

**AN EARLY-STAGE PREDICTIVE MODEL FOR CVD WITH INTUITIVE SIGMOID LOSS
EFFECTIVE MODEL FOR INTERPOLATIVE LAYER PERCEPTRON****Korrapati Srilakahmi Sesha Priya**

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ABSTRACT:

With importance of realizing and identifying the correct type of cardiovascular diseases, known designs with deep learning algorithm have been effective to realize such situations. In order to pre-attack or arrest of Heart due specific metabolism changes in diet or even in exercise indicates the peculiar diseases. Known works from finest researcher have dedicated the study and its importance on the heart disease indicating the overall prediction analysis for the stroke & Heart-disease attacks.

We improvise a solution and its mathematical analysis to indemnify how the different dataset features analysis have affected the overall classification accuracy. The proposed model with ILPM have improved the accuracy from 90.5 to 99.88% as observed in results. We deployed the overall design model with effective accurate design with Intuitive sigmoid loss feature to improve the overall training and testing accuracy.

Keywords:

Convolutional Neural Net (CNN), heart disease (HD), Machine learning (ML), Cardio vascular diseases (CVD), Interpolative layer perception model (ILPM)

INTRODUCTION:

A condition that affects the cardiovascular system is referred to as cardiovascular disease (CVD). It is a broad phrase that encompasses all of the diseases and disorders that may have an effect on the heart or the blood vessels that supply it. This illness increases the risk of having a stroke, as well as heart attacks and chest discomfort. CVD is the most common kind of non-communicable illness; in fact, it is responsible for approximately half of the 36 million fatalities that are brought on by non-communicable diseases [1]. The accumulation of fatty deposits inside the arteries is generally thought to be the root cause of this kind of illness; however, the precise reason why people develop this condition has not been established. Even damage to the arteries that supply other organs in the body might put a person at risk for cardiovascular disease. There are several different factors that might contribute to an increased risk of developing cardiovascular disease (CVD). Things of this kind are referred to as "Risk Factors." Cigarette smoking, elevated cholesterol levels, drinking too much alcohol, and other similar behaviours are all instances of risk factors. It has been observed that the likelihood of a person contracting a disease increases in proportion to the number of risk factors that the individual is exposed to. A machine may be taught to learn using a process known as machine learning, which is a technique that does not involve actively programming the machine to learn. [2] It is a subfield of artificial intelligence whose primary objective is to make it possible for robots to carry out their tasks in an expert manner by using intelligent software. Algorithms that are used in machine learning make use of a wide range of statistical, probabilistic, and optimization techniques in order to learn from previous experiences and identify meaningful patterns in vast datasets that are unstructured and complicated [3]. It utilises many different approaches to learning, and among those approaches, supervised learning algorithms will be evaluated for use in this project. The concept of "using experience to gain expertise" is used in supervised learning, where the "experience" is the training data that contains significant information that is missing in the unseen "test examples" to which the learned expertise is to be applied. This concept is similar to the idea of "using experience to gain knowledge." In a situation such as this one, the gained knowledge is used with the intention of making predictions about the information that is absent from the test data [4]. There are many different examples of supervised algorithms, but some examples are the K-Nearest Neighbours Classifier and the

Decision Tree Classifier. It has come to everyone's attention that, as of the current day, the application of machine learning to the area of medicine has grown much more effective and helpful. Through the use of machine learning and the examination of an individual's characteristics, an accurate early diagnosis of a disease may be achieved. These kinds of early efforts may lead not only to the avoidance of sickness, but also to the prevention of letting disease to progress to a hazardous level.

Problem Statement:

Even though multiple solution model with CNN or RNN architectures as observed in references [1-5] have depicted the importance of the layer and its loss estimation based on the activation function chosen. The dataset has been employed in spite of the fact that the realisation on cardiovascular illness has been vulnerable to the numerous forecasting approaches recommending the dataset. This has been done in order to increase patients' disease detection to be more accurate. The processing and analysis of the data that was carried out by the many researchers is represented in the real-time data observed dataset that was collected from the Kaggle website. This dataset displays the detection rate. Therefore, at this point in time, the design on unbalanced and outliers have shown an appropriate problem to realise the relevance of class balancing in line with the model that was provided. In this paper we tend to cover the loss estimation model based on the Intuitive (Interpolation based approach). With estimating the overall loss we enable the layer with the same functionality.

Objectives:

1. To realize an implement an effective loss solution feature based on Interpolative sigmoid feature.
2. To implement an ILP model with dense feature on ISF (Interpolative sigmoid feature).
3. To compare the results with existing methods and machine learning models.

Overview:

LITERATURE SURVEY:

The Internet of Things (IoT) may be used for a number of different applications; nonetheless, its continuous achievement monitoring system is one of its most vital functions. The Internet of Things (IoT) is seeing an increase in the use of portable sensing devices, which have been continuously providing large volumes of data. The rate at which data on smart sensor devices becomes obsolete has significantly increased. As a direct consequence of this, the amount of data produced by the technology achievement monitoring technique is mind-boggling. The massive quantity of data that is produced by IoT devices in the therapeutic thinking field may be analysed on the cloud rather than being exposed as much as is practically possible, and calculating resources may be located on mobile devices. The chronic kidney disease (CKD) or cardiovascular disease (CVD) assumption from the [1]Open Medicine Decision Support Systems (OMDSS) was offered in this study for the purpose of presenting thought-provoking pharmacological linkages. The strategy that has been developed incorporates a number of stages for the exact collection, preparation, and solicitation of diagnostic data in order to make a diagnosis of CKD as well as coronary artery disease. This work proposes a flexible three-planning technique for storing and managing such a vast amount of biosensor information in order to solve the issue that has been brought to light. The first level of illumination comes from the information collected from sensor-based Internet of Things devices. Level 2 uses Hadoop and HBase to handle the large amount of information collected by sensors embedded in wearable devices as part of the Internet of Things. Religion figures who are breaking the mould Level 3 also made use of Apache Mahout to assist in the creation of its key models for chronic kidney disease (CKD) and cardiac disorders. Last but not least, a receiver operating characteristic curve (ROC) analysis is carried out in order to establish the cut-off values that are the most clinically significant for CKD and coronary disease. One of the most significant advancements in technology that was made possible by the Internet of Things was an ever-improving viewing technique. A ROC analysis is performed in order to establish which medical thresholds are the most significant for CKD and CVD.

The heart is a very important organ in the human body. It is responsible for the circulation of blood and the supply of nutrients to all of the body's organs. In the field of medicine, making accurate projections on the prevalence of cardiac diseases is a challenging endeavour. Machine learning, the Internet of Things, and deep learning have all been shown to be effective solutions for a variety of problems in the healthcare industry, including those involving the biological community and clinical management. [2]They also help in the early diagnosis of sickness by effectively interpreting medical data, which is essential in this process. Methods of machine learning and deep learning that have been used to predict cardiac illness include Random Forest,



Decision Tree, Naive Bayes, Artificial Neural Network, Support Vector Machine, Decision Tree, XGBoost, and K-Nearest Neighbor. K-Nearest Neighbor is another method. This article provides a summary of earlier research in addition to an outline of the approach that is now in use.

The heart is an essential organ found in all living things. Heart disease is perhaps the most lethal disorder in the world; it is characterised by an inability of the heart to pump an adequate amount of blood to the body's various tissues and organs, which may lead to death. Because the slightest error might result in exhaustion or even death, accurate prediction and diagnosis of heart-related disorders need an increased level of precision and accuracy. There is a significant amount of death that is attributed to the heart, and the statistics are growing each day. The conventional approach to determining whether or not an individual has heart disease is not generally acknowledged as a trustworthy procedure. In order to address the problem, it is essential to devise a method that can forecast diseases and increase people's awareness of them. Machine learning is a subfield of artificial intelligence (AI) that provides a distinguished service to forecast various sorts of occurrences by learning from observations of natural phenomena. This service has gained a lot of attention recently. Several different machine learning methods, such as decision trees, K-nearest neighbour, and AdaBoost, are used in this body of work. [3]The primary objective of this study is to develop a method for illness prediction. Following the completion of the implementation of all of the algorithms, an assessment of the algorithms' correctness is carried out. On the Kaggle website, the dataset may be downloaded for free at any time.

While in the medical field of scanning technology, the introduction of the MRI (magnetic resonance imaging) scanner was a revolutionary step forward. The naked eye is unable to evaluate the micro- to macro-form of tissues that grow inside the human anatomical system because the human body was formed or developed in such a way that someone can see it. The diagnosis of these sorts of metabolic responses, in addition to the early detection of minute structures and the mechanical valves of the heart, is the primary emphasis of this magnetic resonance imaging. Because of this technology, reliable extracted features of the afflicted zone of the heart will indeed be able to be obtained. The areas affected by both the cardiac and vascular systems are potential indicators of cardiovascular disease (CVD), which is the area in which we're most worried about the early detection of a heart arrest[4].

