS).

Yoo, Y., Tang, L. Y., Brosch, T., Li, D. K., Kolind, S., Vavasour, I., Rauscher, A., MacKay, A. L., Traboulsee, A., & Tam, R. C. J. N. C. (2018) Deep learning of joint myelin and T1w MRI features in normal-appearing brain tissue to distinguish between multiple sclerosis patients and healthy controls. *17*, 169-178.

Zhang, J., Li, B., Xiang, K., & Shi, X. J. a. p. a. (2019) Method of diagnosing heart disease based on deep learning ECG signal.

Zhang, Q., Zhou, D., & Zeng, X. (2017). *PulsePrint: Single-arm-ECG biometric human identification using deep learning.* Paper presented at the 2017 IEEE

8th Annual Ubiquitous Computing, Electronics and Deep learning FEVEunication Conference (UEMCON).

Zhu, J., Shen, B., Abbasi, A., Hoshmand-Kochi, M., Li, H., & Duong, T. Q. J. P. o. (2020) Deep transfer learning artificial intelligence accurately stages COVID-19 lung disease severity on portable chest radiographs. *15*(7), e0236621.

Zoni-Berisso, M., Lercari, F., Carazza, T., & Domenicucci, S. J. C. e. (2014) Epidemiology of atrial fibrillation: European perspective. *6*, 213.

Ansari, A. Q. & Gupta, N. K., 2011. Automated Diagnosis of Coronary Heart Disease Using Neuro-Fuzzy Integrated System. *2011 World Congress on Information and FEVEunication Technologies,* pp. 1379 - 1384.

Apoor Gami, M. & Neil Sanghvi, M., 2013. *Journal of the American College of Cardiology.*

Arif, M., Malagore, I. & Afsar, F., 2010. Detection and Localization of Myocardial Infarction using K-nearest Neighbor Classifier. *Journal of Medical Systems*, Volume 36, pp. 279-289.

Atkov, O. Y. et al., 2012. Coronary heart disease diagnosis by artificial neural networks including genetic polymorphisms and clinical parameters. *Japanese College of Cardiology Journal of Cardiology,* 59(2), p. 190–194.

Babaeizadeh, S., White, D., Pittman, S. & Zhou, S., 2010. Automatic detection and quantification of sleep apnea using heart rate variability. *Journal of Electrocardiology,* Volume 43, p. 535–541.

Babaoglu, I., Baykan, O. K., Aygül, N. & Bayrak, M., 2009. Assessment of exercise stress testing with artificial neural network in determining coronary artery disease and predicting lesion localization. *Journal of Expert System With Applications,* 36(2), pp. 2562-2566.

Babaoglu, I., Findik, O. & Bayrak, M., 2010. Predicts of principle component analysis on assessment of coronary artery diseases using support vector machine. *Expert Systems with Applications,* 37(3), pp. 2182-2185.

Bach, F. R., Lanckriet, G. R. G. & Jordan, M. I., 2004. *Multi-kernel learning, conic duality and the SMO algorithm.* Alberta, Canada.

Bai, J., Wu, Y., Zhang, J. & Chen, F., 2015. Subset based deep learning for RGB-D object recognition. *Neurocomputing,* Volume 165, p. 280–292.

BBC, 2013. *What causes coronary heart disease?.* [Online] Available at: http://www.bbc.co.uk/science/0/21686950 [Accessed 17 October 2016].

Becker, S. R., Cand`es, E. J. & Grant, M., 2011. Templates for Convex Cone Problems with Applications to Sparse Signal Recovery. *Mathematical Programming Computation,* 3(3), pp. 165-218.

Bengio, Y., 2009. Learning deep architecture for AI. *Foundations and Trends in Machine Learning,* 2(1), pp. 1-127.

Bengio, Y., Courville, A. & Vincent, P., 2013. Representation learning: a review and new perspectives. *IEEE Transactions on Pattern Analysis and Machine Intelligence ,* 35(8), pp. 1798 - 1828.

Bengio, Y., Delalleau, O. & Le Roux, N., 2005. *The curse of highly variable functions for local kernel machines.* British Columbia, Canada, NIPS'05 Proceedings of the 18th International Conference on Neural Information Processing Systems.

