

AI-Driven E-Healthcare Prediction and Monitoring: Leveraging Big Data Intelligence for Immediate Impact

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ABSTRACT

Smart diagnosis has been used successfully in a variety of healthcare applications over the last decade. Early detection and diagnosis of heart disease is critical; heart patients can be treated very effectively if they are treated before they suffer a heart attack. Researchers in this field have recently introduced a number of deep learning-based systems for predicting and diagnosing heart disease. However, because of the lack of an intelligent framework that can use multiple sources of data to predict heart disease, these systems are incapable of handling high-dimensional data sets. In this paper, an intelligent health monitoring / prediction model is proposed to predict Cardiovascular disease using modern AI algorithms, which aids in correctly diagnosing heart disease and attempting to reduce the expected error rate. For training the proposed model, a dataset is prepared here, and modern AI algorithms such as K-NN, DT, NB, MLP Classifier, Feed forward ANN, and CNN were used. The proposed system has demonstrated reliability, with an accuracy of 91.27% using the convolutional NN. As a result, the proposed model can be used in an intelligent healthcare system as a disease diagnosis tool.

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Introduction

Heart disease is a major concern in many parts of the world, particularly the Middle East and North Africa. Heart disease has become a chronic condition affecting an increasing number of patients [1]. Cardiovascular diseases considered as the leading death cause all around the world, causing the deaths of 17.9 million people each year [2]. Unhealthy diet, lack of physical activity, smoking, and injurious alcoholic are the most important behaviour danger factors for heart disease and stroke. Those people may experience the effects of behavioural danger rates. These intermediate danger rates are detectable in the main care settings and leads to a risky heart attack possibility, stroke, heart failure, and other complications [3]. Quitting smoking, lowering salt intake, eating more fruits and vegetables, appealing in daily physical activities, and avoiding high rates of alcoholic have proved reducing the cardiovascular disease risk [4]. Identifying people at risk of developing cardiovascular disease and guarantee they get the exact treatment can save lives. Intelligent employment of AI techniques has proved significant enhancements in many applications.

Recent advances in AI, Internet of Things (IoT), and cloud computing have transformed the traditional healthcare system

into an intelligent one. Healthcare services can be greatly improved using the IoT, AI, and deep learning. Advanced methods and scientific theory are now generating vast amounts of digital data that can be used to create clinical applications that help diagnose heart disease more efficiently [5].

In this paper, we propose an electronic healthcare (E-Healthcare) system for assessing, predicting, and monitoring patients with cardiovascular disease. The proposed model includes several stages, including data collection, pre-treatment, classification, and final disease diagnosis. This system allows patients to be evaluated based on a set of critical data for each patient condition, allowing us to correctly diagnose them. The data collected from each patient is processed and classified as normal or abnormal. Several algorithms have been used to demonstrate the system's effectiveness in order to achieve the highest accuracy value. This study is critical for two reasons. The first is to speed up the treatment of patients suffering from heart disease, because the earlier intervention, the better the patient's condition [6]. The second reason is the ease of use and speed of diagnosis, which is less costly than EKG devices.

Artificial intelligence has been employed with many human applications such as intelligent transportation systems, smart medicine, intelligent health, smart agriculture, as well as many other applications [7-12]. Many previous researchers investigated

in diagnosing heart diseases using deep learning techniques, and these techniques have gained great popularity in recent years as a result of improved accuracy and efficiency in diagnosing and disease prediction. The importance of research conducted in this field lies in the possibility of developing and testing techniques that are higher in terms of accuracy and efficiency.

Rohit Bharti et al used AI to compare outcomes and analyze the UCI Machine Learning Cardiology dataset. While A Mehmood et al. used the cardiac assist method, which predicts the likelihood of heart disease by incorporating a self-learning CNN, and achieved an accuracy of 97%. A Amin Ali et al. compared machine learning algorithms to group learning methods (boost and fill) [13-15].

R. Rani et al. proposed a hybrid decision support system for detecting heart disease. While the study by R Thanga selvi et al was based on a large health application utilizing the Optimized Artificial Neural Network (OANN) for heart disease diagnosis [16,17]. The simulation results showed that the OANN model was improved by providing a high sensitivity of 97.33%, a specificity of 93.23%, and an accuracy of 95.41% using this method.

GT Reddy et al. proposed a new method for classifying heart diseases that employs coarse clustering and fuzzy base classification via an adaptive genetic algorithm. While M Abdel-Rasset et al proposed a new decision-making model for detecting and monitoring heart failure patients based on the IoT [3,18].