This work processes and analyses MRI cardiac images using a hybrid strategy that removes noise with image enhancement and then applies advanced picture segments on the best-filtered image. This would help doctors trace quickly. It also precisely augments the injured cardiac area to increase image clarity and early diagnosis. Comparing PSNR values.

Predicting cardiovascular disease is currently one of the most difficult medical tasks today. Recently, one cardiac patient died each minute. Machine learning is an essential component in the process of analysing a massive amount of data in the field of healthcare. Because predicting cardiac illness is a difficult task, the prediction process has to be mechanised so that risks associated with it may be minimised and patients can be forewarned. The proposed research anticipates the likelihood of patients developing heart disease by making use of a number of machine learning techniques, including SVM, decision trees, logistic regression, and random forest, among others, and categorises patient risk. The purpose of this study is to give a comparative analysis that analyses the capabilities of a variety of approaches to machine learning. According to the data, the SVM algorithm has a greater efficiency of 94% compared to other applicable ML approaches than any of the others [6].

Through the use of a method that may be performed at home, this research builds a foundation for individualised treatment to combat the risk of heart disease. Logistic regression, K-nearest neighbour, support vector machine, naive bayes, decision trees, random forests, and XG boost are examples of machine learning models that are used in the process of predicting cardiovascular disease. The early and accurate diagnosis of cardiovascular illness is an essential component of quality medical treatment. It is crucial to recognise cardiovascular disease (CVD) in its early stages, see a specialist physician before the illness's severity, and begin treatment with medication as soon as possible. The Cleveland Heart Disease dataset that is accessible in the UCI Machine Learning Repository was used in order to evaluate the effectiveness of the model that was suggested. The [7] Random Forest method has superior performance accuracy, scoring 90.16 percent, in comparison to all other machine learning algorithms. It's possible that the most effective strategy involves evaluating patients' fitness levels rather than their usual hospital visits. The work that is suggested would lighten the load on hospitals and make it easier for them to treat just the most urgent patients.

In recent years, there has been a discernible rise in the overall prevalence of cardiovascular illnesses among the world's population. The sedentary lifestyle, certain hereditary factors, obesity, insufficient physical activity, and stressful work situations all have a role in the progression of the illness. Heart failure is one of the conditions that fall under the umbrella of cardio-vascular disorders, and it can be caused by inefficient blood circulation and a lack of oxygen in the blood. In order for researchers to uncover the critical elements that are implicated in cardiac disorders, they use machine learning algorithms. In order to arrive at results that are reliable and pertinent [8], the data that was collected from the patients is investigated and examined using a variety of data mining methods. In this paper, the widely used machine learning platforms Scikit-Learn and Orange are analysed by utilising seven different machine learning strategies and boosting algorithms. Additionally, their performance on the Heart Failure dataset is investigated using a variety of different training-to-testing ratios. The optimal training regimen for them, as well as the testing split, are both defined. Both the performance of the data mining tools and the numerous metrics that may be measured are analysed. Methods of machine learning with greater prediction accuracy include the classic Logistic Regression, Naive Bayes, and ensemble Random Forest models. With an efficiency level of 89%, the boosting algorithms worked more effectively than other typical models.

Heart disease is consistently ranked high on the list of leading causes of mortality around the world. Because the heart is responsible for ensuring that every cell in the body receives oxygenated blood, any problems with the heart will result in serious complications throughout the human body, and the likelihood of mortality will be fairly high. It has come to our attention that testing encompasses a number of different datasets, each of which has a number of different properties [9]. Each property will have an effect on the outcome that is desired. It has been seen again and again that high blood pressure and diabetes are the primary factors contributing to cardiovascular illnesses. This article discusses many approaches to machine learning, including technology and methodologies. It then goes on to highlight some of the concerns regarding cardiovascular disease, including how attributes are related to the output, how techniques such as machine learning and data mining are used to predict cardiovascular diseases, and how the output of a given dataset can help save lives by utilising these techniques. The data are evaluated, and the findings are taken into consideration. The algorithms are used on the datasets, and the characteristics or qualities of the dataset serve as the foundation for their application. All of these algorithms are put to use in order to ensure that the analysis is carried out in the most effective manner.

In the most recent generations of the healthcare system, mining and collecting knowledge technologies have played an increasingly essential role, with the goal of putting all data into a format that can be understood. According to numerous design guidelines, medical experts are inaccurate in their predictions between 12 and 13 percent of the time during the prognosis procedure. Because of this, an automated disease forecasting system is necessary for enhanced health diagnosis, and increased dependability is emphasised for the purposes of assessment. In addition, a large number of scholars have emphasised the significance of prediction performance as an important factor in the development of an improved computerised approach. The established automation approach is particularly well-suited to the prediction of cardiovascular disorders since it reduces the computing load as well as the elements that contribute to the effort required to compute. The information that has been obtained and selected is then entered into the classifier model in order to improve the accuracy of the prediction. Investigations are being carried out using the freely accessible baseline heart disease information, with various degrees of success. In order to investigate the qualities in a linear as well as a non-linear fashion, pattern learning approaches are used. Linearly iterated support vector regression (LISVR) and stacked monkey optimization (SMO) are two methods that are used for classification in order to increase the accuracy of predictions. These computations were carried out within the context of MATLAB 2016b, and the analysis was carried out using a wide number of approaches that are readily accessible. The exactness of the projected model is at 98.5 percent, its specificity is at 98.8 percent, its recall is at 99.5 percent, and its F measure is at 99.28 percent. The data obtained show that, in contrast to the current processes, the anticipated LISVR-SMO strategy likely outperforms the prior strategies and provides a good trade. This is indicated by the fact that it provides good trading.

According to the World Health Organization (WHO), cardiovascular diseases account for 31% of the worldwide human mortality rate, 85% of which are caused by heart attacks and strokes. Several machine learning (ML) algorithms are used in the early prediction of heart attacks in an effort to reduce the number of fatalities caused by this condition. There are a few different methods for selecting features that may help cut down on the amount of time needed to compute the ML models [9]. In this study, we calculated the feature importance ranking of two gradient boosting algorithms called XGBoost and CatBoost on three different cardiac data sets: Cleveland,



Statlog, and SA hearts. Subsets of features were created by using the relevance rank of each individual characteristic as a threshold. On these subsets, the classifiers XGBoost, CatBoost, and Majority Voting Ensemble were used to do modelling, and the feature subset that produced the best accuracy was found. In this body of work, the range of feature significance rankings that were found to be among those from which the feature subset with the best accuracy would be derived was determined. When contrasted with their performance across the board, the classifiers demonstrated significant gains in some aspects of their functionality. When compared to the other classifiers, CatBoost performed much better than the others [10].

Heart illness, also known as CVD (cardiovascular disease), encompasses a variety of environments that have an influence on the spirit, and it has been the primary physical basis of the end of life for the majority of people throughout the course of the last several decades. In addition, it was associated with a great number of risk factors for the illness (disease) of the heart, and it was necessary at times to identify methods that were appropriate, reliable, and practical in order to produce an early identification of the problem in order to meet a goal set by those in charge of the organisation that dealt with the illness. Data mining is a common practise that involves going through a number of steps to arrive at a desired conclusion from extremely vast amounts of data. [11] It is often used in the healthcare industry. Researchers used a variety of data mining and machine intelligence techniques to conduct an analysis of a massive amount of complicated medical information and present the findings in a visual style. This helped medical practitioners better predict the onset of coronary artery disease. This paper stating beliefs presents a variety of heart disease-related characteristics, as well as the model in advance of action of supervised knowledge algorithms such as Naive-Bayes, resolution reached with abundant plant placed within in bark and peeling leaves, K-nearest neighbor, and haphazard area with a large number of trees. It makes use of an existing dataset from the Cleveland collection of data at the UCI storage location for the required nature medication for the soul healing question. There are 303 occurrences and 76 characteristics that make up the fundamental document file. Only 14 of these 76 traits are ever intended for experimentation and are significant factors in the planning and execution of a variety of algorithmic processes. This extensive article on people who are actively learning attempts to conceptualise the possibility of something occurring in the human being's existence that appears to be a nurturing sickness of the soul and is treated for mending inquiry. The findings provide the impression that the highest possible precision or correctness score that occurs leads to lucrative decisions following the K-expected neighbour.