Bengio, Y. & LeCun, Y., 2007. Scaling learning algorithms towards AI. In: O. C. D. D. J. W. L. Bottou:MIT Press.

Billing, A. & Zheng, G., 1995. Radial basis function network configuration using genetic algorithms. *Neural Networks,* 8(6), p. 877–890.

Birgmeier, M., 1995. *A fully Kalman-trained radial basis function network for nonlinear speech modeling.* s.l., IEEE International Conference.

Bitzer, S. & Kiebel, S. J., 2012. *Recognizing recurrent neural networks (rRNN): Bayesian inference for recurrent neural networks.* s.l., s.n., pp. 201-217.

Bo, L., Lai, K., Ren, X. & Fox, D., 2011. Object recognition with hierarchical kernel descriptors. *CVPR '11 Proceedings of the 2011 IEEE Conference on Computer Vision and Pattern Recognition,* pp. 1729-1736.

Bo, L., Ren, X. & Fox, D., 2010. Kernel descriptors for visual recognition. *NIPS'10 Proceedings of the 23rd International Conference on Neural Information Processing Systems,* pp. 244-252.

Bouvrie, J., Rosasco, L. & Poggio, T., 2009. On invariance in hierarchical models. *22nd International Conference on Neural Information Processing Systems,* pp. 162-170.

Brebisson, A. D. & Montana, G., 2015. Deep neural networks for anatomical brain segmentation. *Computing Research Repository (CoRR),* Volume abs/1502.02445.

British Heart Foundation, 2015. *Risk factors.* [Online] Available at: https://www.bhf.org.uk/heart-health/risk-factors [Accessed 6 March 2016].

Broomhead, D. & Lowe, D., 1998. *Multivariable functional interpolation and adaptive networks*.

Cai, J.-F., Candès, E. J. & Shen, Z., 2010. A singular value thresholding algorithm for matrix completion. *SIAM Journal on Optimization* , 20(4), pp. 1956-1982.

Cambridge University Press, 2009. *Linear versus nonlinear classifiers.* [Online] Available at: http://nlp.stanford.edu/IR-book/html/htmledition/linear-versus-nonlinear-classifiers-1.html [Accessed 11 January 2017].

Caples, S. M., 2007. Sleep-disordered breathing and cardiovascular risk. *Sleep,* 30(3), pp. 291-303.

Carnegie Mellon University , 2009. *Linear Classifiers and the Perceptron Algorithm.* [Online] Available at: http://www.stat.cmu.edu/~cshalizi/350/lectures/25/lecture-25.pdf [Accessed 11 January 2017].

Castro, B., Kogan, D. & Geva, A. B., 2000. ECG feature extraction using optimal mother wavelet. *The 21st IEEE Convention of the Electrical and Electronic in Isreal,* pp. 346-350.

Chatzis, S. P., Korkinof, D. & and Demiris, Y., 2011. *The One-Hidden Layer Non-parametic Bayesian Kernel Machine.* s.l., IEEE, pp. 825 -831.

Chazal, F. d. & Reilly, R. B., 2006. A patient adapting heart beat classifier using ECG morphology and heartbeat interval features. *IEEE Trans. Biomed. Eng.,* 53(12), p. 2535–2543.

Chazal, P., Penzel, T. & Heneghan, C., 2004. Automated detection of obstructive sleep apnoea at different time scales using the electrocardiogram. *Physiological Measurement,* Volume 25, pp. 967-983.

Chazal, P., Penzel, T. & Heneghan, C., 2004. Automated Detection of Obstructive Sleep Apnoeaa at Different Time Scales Using the Electrocardiogram. *Institute of Physics Publishing,* August, 25(4), pp. 967-983.

Chaza, P. d., O'Dwyer, M. & Reilly, R. B., 2004. Automatic classification of heartbeats using ECG morphology and heartbeat interval features. *IEEE Transactions on Biomedical Engineering,* 51(7), p. 1196–1206.

Chen, S., Grant, P. & Cowan, C. F. N., 1991. *Orthogonal least-squares algorithm for training multi-output radial basis function networks.* Bournemouth, IET, pp. 336 - 339.