S Tuli et al. proposed a new structure for incorporating collaborative DL into high-end smart nodes and run in a real-world for intelligent analysis of heart disease, it called HealthFog [19]. While M Elhoseny et al. proposed the AHDD system for disease diagnosis, which combines the proposed MAFW and binary CNN, the proposed MAFW defines features and optimize several tasks, while CNN completes classification tasks. The best accuracy of 90.1% has been achieved using the hybrid model [20].

Methodology

Predicting and diagnosing heart disease is one of the most difficult challenges in the medical industry and healthcare sector; it is dependent on a number of factors, including the physical examination and the various symptoms and signs that the patient exhibits. Due to the heart's inability to push the required amount of blood to the remaining body organs to perform regular functions in the human body, heart disease is regarded as the world's deadliest disease for human life. Cholesterol levels, smoking habits, obesity, family history of diseases, blood pressure, and work environment are all risk factors for heart disease.

Heart disease is one of the most dangerous and prevalent diseases these days, affecting millions of people worldwide each year. If the disease is detected early on, it can be treated, saving lives from death and serious complications. In addition to diagnostic errors, one major challenge problem is the difficulty of diagnosing heart disease in its early stages. Figure 1 depicts a cross sectional sample of heart attack.

In this study, the data science pipeline research methodology is used. Data science is the study of vast amounts of data using modern techniques and tools to derive meaningful information, discover unseen patterns and make decisions. The data used for analytics can come from a variety of sources and be presented in a variety of formats.

The significance of this study stems from the increased prevalence of heart disease, the difficulty of diagnosing heart disease in its early stages, the significantly higher mortality rate, and doctor diagnostic errors. As a result, we used many machine learning algorithms to predict heart disease using a relatively large database to train the model and obtain correct and high-accuracy results to correctly diagnose the disease.

A. The Proposed System

A set of algorithms was implemented in this work. A subset of the collected data has been pre-processed to be used correctly in the algorithms. The training process is then performed on this data so that the model can classify these data with high accuracy. Classifications algorithms such as neural networks, NB, KNN, DT, MLP classifier, and feed forward ANN are used to classify this data as infected or uninfected, this is based on the set of inputs used to classify the infection. Furthermore, we compare these algorithms so that we can select the best algorithms in terms of accuracy and efficiency. For example, a set of medical information of the patient (age, alcohol intake, sugar level, etc.) are applied to the model, then it is processed by the different ML algorithms, and finally the patient is diagnosed with heart disease or not. Figure 2 illustrates the proposed heart disease classification model and how it can be employed in the intelligent healthcare system, which is illustrated in Figure 3.

B. Data Collection

The proposed system's input is a set of medical information for a group of patients obtained from an Internet-based source. The heart disease data set has been processed to design a prediction model based on the occurrence of heart disease using several algorithms. The data set was compiled using Kaggle and the CDC's 2020 annual health survey of 400,000 adults. There are 18 traits in this data set. The dataset contains 400,000 adults regarding their health status. Including 151,990 males and 167,805 females of various ages ranging from 18 years to 80 years.

We used Python to change the nature of this data so that algorithms could properly analyze it and produce accurate results. Because the performance of a ML approach is dependent on how well the dataset is setup, data pre-processing is required for any ML or data mining approach.

The data was modified in several stages

- Attributes' values of "heart disease, smoking, drinking alcohol, stroke, pedestrians, physical activity, asthma, kidney disease, skin, gender." are re-encoded from [Yes, No] to [0, 1].
- GenHealth values are re-encoded from [Excellent, Fair, Good, Poor, Very Good] to [1, 2, 3, 4, 5].
- Diabetes value is re-encoded from [No, no diabetes limits, yes, yes during pregnancy] to [1, 2, 3, 4].
- Ethnicity value is re-encoded from [American Indian/Alaska Native, Asian, Black, Latino, Other, White] to [1, 2, 3, 4, 5, 6].
- Age range values are re-encoded from [18-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64] to [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13].

The number of items in each of these samples was counted, and the output was reviewed to confirm that the data had been altered. However, an issue with unbalanced data was discovered in this data. To eliminate a biased prediction and a false sense of accuracy, the Synthetic Minority Oversampling Technique (SMOTE) was also used for data balancing.

C. Machine Learning (ML) Classification Algorithms

Five classification techniques have been employed here on the collected dataset and compared to find the best performing algorithm by validating the classification of these algorithms and comparing accuracy and other statistical variables. KNN, Naive Bays, Decision Tree (DT), MLP classifier and feed forward ANN were the algorithms used. The used ML algorithms are examples of supervised learning, in which a labeled training dataset is used to practice the underlying algorithm first and foremost. This qualified model is then fed an unclassified data set to be classified into relevant categories.