Because of the presence of various interferential noises, such as blood flow sounds, when abdominal microphones are used for foetal heart rate (FHR) monitoring, analysing the produced abdominal phonocardiogram (PCG) signals may be difficult. This makes the interpretation of the data difficult. A pilot investigation was performed on one healthy volunteer and was meant to characterise the PCG signals all throughout the abdomen. This was done in order to better our knowledge of abdominal phonocardiography, which was the purpose of the study. In addition to the acquisition of one thoracic PCG signal and one electrocardiogram signal, we were also able to acquire PCG signals in several abdominal regions simultaneously. The procedure of analysis was carried out with an emphasis on the temporal behaviour, amplitude, and mean pattern of each signal. The fact that each signal has a synchronised rhythmic pattern lends credence to the theory that the PCG signals collected in the abdomen region are due to the activity of the heart. However, the patterns of the abdominal PCG are completely distinct from those of the thoracic PCG, which suggests that the recording of vascular blood flow sounds on the abdomen rather than the sounds of cardiac valves was taking place. In addition, the amplitude of the abdominal signal is determined by the location of the sensor and, as a result, the size of the artery that is under the skin. The acoustic characterization of abdominal PCG signals has the potential to assist in the enhancement of the processing of such signals for the purpose of FHR monitoring [12].

In the treatment of Parkinson's disease (PD), electrical stimulation of the motor cortex, also known as EMCS, has been used. According to the findings of several investigations, different cell types could be responsible for producing selective effects. Parvalbumin (PV) neurons, which make up the biggest subgroup of interneurons, have been shown to be involved in the processes that determine the therapeutic success of treatments for Parkinson's disease (PD). On the other hand, very little information is known regarding their reactions to the EMCS. In this work, we recorded the calcium activity of PV neurons (specific type) and all neurons (non-specific type) in layer 2/3 of the primary motor cortex (MI) during EMCS with varied stimulus settings using in vivo two-photon imaging. When compared to those of other neurons, the activity patterns of PV neurons were significantly different from those of other neurons. When exposed to a high-frequency stimulus, the cathodal polarity preference of PV neurons became less pronounced. The calcium transients of PV neurons produced by

EMCS tended to have a big amplitude but a short active period. This pattern was seen rather often. PV neurons have a frequency of optimum activation that is much greater than that of other neurons. Because of these findings, our knowledge of the selective effects of EMCS on distinct cell types was enhanced, which may lead to the development of stimulation regimens that are more successful for the treatment of PD [13].

Cardiovascular disease is one of the leading causes of death in the modern world. It is also one of the most preventable causes of death. Within the realm of medical information assessment, the presumption of disturbance might function as a basic test. It has been shown that artificial intelligence (AI) may be useful in assisting with the resolution of options and hypotheses derived from the vast amounts of clinical data given by the medical services sector. In addition to this, it is believed that ML techniques are now being used in a number of the continuing enhancements that are being made to the Internet of Things (IoT). Different investigations only provide a high-level overview of diagnosing cardiac conditions using ML techniques. An extraordinary method has been devised to complete the essential aspects of this research project. It does so by making use of AI tactics, which stimulate and illuminate accuracy within the context of an anticipated state of chaos. The forecast model is presented with numerous combinations of highlights, in addition to several other well-known grouping procedures, and finally, an improved exhibition level is produced through the expectation replica for a cardio-vascular condition using the hybrid random forest with a linear model that has a precision level of 88.7%. Chronic Kidney Disease, often known as CKD, is a long-term condition that affects the kidneys of humans and either prevents them from functioning normally or leads to full loss of kidney function. It lowers the quality of life and may lead to complications such as dialysis or other disorders associated with kidney disease. It is not possible to recognise the signs of this illness in the early stages of the disease. Only a very small percentage [14] of the population is aware of this condition and is able to recognise its symptoms in their early stages. On the other hand, this creates a persistent disturbance of renal function, which, in the end, leads to kidney failure and entirely eliminates the function of the kidneys. This may be caused by diabetes that has been untreated for a long time, and it is also linked to other conditions, such as cardiovascular disease (CVD). There is a delay in treating the patients during the early stages of the illness because of a lack of awareness and insufficient prediction methodologies in the preliminary stage. According to the findings of a number of research projects conducted on the subject in the past, chronic kidney disease (CKD) is treatable and may be predicted using soft computational methods at an earlier stage. The earlier CKD predictor model has to be upgraded so that it has a greater level of both accuracy and precision in its predictions. As a result of this, there is a need for a decision-support system that provides assistance to nephrologists in the event of emergency circumstances. As a result, the Naive Bayes classifier is used in this study for the purpose of classification in conjunction with the Choice-based Hierarchy (NB-CbH). The NB classifier is able to operate well with large datasets while also reducing the complexity of the calculation. When using NB, both the prediction rate and the degree of severity of the illness analysis are significantly increased [15].

Cardiac illnesses have accounted [16] for a substantial number of fatalities during the last several decades and have emerged as the most life-threatening disease on a worldwide scale. They are the top causes of morbidity and mortality around the globe. The ability to accurately anticipate cardiac illnesses has been significantly helped by developments in machine learning and artificial intelligence. A pertinent collection of features might be of great assistance in making an accurate prediction about the condition. In this work, we offered a comparative analysis of four distinct strategies for selecting features and assessed their effectiveness using raw data (an unbalanced dataset) as well as selected data (a balanced dataset). The Z-Alizadeh Sani dataset, which is open to the general public, was used for this investigation. Four distinct feature selection techniques This research makes use of data analysis, a method called minimal redundancy maximum relevance (mRMR), and a technique called recursive feature elimination (RFE). In order to achieve the highest level of accuracy feasible with these methodologies, eight distinct categorization models are used in the testing process. The research, which used both balanced and unbalanced datasets, reveals encouraging findings in terms of a variety of performance criteria with regard to effectively predicting heart disease. The suggested technique yielded experimental results with a maximum AUC of 100%, a maximum F1 score of 94%, a maximum SENS of 98%, and a maximum precision (PREC) of 93% when applied to the raw data. In contrast, the findings obtained with the balanced dataset are as follows: maximum AUC of 100%, maximum F1-score of 95%, maximum SENS of 95%, and maximum PREC of 97%. The leading cause of mortality worldwide each year, cardiovascular diseases (CVDs) are responsible for about 17.9 million fatalities. Eighty percent of fatalities from cardiovascular disease are caused by strokes and heart attacks, and twenty-six percent of those deaths occur in persons who are under the age of seventy. The majority of individuals all over the globe are having trouble getting a handle on the variables that put them at risk for



cardiovascular disease, while the remainder of the population is unaware that they are in danger. The shortage of oxygen and nutrients reaching the heart is a common component that contributes to the development of this condition. In order to determine a person's likelihood of getting coronary heart disease in the next decade, the purpose of this study is to establish a prognosis based on the individual's medical history as well as his or her way of life. The information that was obtained was analysed in order to make it easier to grasp, and then it was visualised. On the Framingham dataset, machine learning (ML) methods including logistic regression (LR), random forest (RF), K-nearest neighbours (KNN), support vector machine (SVM), and decision tree (DT) are used in order to forecast the likelihood of illness.

Imaging of the heart is essential in the process of determining the presence or absence of cardiovascular disease. The primary objective of this project is to develop a method for diagnosing heart conditions using computed tomography (CT) imaging in conjunction with a method based on machine learning (artificial neural network). During the processing of the picture, several image processing methods such as pre-processing, segmentation, and classification are used. In this case, the segmentation and classification of the CT image play a crucial part in the process of diagnosing the condition. The ANN algorithm is used for segmentation, while the SVM algorithm is used for classification; both of these approaches fall under the umbrella of machine learning. The use of methods that are associated with machine learning stands out as an artificial intelligence tool that will be helpful in the diagnosis of cardiovascular disorders. We are able to generate output that is both precise and automated if we design unique algorithms for each of the processes. Therefore, the results of the experiment assist the doctor in making a more accurate diagnosis of the heart diseases, allowing for the next step in therapy to be undertaken [19].

Pulse wave velocity, often known as PWV, is the method that is now considered to be the gold standard for quantitatively evaluating arterial stiffness. This is an extremely important factor for the prompt diagnosis and efficient prevention of cardiovascular and cerebrovascular illnesses. The ultrasonic transit time-based approach with its easy premise is preferred for the detection of the local PWV of the carotid artery now that ultrafast ultrasound imaging based on the plane wave technique has been developed. On the other hand, the filtering parameter settings in this approach are difficult to alter flexibly, and the results of estimating the pulse wave transit time are unreliable. An adaptive local PWV estimate based on the particle swarm optimization technique is developed with the intention of addressing the aforementioned issues. An ultrasound simulation model is employed for all three age groups in order to do a quantitative evaluation of the new adaptive local PWV estimate approach that has been suggested (PSO RUT). According to the findings, the mean PWV deviations from theoretical values projected using the suggested PSO RUT approach are only slightly more than 3.8%, which is a lower value than that anticipated using the RUT method. As a result, the PSO RUT technique may provide an effective means for improving the accuracy of the ultrasound-based carotid PWV calculation that was suggested in this work [20].