Cho, Y. & Saul, L., 2009. Kernel methods for deep learning. *Advances in Neural Information Processing Systems,* Volume 22, p. 342–350.

Cho, Y. & Saul, L., 2010. Large margin classification in infinite neural networks. *Neural Computing,* 22(10), pp. 2678-2697.

Ciocoiu, I. B., 2002. RBF Networks Training Using a Dual Extended Kalman Filter. *Neurocomputing,* 48(1-4), pp. 609-622.

Clifton, D., Gibbons, J., Davies, J. & Tarassenko, L., 2012. *Machine Learning and Software Engineering in Health Informatics.* Zurich, s.n., p. 37 – 41.

Comak, E. & Arslan, A., 2010. A Biomedical Decision Support System Using LS-SVM Classifier with an Effecient and New Parameter Regularization Procedure for Diagnosis of Heart Valve Diseases. *Journal of Medical Systems,* Volume 36, p. 549 – 556.

Corbett, F., Michel, O. & Herrmann, A., 1943. *History of the Perceptron.* [Online] Available at: http://web.csulb.edu/~cwallis/artificialn/History.htm [Accessed 26 October 2016].

Cornell University, 2003. *Performance Measures for Machine Learning.* [Online] Available at: https://www.cs.cornell.edu/courses/cs578/2003fa/performance_measures.pdf [Accessed 20 January 2017].

Cortes, C. & Vapnik, V., 1995. Support-vector networks. *Machine Learning,* 20(3), pp. 273-297.

Creswell, J. W., 2012. Conducting and Evaluating Quantitative and Qualitative Research.

Educational Research Planning.

Cui, Z., Yang, C. & Sanyal, S., 2012. Training artificial neural networks using APPM. *International Journal of wireless and deep learning computing,* 5(2), pp. 168-174.

Dalrymple, P., 2011. Data, Information, Knowledge: The Emerging Field of Health Informatics. *Bulletin of the American Society for Information Science and Technology,* 37(5), pp. 41-44.

Dalrymple, P. W., 2011. Data, Information, Knowledge:The Emerging Field of Health Informatics. *Bulletin of the American Society for Information Science and Technology*, 37(5), pp. 41-44.

Damtew, A., 2011. *Designing A Predictive Model For Heart Disease Detection Using Data Mining Techniques,* Addis Ababa: School of Graduate Studies of Addis Ababa University.

Das, R., Turkoglu, I. & al, e., 2009. Productive diagnosis of heart disease through neural networks ensembles. *Journal of expert system with applications,* Volume 93, p. 7675–7680.

Davis, W. & Thu, T. N. T., 2006. *Predicting Cardiovascular Risks Using Possum-Ppossum And Neural Net Techniques.* s.l., Proceedings of the Eighth International Conference on Enterprise Information Systems.

De Castro L. N., V. Z. F. J., 2001. *An immunological approach to initialize centers of radial basis function neural networks.* Brazil, s.n., pp. 79-84.

De Castro, L. N. & Von Zuben, F. J., 2001. *An immunological approach to initialize centers of radial basis function neural networks.* Brazil, s.n., pp. 79-84.

DE CHAZAL, P. et al., 2000. Automatic classification of sleep apnea epochs using the electrocardiogram. *Computers in Cardiology,* Volume 27, p. 745–748.

Deng, J., Zhang, Z., Eyben, F. & Schuller, B., 2014. Autoencoder-based unsupervised domain adaptation for speech emotion recognition. *IEEE Signal Process. Lett,* Volume 21, p. 1068–1072.

Dong, B. & Wang, X., 2016. *Comparison Deep Learning Method to Traditional Methods Using for Network Intrusion Detection.* s.l., s.n., p. 581 – 585.

Dong, C., 2005. MATLAB Neural Network and Its Applications. In: *National Defense Industry Press.* Beijing: s.n., p. 121.

Dong, Z., Hao, Y. & Song, R., 2011. Injection Material Selection Method based on Optimizing Neural Network. *Advances in Intelligent and Soft Computing,* Volume 104, pp. 339-344.

Dorffner, G., 1994. A unified framework for MLPs and RBFNs: introducing conic section functions networks. *Cybernetics and Systems,* Volume 4.