According to a report that was provided by the World Health Organization (WHO), cardiovascular diseases (also known as CVDs) are the condition that is responsible for the deaths of over 18 million people each year, making them the condition that is responsible for more deaths in humans than any other condition. On the other hand, it has been found that prompt action and the receipt of rapid treatment from a physician may avert a surprising proportion of these fatalities. This can be accomplished by acting swiftly and receiving prompt support from a physician. As a result, the administration of the hospital needs a reliable system that is capable of providing instant alerts in the event of an emergency. A new phase of technology known as "smart technology" has seen tremendous growth in recent years. The solution is presented in the form of a solution that is provided in this paper [21].

A problem with the heart or the blood vessels is the leading cause of death. According to data compiled by the WHO, one out of every four individuals throughout the globe will have a heart attack in their lifetime. Every minute in the United States of America, there is at least one person who passes away as a result of this catastrophic heart attack. These conditions may have been brought on by factors such as an unhealthy diet, a lack of physical exercise, or the use of tobacco products. It is responsible for 31% of all deaths around the globe. The detection of cardiac illness by the use of a machine-learning model assisted by a computer might make this procedure simpler. There are a lot of ways that may be used, but most of them aren't very effective. However, you can still choose which model is the most effective compared to the ones that are out there. Diabetes mellitus is a critical health issue that affects a significant percentage of the world's population. Diabetes may be caused by a number of factors, the most significant of which include getting older, developing poor eating and sleeping patterns, having genetic predispositions, and not getting enough exercise. Diabetes is a risk factor for a number

of other serious medical conditions, including cardiovascular disease, renal disease, lung illness, and others. Diabetes may lead to the dysfunction or failure of several organs in the body if it is not managed effectively. It is essential for the patient's health to have an accurate diagnosis as well as appropriate treatment for diabetes. The use of machine learning in the healthcare industry is growing at an increasing rate. The extraction of meaningful information from raw medical data, which is helpful for identifying illness, is facilitated by machine learning, which was developed by IBM. For the purpose of predicting diabetes, the authors of this research make use of artificial neural networks (ANN) with variable batch sizes and epochs, as well as methods such as K-nearest neighbour and support vector machines (SVM). ANN has shown superior performance compared to the other two methods [22].

Cardiovascular illnesses (also known as CVD) are at the forefront of the list of conditions that are responsible for greater mortality rates. When just classic cardiovascular risk factors are taken into consideration, a great deal of work has been done for a very long time in an effort to forecast the accuracy of mortality prediction using models such as data mining, logistic regression, neural networks, and many more. As more time passed and advancements in technology allowed for the addition of more recent characteristics, these models eventually reached an accuracy level of 60–70% for predicting death rates. There are a great many more aspects to be investigated that are relevant in forecasting the mortality rate in patients who have cardiovascular disease, which opens up a considerably larger range of possibilities for developing prediction models using standard and non-traditional risk variables. The purpose of this study is to forecast rates of mortality using three different models. The correctness of each model is evaluated based on the results of the calculation of its performance metrics. One may use this information to construct models that are better able to anticipate the result. The use of the ensemble learning approach led to an improvement in the prediction accuracy to 91%. This contributes to the validation of the choice by providing more precise information on mortality forecasts and, as a result, appraising the risk [23].

EXISTING WORK:

Mri data identification and fragmentation were used to diagnose CVD. Locating the location of importance, especially in the heart, might take time. To eliminate cardiac activity, we began photo pre-processing. MRI DICOM images use filtration, categorization, and pattern recognition to reinforce the problem area for early diagnosis.

In the early days of healthcare, before image processing was widely used, doctors had to spend a lot of time diagnosing patients to be able to treat patients early on. Cardio surgeons like catheterizing individuals with heart illnesses or heart conditions to evaluate the heart, or they apply the newest medical technology to analyse CT [9] and MRI scans. Due to calcium build-up from an unclean diet, cardiac valves that carry oxygenated blood from the lungs to the heart would have trouble. This may cause plaque (arteriosclerosis), which hardens the valves. The heart is a sensitive organ with valves and fragile tissues that pumps oxygenated blood to all areas of the body. Manual viewing and checking are laborious and time-consuming. Thus, we are developing a non-invasive technique for early patient diagnosis using MATLAB-embedded image processing and machine learning algorithms. This approach will identify or remove arteriosclerosis-damaged tissue. York University's cardiac MRI DICOM pictures of patients with a wide range of cardiovascular diseases [23]. Filters like the mean, median, gaussian, Wiener, NASFM, and fuzzy filters like ATMED and TMED are used in this procedure as pre-processing steps to help isolate the damaged region in cardiac MRI scans. The photos were filtered using these tools before being extracted. The filtered images are compared in terms of their PSNR values, with the highest-scoring image being considered for further processing using segmentation techniques. Improved readability of the ROI (recovery objective area) was achieved with the use of segmented techniques such as OTSU, Watershed, and fuzzy c-mean segmentation. The process for extracting enhanced images is outlined in the preceding paragraph.

a) Pre-Processing Techniques

It is general known that obtained images, whether ordinary photographic photographs, digital images, or MRI images, include noise [4]. This noise might be caused by the imaging devices hardware, inadequate lighting, or other external factors. The presence of the disturbance captured in the photograph has an effect on the image's features and resolution, such as brightness, contrast, etc., and this results in oscillations in the adjacent pixels. Therefore, the linear and non-linear image pre-processing filters that have been discussed, such as the average, midpoint, logarithmic, gaussian, Wiener, NASFM, and fuzzy filters, notably ATMED and TMED, aid in the

elimination of noise and the preservation of high functionality within those MRI images. Those filters consist of the average, the midpoint, the logarithmic, the Stochastic, the Wiener, ATMED, and TMED.

b) The Segmenting of Photographic Images

Utilizing this method, you may pinpoint the precise position of the area of interest in a picture as well as its borders, characteristics, and edges. Since plaque and calcification in the heart valves cause cell damage, the segmented method is performed to remove the affected area. The segmentation results employed in this study are Otsu, Watershed, and fuzzy c-mean. Comparatively, region-based segmentation relies largely on the similarity of the images being analysed, whereas OTSU is a separation approach that uses a global adaptive binarization threshold. The thresholds is chosen by considering the largest covariance variance of the image pixels and the reference image. With its origins in template matching, the watersheds segmentation algorithm is a regionally-oriented technique. Fuzzy C-Means (FCM) incorporates either local storage disparities and modified local supplement adherence. The method is often used for its utility in unsupervised image segmentation. As a consequence, the FCM approach is susceptible to additive noise, which compromises the quality of the picture's individual pixels.

c) Graphical User Interface

Because it facilitates easy and intuitive interaction between the user and the system, the GUI is crucial. [5] It establishes a communicative computing setting whereby one may, for example, generate graphs and tables and have dialogues with other UTs. As part of this study, researchers have developed a set of MATLAB GUI-based interface tools. Every procedure has been given its own section inside this GUI for optimal readability and accessibility. In this scenario, the axes were separated using a high-quality image. Each axis has a certain job to do when it comes to displaying the final output image. Above the first axis, the researchers have included a button that will let you choose the desired image source. When you click this button, the required RGB image will be imported into the first axis. When the RGB picture reaches that point, it undergoes a conversion to grayscale. The apply filter button has been added to the space between the first and second axes. After the grayscale picture has been shown, the image is sent to the second axis, where it is processed using seven filters (the average, midpoint, ATMED, WIENER, NASFM, and TMED). For each filter, the PSNR value was determined and shown in a separate result box. The peak signal-to-noise ratio is defined as the ratio of the maximum possible signal strength to the strength of any noise that is present in the image and has an effect on its perceived quality. It may be expressed using the following formulas: Calculating PSNR requires the following formula: $PSNR = 20 * \log_{10} (255/\sqrt{MSE})$ [4].

To the right of the third axis are the toggles for segmentation and applied segmentation. The best PSNR-determined image from the second axis is sent into the third axis at this point. Researchers have used three distinct segmentation strategies in this case, including OTSU, Watershed, and fuzzy c-means. The segmented images' PSNR values will be shown in the PSNR value segmentation box.

d) Experimental Work

The first collection of images comes from a single York University cardiac MRI dataset [3]. Time-slices of a cardiac MRI were used to compile the dataset. After analysing all estimated time segments and timescales, a fifth time frame and fifth time slice were selected, and the corresponding MATLAB files were exported as 512-by-512 pixel image files. Next, the images undergo normalisation, during which they are processed using a variety of filtration methods, including the average, maximum, logarithm, Wiener-filter, and NAFSM filters, and the TMED and ATMED fuzzy filters.




























File Name	Original	Mean	Median	Gauss	Wiener	LoG	NAFSM	ATMED	TMED	PSNR values	
pat1low.jpg										median = 29.2016 gauss = 40.3760 average = 26.3087 wiener = 39.2287	naism = 24.6379 LOG = 2.089 atmed = 34.8851 tmed = 22.3263
pat2low.jpg										median = 29.5732 gauss = 41.4803 average = 26.6554 wiener = 42.1459	naism = 24.6364 LOG = 2.285 atmed = 36.7889 tmed = 22.9437
pat3low.jpg										median = 29.2359 gauss = 40.3769 average = 26.2938 wiener = 40.0302	naism = 24.4968 LOG = 2.194 atmed = 35.0561 tmed = 22.2256

Figure 1: Representing the overall CT scan Images for analysing the Segmentation feature for CVD.

PROPOSED WORK:

In the proposed work, we have gathered multiple datasets in the aspects of finding an advanced features indicating the different aspects of the CVD cases. Presently, in [24] & [25] the overall dataset features are being utilized with 22 features. In this case, we improve the overall dataset with Effective collaboration filter indicating the new changes in disease identification. The design implementation of the filtering analysis has effectively improved with custom loss estimation model as described in the Algorithm-2 with ILP model. The novelty is implicating the different aspect of the interpolation feature for Dense layer loss and its implementation on Sigmoid loss as represented in section -V.

1. System Model

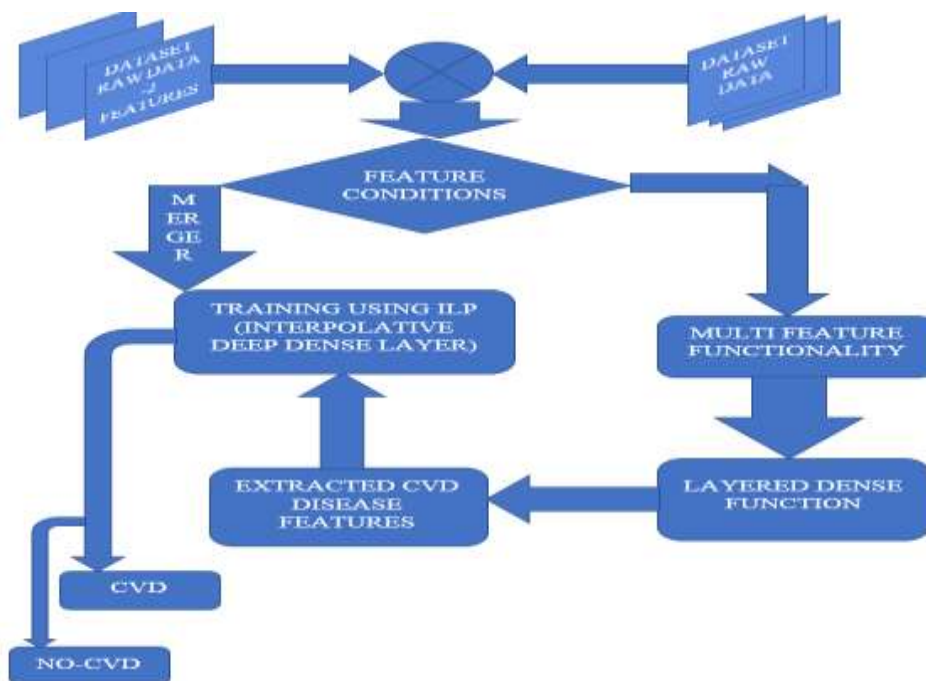


Figure 2: Representing the overall Flow model for the proposed design indicating the feature analysis.

In this work, we provide an early prediction feature of the two dataset chosen from the Kaggle website realizing the overall all effective statistical aspects. With this aspect of statistics, we improvise the two different datasets as merger feature combining similar column values to provide better prediction feature. The overall functionality is explained below with the feature implementation as mentioned below.

2. Design process

The overall design model based on the intuitive approach on sigmoid feature with Interpolation indicating the two different datasets to be merger case. We instantiate the design with multifeatured function with 1.4 million datasets for classification and prediction analysis. The feature analysis on the dataset is improvised with random probability function as mention in equation (1)-(6). Now, with this function we analyse, multifeatured model as described with the heat map functionality with both classes of CVD and NO-CVD. The overall dataset features have been restricted to 13 features only indicating the importance of the feature analyzation based on the 12 features and also 1 for classification feature of CVD or NO-CVD. In the next section we analyse, different feature implementation to realize the how the data0feature values are incremented within the range of features as effected.

3. CVD- Feature analysis age, gender, height, weight, bp_hi, bp_lo, cholesterol, glucose, smoke, alchol active

In feature analysis, we have considered 12 aspects that governs the overall classification and prediction of the CVD indicating how the linear and non-linear functionality would change the overall accuracy. We have demonstrated the overall formulation as mentioned below from equations (1)-(7).

The figure 3 represents the overall classification problem to realize the representation of the data overall based on the heat-map plot indicating the different functionality for each aspect of the feature to realize the classification and prediction analysis on the design. In the next phase of the design we instantiate the overall formulation for the ILP learning model to realize the loss estimation.

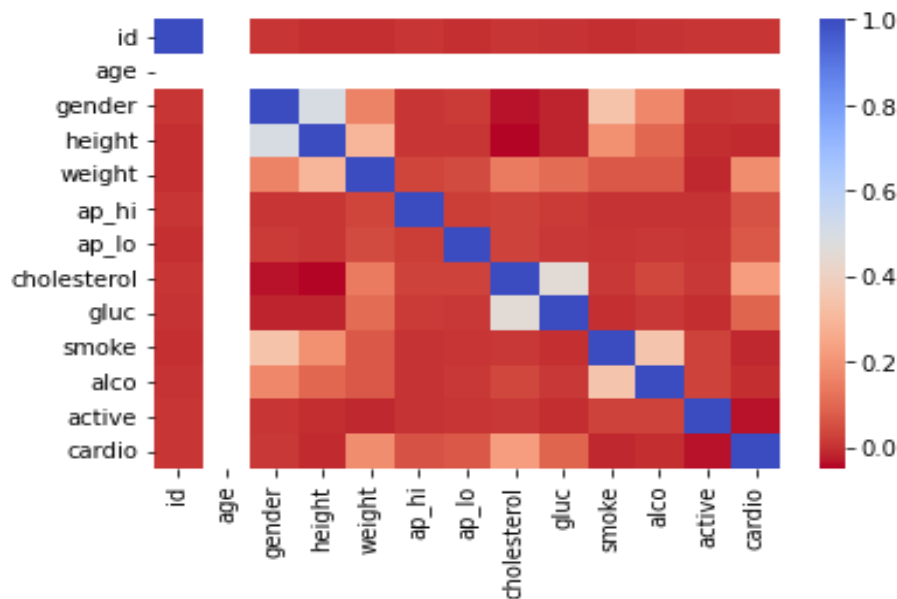


Figure 3: Representing the Heat-Map model for the extracted features on the Dataset chosen

4. Algorithm

ILP-DNN Algorithm:

Let X_i be the random variable for estimating the input sequences (images). Assuming the Sigmoid filter as feature noise removal for post and pre cases,

$$f(x) = \frac{1}{1+e^{-x}} \text{ for } x > 0 \text{ and } x < 1 \quad (1)$$

$$f_m(x) = w_i * \frac{1}{1+e^{-x_i}} + f_m(x_i - k) \quad (2)$$

Here, $f_m(x_i - k)$ is an interpolative prediction feature estimated as

$$H(k) = (x_1 * w_1 + x_2 * w_2 \dots x_n * w_n) / (y_1 * w_1 + \dots w_k y_k) \quad (3)$$

The interpolative feature for $H(k)$ is given by

$$H(k) = \sum_{i=1}^n \sum_{j=1}^k x_i * w_i / y_j w_j \quad (4)$$

For all, $w_j, w_i \in (0,1)$, the prediction algorithm for which every iterative value of y can be predicted with input x is represented as:

$$d(n) = x_i + \eta(n) \quad (5)$$

Here η defines the overall noise for list of input data features. Let's consider the input x_i as the input data for the data frame "df" for which the filtering feature is considered. $d(n)$ being the effective feature values for the input from x_i with error probability er_n is stated as:

$$er_n(n) = d(n) - y_n \quad (6)$$

Where, y_n be the output filtered for each iterated criteria on the employed dataset. The estimation of y_n is calculated with the weight feature as:

$$w_{n+1} = w_n + \delta * \left(\frac{1}{1 - e^{\beta x}} \right) * H(k) \quad (7)$$

Here β, δ are the conditional parametric values chosen for every feature change on the datasets to improvise the interpolative change in the features.