Duch, W. & Jankowski, N., n.d. *Transfer functions: hidden probabilities for better neural networks.* [Online] Available at: http://www.fizyka.umk.pl/publications/kmk/01Esann-intro.pdf [Accessed 11 January 2017].

Duna, i. A., Mucsi, I., Juhász, J. & Novák, M., 2006. Obstructive sleep apnea and cardiovascular disease. *Orv Hetil.,* 147(48), pp. 2303-2311.

Efrati, A., 2013. *How 'Deep Learning' Works at Apple, Beyond.* [Online] Available at: https://www.theinformation.com/How-Deep-Learning-Works-at- Apple-Beyond [Accessed 26 October 2016].

Erhan, D., Courville, A., Bengio, Y. & Vincent, P., 2010. Why does unsupervised pre- training help deep learning?. *Journal of Machine Learning Research,* Volume 11, p. 625−660.

Eric Cohen, M., 2014. *Can Sleep Apnea Predict a Heart Attack?.* [Online] Available at: http://www.everydayhealth.com/columns/eric-cohen-breathe-well- sleep-well/can-sleep-apnea-predict-a-heart-attack/
[Accessed 20 January 2017].

ESCAP, 2010. *Statistical Yearbook for Asia and the Pacific 2009.* [Online] Available at: http://www.unescap.org/stat/data/syb2009/9.Health-risks-causes- of-death.asp [Accessed October 2016].

Foundation, B. H., 2015. *Risk Factors of Coronary Heart Disease.* [Online] Available at: https://www.bhf.org.uk/heart-health/risk-factors [Accessed 17 October 2016].

Fukushima, K. & Miyake, S., 1982. Neocognitron: A new algorithm for pattern recognition tolerant of deformations and shifts in position. *Pattern Recognition,* 15(6), pp. 455-469.

G.E., H., S., O. & Y.-W, T., 2006. Teh Y.-W. A fast learning algorithm for deep-belief nets. *Neural Computation,* 18(27), pp. 1527 - 1554.

Gale Nutrition Encyclopedia, 2011. *Heart Disease.* [Online] Available at: http://www.answers.com/topic/ischaemic-heart-disease [Accessed January 2017].

Genders, T. S. S., Steyerberg, E. W., Hunink, M. & Laule, M., 2012. Prediction model to estimate presence of coronary artery disease: retrospective pooled analysis of existing cohorts. *British Medical Journal,* Volume 344, pp. 1-13.

Genders, T., Steyerberg, E., Hunink, M. & Nieman, K., 2012. Prediction model to estimate presence of coronary artery disease: retrospective pooled analysis of existing cohorts. *British Medical Journal,* Volume 344, pp. 1-13.

Gillies, A. & Sterratt, D., 2012 . *Neuron Tutotial.* [Online] Available at: http://www.anc.ed.ac.uk/school/neuron/ [Accessed 26 October 2016].

Goldberger, A. et al., 2000. PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. *Circulation*, 101(23), p. e215–e220.

Gomm, J. & Yu, D., 2000. Selecting radial basis function network centers with recursive orthogonal least-squares training. *IEEE Transactions on Neural Networks,* 11(2), pp. 306-314.

Goodfellow, I., Bengio, Y. & Courville, A., 2016. *Deep Learning.* s.l.:MIT Press.

Güler, I. & Übeyli, E. D., 2005. ECG beat classifier designed by combined neural network model. *Pattern Recognition,* 38(2), p. 199–208.

Gunter, D. & Terry, P., 2005. Emergence of National Electronic Health Record Architectures in the United States and Australia: Models, Costs, and Questions. *Journal of Medical Internet Research,* 7(1), pp. 1-13.

Hannan, S. A., Manza, R. R. & Ramteke, R. J., 2010. Generalized Regression Neural Network and Radial Basis Function for Heart Disease Diagnosis. *International Journal of Computer Applications,* 7(13), p. 7–13.

Hayat, M., Bennamoun, M. & An, S., 2015. Deep reConstruct ion models for image set classification. *IEEE Trans. Pattern Anal. Mach. Intell,* Volume 37, p. 713–727.