Let $f(x)$ be the sigmoid function for which the loss characteristics $\forall x, \delta, \varepsilon \in (0,1)$ is expressed by:

$$f(x) = \omega + \gamma \left(\frac{1}{1 - e^{\frac{\delta x}{1 - \varepsilon}}} \right) \quad (8)$$

The log characteristic feature of the overall loss is defined by:

$$loss_{fn} = \lim_{n \rightarrow 0} \log \left(\frac{1}{1 - e^{f(x/n)}} \right) \quad (9)$$

Non linearity is observed for the sigmoid function as proposed in (6) and (7). The process of loss estimated with function $f(x/n)$ where $n \rightarrow 0$ indicates the PDF value for $f(x)$ is one. The PDF ($f(x/n) \rightarrow 1$) resulting overall loss can be estimated less the 1%. The as a nonlinear activation function i.e., Sigmoid function (eqn (9)) has been used, thus high loss function are obtained when implemented with different layers. With the convolution and dense layers, we have designed an autoencoder model for the overall filter structures utilized in the convolution layers. The convolution layer formulation is given below equation (10) and figure 4.

$$Z_i = W_i x_i + y_i \quad (10)$$

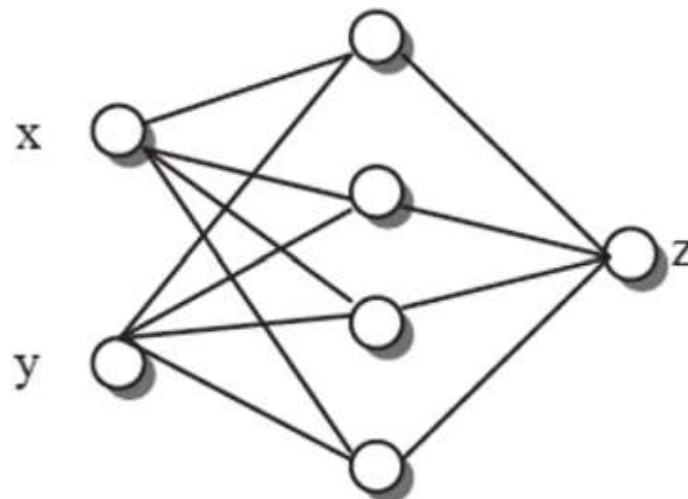


Figure 4: Representing the layer model for the Interpolative dense model with perception features.

With the formulations we indicate the changes in the design with tensor flow model realizing the overall implementation model. In section V the overall implementation details are mentioned.

I. RESULTS AND DISCUSSION

1. Data Acquisition

In this feature acquisition we improvise two different datasets from the Kaggle website consisting of 70K patients and 2.4 million patients. We use linear interpolation model to merge the dataset to increase the overall the sample size of 1.4 million as mentioned below.

df

	id	age	gender	height	weight	ap_hi	ap_lo	cholesterol	gluc	smoke	alco	active	cardio
0	0	18393	2	168	62.0	110	80	1	1	0	0	1	0
1	1	20228	1	156	85.0	140	90	3	1	0	0	1	1
2	2	18857	1	165	64.0	130	70	3	1	0	0	0	1
3	3	17623	2	169	82.0	150	100	1	1	0	0	1	1
4	4	17474	1	156	56.0	100	60	1	1	0	0	0	0
...
69995	99993	19240	2	168	76.0	120	80	1	1	1	0	1	0
69996	99995	22601	1	158	126.0	140	90	2	2	0	0	1	1
69997	99996	19066	2	183	105.0	180	90	3	1	0	1	0	1
69998	99998	22431	1	163	72.0	135	80	1	2	0	0	0	1
69999	99999	20540	1	170	72.0	120	80	2	1	0	0	1	0

70000 rows × 13 columns

	id	age	gender	height	weight	ap_hi	ap_lo	cholesterol	gluc	smoke	alco	active	cardio	
	0	0	0	2	168	62.0	110	80	1	1	0	0	1	0
	1	1	0	1	156	85.0	140	90	3	1	0	0	1	1
	2	2	0	1	165	64.0	130	70	3	1	0	0	0	1
	3	3	0	2	169	82.0	150	100	1	1	0	0	1	1
	4	4	0	1	156	56.0	100	60	1	1	0	0	0	0
...
69995	99993	0	2	168	76.0	120	80	1	1	1	0	1	0	0
69996	99995	0	1	158	126.0	140	90	2	2	0	0	1	1	1
69997	99996	0	2	183	105.0	180	90	3	1	0	1	0	0	1
69998	99998	0	1	163	72.0	135	80	1	2	0	0	0	0	1
69999	99999	0	1	170	72.0	120	80	2	1	0	0	1	0	0

1120000 rows x 13 columns

Figure 5: Representing the overall dataset Indicating the improved merging of values using linear interpolation.

2. Data Analysis

```
df2.isnull().values.any()
```

False

Figure 6: Representing NULL or NAN values in the dataset feature analysis.

The design improves the importance of the plots and pre-processing analysis that have been mentioned in the figures 5-6. These figures indicate the overall sample dataset increase with 1.2 million patients with linear interpolated values as per the changes in the values based on the equation (4).

3. CVD feature visualization

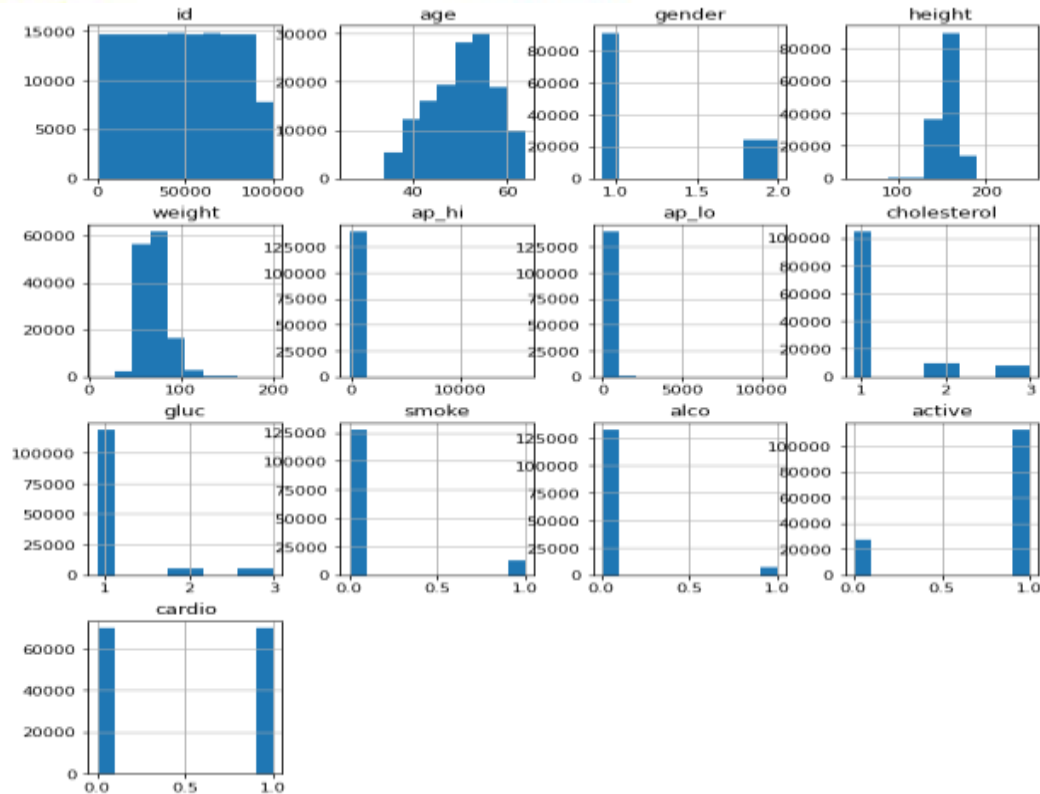


Figure 7: Representing Histogram plot for 100 samples for the proposed dataset

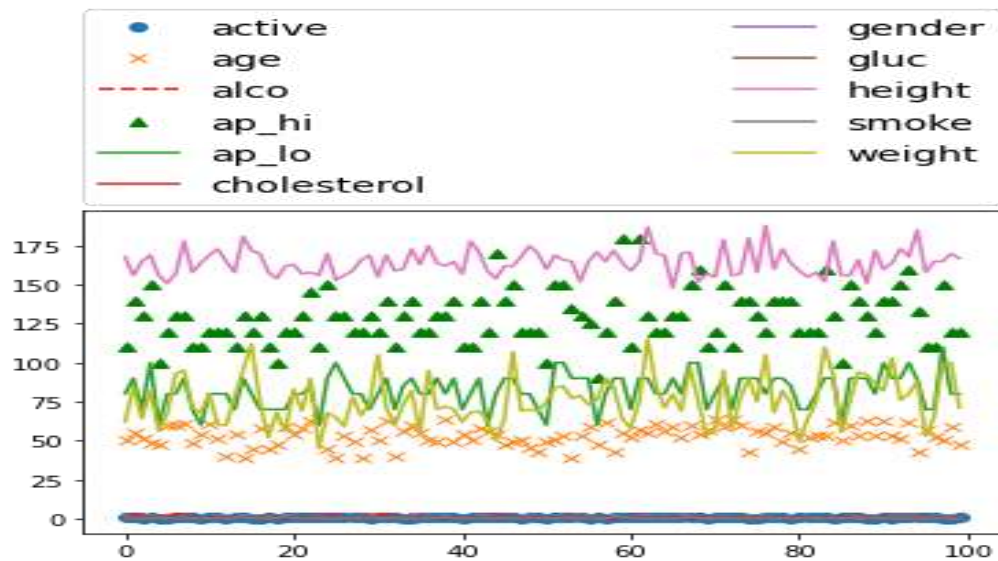


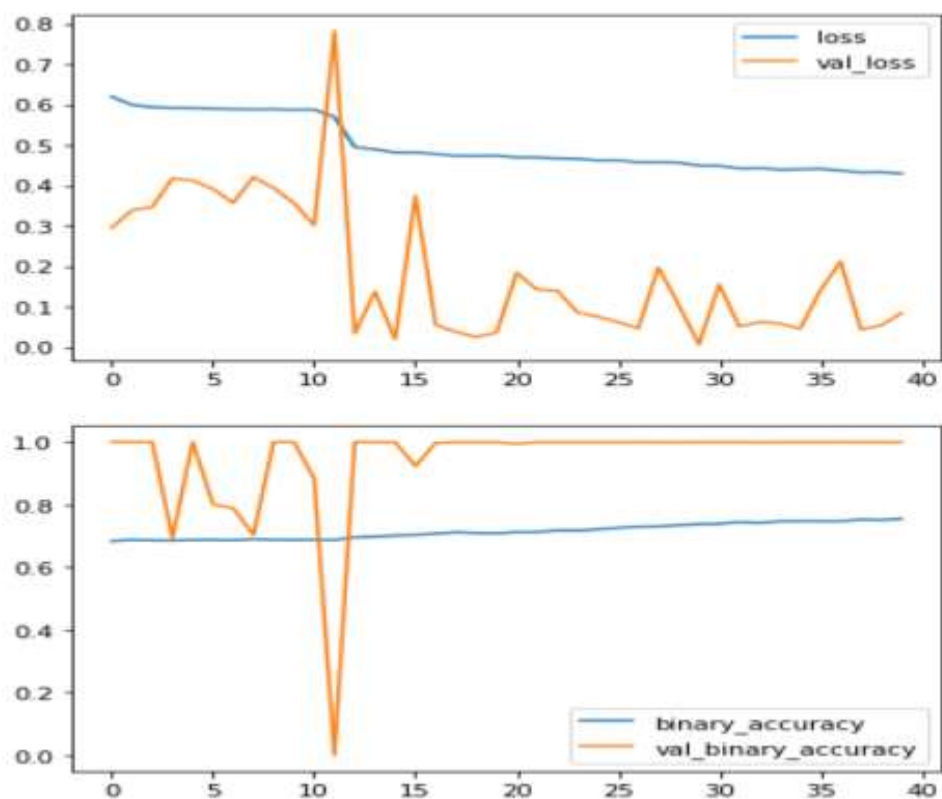
Figure 8: Representing the overall anchor plot representation of the data.

In figures 7-8 indicates the overall dataset values that are utilized to predict the CVD or No-CVD depending on the plotting values. The overall sample size of the design X variant is based on the implicating how the data would vary for CVD or No-CVD case in figure 8.

4. Loss Estimation

Best Validation Loss: 0.0067

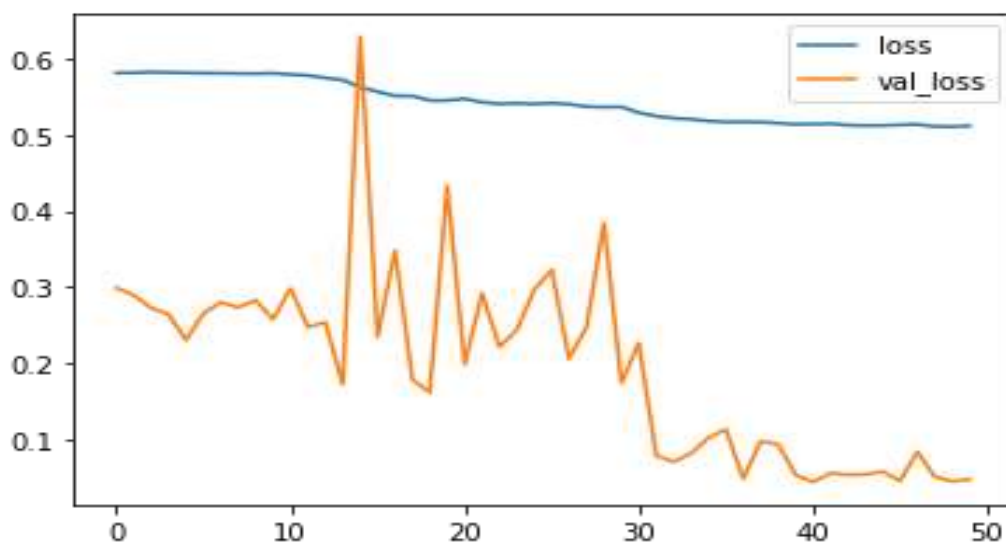
Best Validation Accuracy: 1.0000

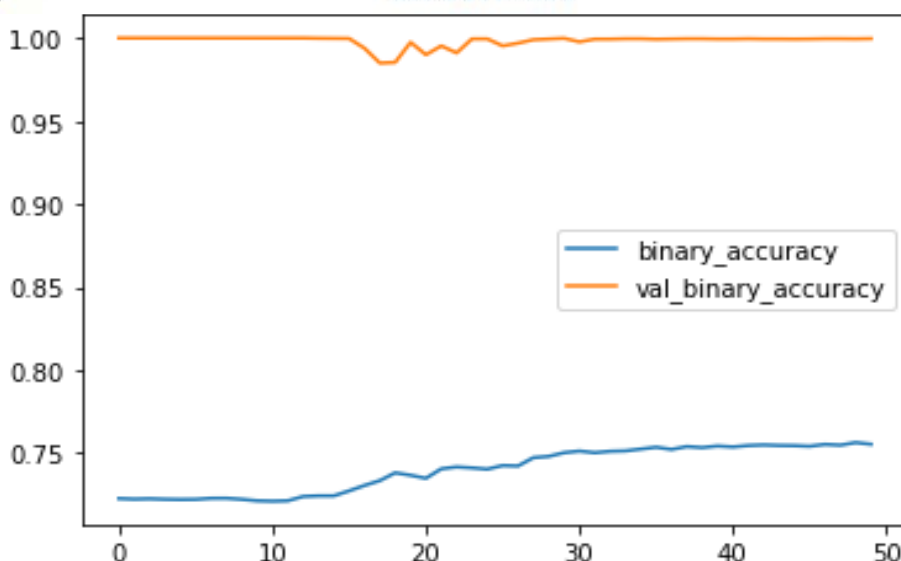


```
history_df1.mean()
```

```
loss          0.498448
binary_accuracy 0.714590
val_loss      0.186999
val_binary_accuracy 0.944104
dtype: float64
```

Figure 9: Representing the overall Accuracy and Loss graph for Proposed design for imbalanced data using Intuitive sigmoid function for loss estimation.





```
history_df2.mean()
```

```
loss          0.542868
binary_accuracy 0.740059
val_loss      0.195798
val_binary_accuracy 0.998290
dtype: float64
```

Figure 10: Representing the plots and values observed for Balanced data using linear interpolation.