Hedeshi, N. & Abadeh, M., 2014. Coronary Artery Disease Detection Using a Fuzzy- Boosting PSO Approach. *Computational Intelligence and Neuroscience,* 2014(6).

Heller, R. F., Chinn, S., Tunstall Pedoe, H. D. & Rose, G., 1984. How well can we predict coronary heart disease? Findings in the United Kingdom Heart Disease Prevention Project. *British Medical Journal(Clinical Research Edition),* 12 May, 288(6428), pp. 1409-1411.

Helma, C., Gottmann, E. & Kramer, S., 2000. *Knowledge discovery and data mining in toxicology.*

Heydari, S. T., Ayatollahi, S. M. & Zare, N., 2012. Comparison of Artificial Neural Networks with Logistic Regression for Detection of Obesity. *Journal of Medical Systems,* 36(4), pp. 2449-2454.

Higuera, V., 2014. *Healthline Media Overview of Basics of Heart Disease.* [Online] Available at: http://www.healthline.com/health/heart-disease/types#Overview1 [Accessed 09 October 2016].

Hinton, G. et al., 2012. Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. *IEEE Signal Process. Mag,* Volume 29, p. 82–97.

Hinton, G. E. et al., 2012. Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. *IEEE Signal Processing Magzine,* 29(6), p. 82–97.

Hoffmann, G. A., 2004. Adaptive transfer function in radial basis function (RBF) networks. In: *Computational Science - ICCS 2004.* s.l.:Springer Link, pp. 682- 686.

Hongzong, S. et al., 2007. Support vector machines classification for discriminating coronary heart disease patients from non-coronary heart disease. *West Indian Medical Journal,* 56(5), p. 451 – 457.

Huang, H., J. Liu, Q. Z. & R. Wang, G. H., 2014. A new hierarchical method for inter- patient heartbeat classification using random projections and RR intervals. *Biomedical Engineering,* pp. 1-26.

Huang, P.-S.et al., 2014. *Kernel methods match deep neural networks on TIMIT.* Florence, Italy , IEEE.

Huang, Z., Wang, R., Shan, S. & Chen, X., 2015. Face recognition on large-scale video in the wild with hybrid Euclidean-and-Riemannian metric learning. *Pattern Recognition,* Volume 48, p. 3113–3124.

Isa, S. M., Fanany, M. I., Jatmiko, W. & Murni, A., 2010. *Feature and Model Selection on Automatic Sleep Apnea Detection using ECG.* s.l., International Conferences on Advanced Computer Science and Information Systems.

JARVIS, M. & MITRA, P., 2000. Apnea patients characterized by 0.02 Hz peak in the multitaper spectrogram of electrocardiogram signals. *Computers in Cardiology,* Volume 27, p. 769–772.

Jezzini, A., Ayache, M., Elkhansa, L. & Ibrahim, Z. a. a., 2015. *ECG classification for sleep apnea detection.* Beirut, IEEE.

Johnson, C. R., 1990. *Matrix Completion Problems: A Survey.* s.l., Matrix Theory and Applications .

Jones, N., 2014. Computer science: The learning machines. *Nature,* 505(7482), pp. 146- 148.

Jose, C., Goyal, P., Aggrwal, P. & Varma, M., 2013. Local deep kernel learning for Effecient non-linear SVM prediction. *The Journal of Machine Learning Research (JMLR)*, 28(3), p. 486–494.

Julier, S. J. & Uhlmann, J. K., 1997. New extension of the Kalman filter to nonlinear systems. *International Society for Optics and Photonics,* Volume 3068.

Kaggle, 2014. *Higgs boson machine learning challenge.* [Online] Available at: http://www.kaggle.com/c/higgs-boson [Accessed 26 October 2016].

Kaggle, 2014. *National Data Science Bowl.* [Online] Available at: https://www.kaggle.com/c/datasciencebowl [Accessed 5 Janurary 2017].

Kaguara, A., Myoung Nam, K. & Reddy, S., 2014. A deep neural network classifier for diagnosing sleep apnea from ECG data on smartphones and small embedded systems. In: *Thesis.* s.l.:s.n., p. December.