5. Tabulations

ALGORITHMS	ACCURACY (EXISTING) Without balanced class	PROPOSED (ACCURACY) With balanced class
LR	84.29	65
DT	82.36	57
SVM	81.26	65
ENSEMBLE- HYBRID	84.34	62.56
IGP-CNN	85.32	70.32
IGPA-CNN	90.85	90.52
ILPM-DNN	94.85	99.98

CONCLUSION:

After comparison of the accuracies obtained, it is observed that the proposed ILPM-DNN gives the highest accuracy in prediction and this further increases the accuracies when three additional risk factors – Glucose, cholesterol and Blood Pressure – are utilized in the dataset. Also, while comparing the computational times, we observed that our modified dataset, which has more feature than the original dataset, is taking little extra computational time in proposed classifier with ILPM-CNN model. Still, it is giving exceptional good accuracy as compared to the original dataset.

SCOPE:

We indicate the different features of the dataset analysing the conditions and its linear capabilities with the prediction weights features as modelled. While the non- linear capabilities have to be realized to effectively prove the importance of the proposed design of interpolation model and its analysis. A Custom layer intuition-based approach have to be initiated to realize the overall loss and prediction feature indicating 100% accuracy.

REFERENCES:

1. S. Chitra and V. Jayalakshmi, "Analyze the Medical Threshold for Chronical Kidney Diseases and Cardio Vascular Diseases using Internet of Things," 2021 4th International Conference on Computing and Communications Technologies (ICCCT), Chennai, India, 2021, pp. 189-193, doi: 10.1109/ICCCT53315.2021.9711829.
2. T. Kavitha, S. Hemalatha, S. Mownika, G. M. Priya and J. K. Vigashini, "Review on Cardio Vascular Disease Prediction Using Machine Learning," 2022 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 2022, pp. 1-4, doi: 10.1109/ICCCI54379.2022.9740953.
3. C. Singla, B. K. Sahoo, R. Kaur, P. Sahu, H. Singh and U. Kaur, "Prediction and Classification of Cardio Vascular Diseases using Ensemble Learning," 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, 2022, pp. 1665-1667, doi: 10.1109/ICACITE53722.2022.9823750.
4. G. U. Santosh Kumar, T. V. Rajini Kanth, S. V. Raju and S. Malyala, "Advanced Analysis of Cardiac Image Processing Using Hybrid Approach," 2021 International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT), Bhilai, India, 2021, pp. 1-6, doi: 10.1109/ICAECT49130.2021.9392390.
5. B. Anishfathima, R. Vikram, S. R. T, M. Sri Vishnu and C. Venumadhav, "A Comparative Analysis on Classification Models to predict Cardio-vascular disease using Machine Learning Algorithms," 2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS), Coimbatore, India, 2022, pp. 259-264, doi: 10.1109/ICAIS53314.2022.9741831.
6. G. Kumar Sahoo, K. Kanike, S. K. Das and P. Singh, "Machine Learning-Based Heart Disease Prediction: A Study for Home Personalized Care," 2022 IEEE 32nd International Workshop on Machine Learning for Signal Processing (MLSP), Xi'an, China, 2022, pp. 01-06, doi: 10.1109/MLSP55214.2022.9943373.
7. G. Shobana and S. N. Bushra, "Prediction of Cardiovascular Disease using Multiple Machine Learning Platforms," 2021 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICES), Chennai, India, 2021, pp. 1-7, doi: 10.1109/ICES52305.2021.9633797.
8. G. M. Shree Raksha, R. Hegde, M. N. Shivani, P. S. Shrinidhi, M. M. Thashwin Monnappa and S. M. Soumyasri, "A Novel Technique for Prediction of Cardiovascular Disease," 2022 IEEE International Conference on Data Science and Information System (ICDSIS), Hassan, India, 2022, pp. 1-5, doi: 10.1109/ICDSIS55133.2022.9915934.
9. N. Sarmiladevi, K. Basker, R. Tamilarasu and L. Nivetha, "An Efficient Detection System For Cardio Vascular Disease Using Machine Learning Algorithms," 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, 2022, pp. 951-955, doi: 10.1109/ICACITE53722.2022.9823598.
10. P. Anuradha and V. K. David, "Feature Selection and Prediction of Heart diseases using Gradient Boosting Algorithms," 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS), Coimbatore, India, 2021, pp. 711-717, doi: 10.1109/ICAIS50930.2021.9395819.
11. A. K. Shukla, "Prediction of Heart Disease through Machine Learning Algorithms and Techniques," 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), Noida, India, 2021, pp. 1-6, doi: 10.1109/ICRITO51393.2021.9596319.
12. J. Fontecave-Jallon, A. Haouas and S. Tanguy, "Abdominal cardiovascular sound recording and analysis using cardio-microphones," 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Glasgow, Scotland, United Kingdom, 2022, pp. 820-823, doi: 10.1109/EMBC48229.2022.9870910.
13. R. Wang et al., "Calcium Activation of Parvalbumin Neurons Induced by Electrical Motor Cortex Stimulation," 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Glasgow, Scotland, United Kingdom, 2022, pp. 2353-2356, doi: 10.1109/EMBC48229.2022.9871749.



14. P. M., S. V. M., J. A. and A. Mayan, "Cardiovascular Disorder Prediction using Machine Learning," 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2021, pp. 1665-1670, doi: 10.1109/ICICCS51141.2021.9432199.
15. C. Saravanabhavan, T. Saravanan, D. B. Mariappan, N. S, D. Vinotha and K. M. Baalamurugan, "Data Mining Model for Chronic Kidney Risks Prediction Based on Using NB-CbH," 2021 International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, 2021, pp. 1023-1026, doi: 10.1109/ICACITE51222.2021.9404558.
16. S. Patil and S. Bhosale, "Assessing Feature Selection Techniques for Machine Learning Models using Cardiac Dataset," 2022 IEEE Fifth International Conference on Artificial Intelligence and Knowledge Engineering (AIKE), Laguna Hills, CA, USA, 2022, pp. 126-130, doi: 10.1109/AIKE55402.2022.00027.
17. D. Lakshmi Padmaja, B. Sai Sruthi, G. Surya Deepak and G. K. Sri Harsha, "Analysis to Predict Coronary Thrombosis Using Machine Learning Techniques," 2022 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), Erode, India, 2022, pp. 21-27, doi: 10.1109/ICSCDS53736.2022.9760765.
18. K. Nithyakalyani, S. Ramkumar, S. Rajalakshmi and K. A. Saravanan, "Diagnosis of cardiovascular disorder by CT images using Machine learning technique," 2022 International Conference on Communication, Computing and Internet of Things (IC3IoT), Chennai, India, 2022, pp. 1-4, doi: 10.1109/IC3IoT53935.2022.9768020.
19. L. Deng, Y. Zhang, Z. Li and K. Wu, "An Adaptive Estimation of Ultrasound Transit Time-based Local PWV in Carotid Artery using Particle Swarm Optimization Algorithm," 2021 IEEE International Ultrasonics Symposium (IUS), Xi'an, China, 2021, pp. 1-4, doi: 10.1109/IUS52206.2021.9593564.
20. T. Venkat Narayana Rao, G. Vishal Sai, P. H. Vardhan Reddy, S. Harsha Bandrupally and C. Nikhil, "SHANE – Smart HeartRate Analysis and Notification System for Emergencies," 2021 Fifth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), Palladam, India, 2021, pp. 1104-1107, doi: 10.1109/I-SMAC52330.2021.9640975.
21. R. Kumar M, G. K. E, D. R and D. K. M, "Detection Of Arrhythmia Using Machine Learning(Heart Disease) And ECG," 2022 International Conference on Advanced Computing Technologies and Applications (ICACTA), Coimbatore, India, 2022, pp. 1-4, doi: 10.1109/ICACTA54488.2022.9752920.
22. M. Revathi, A. B. Godbin, S. N. Bushra and S. Anslam Sibi, "Application of ANN, SVM and KNN in the Prediction of Diabetes Mellitus," 2022 International Conference on Electronic Systems and Intelligent Computing (ICESIC), Chennai, India, 2022, pp. 179-184, doi: 10.1109/ICESIC53714.2022.9783577.
23. B. S. K. Jayasudha, P. N. Sudha, K. Keshav and N. Ramesh, "Ensemble learning as a prerogative method of predicting mortality of patients with cardiovascular diseases," 2021 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), Bangalore, India, 2021, pp. 01-05, doi: 10.1109/CONECCT52877.2021.9622600.