K-Nearest Neighbor (KNN) is One of the most straightforward classification algorithms, it has several advantages, including being analytically traceable and simple to implement. Decision Tree (DT) creates decision logic that evaluates and matches the outcomes of classifying data samples into a tree-like structure. DT is well-known for being simple to understand and learn. Naïve bayes (NB) is a simple bayes theorem-based probability classifier. It process in the solution of diagnostic and predictive problems, as well as the capture of the uncertainty model in an elementary fashion through the identification of probabilities. NB helps in solving diagnostic and predictive problems and allows us to capture model uncertainty in an initial way by identifying probabilities.

$$P(class_i | x) = \frac{P(x | class_i) \times P(class_i)}{P(x)} \quad (1)$$

Where,

- $P(Class_i)$: probability of class ($Class_i$) being true, also known as the prior probability.
- $P(x)$: is the probability of the features.
- $P(x | class_i)$: is the probability of the features given that class is true
- $P(class_i | x)$: is the probability of the features with a given class.

Multi-Layer Perceptron (MLP) Classifier is the most useful neural network. MLP check how simple models of brains can be employed to solve large computational tasks in ML, such as predictive modeling. A layer in MLP is represented as

$$y = f(W^T x + b) \quad (2)$$

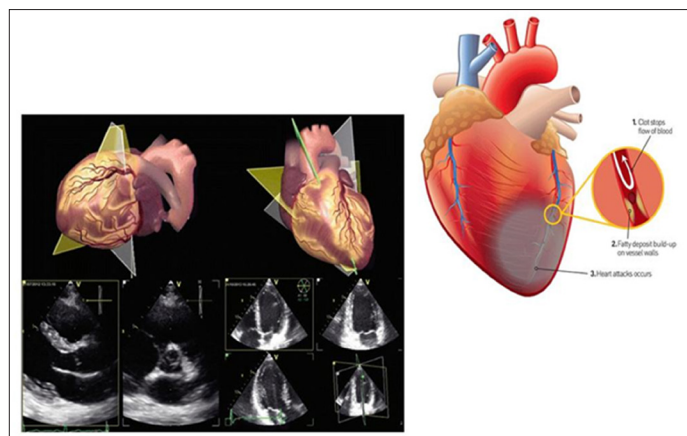


Figure 1: Cross-Sectional Sample Image of a Heart Attack

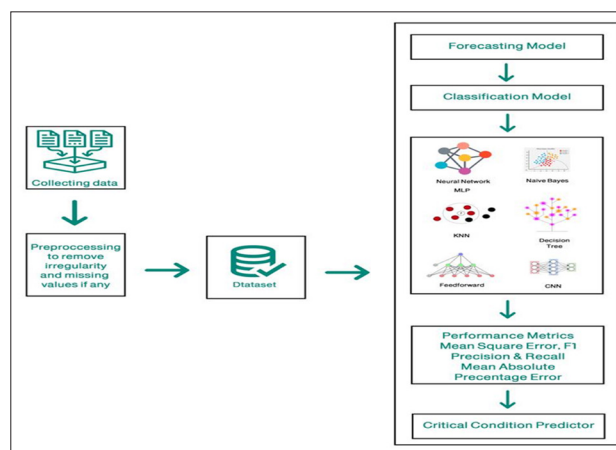


Figure 2: Heart Disease Classification Algorithm

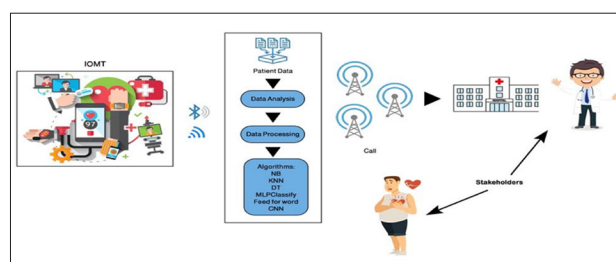


Figure 3: Intelligence Healthcare System

where x is the input vector, W is the matrix of weights, and b is the bias. Feed forward ANN are physically stimulated algorithms that have many neurons as parts prepared in layers. Feeder NN are also known as Multi Layer NN (MLNNs). A network of neurons is called feed forward in which information only flows in the forward way inside the network via input nodes. As there is no feedback movements, the network output is fed back into the network without flowing out. Unlikely, Convolutional Neural Network (CNN) is a supervised machine learning algorithm used for data analysis. CNNs are useful for image processing, natural language processing, and other cognitive tasks. CNN consists of an input layer, an output layer, and numerous hidden convolutional layers transferring the results to subsequent layers via a mathematical model.

D. Feature Extraction

Feature extraction and selecting the most important Feature is an important and widely used analysis technique in machine learning and AI. It is especially applied in fields such as bio-medicine and social sciences because of its simplicity and the possibility of interpreting feature classification or risk analysis. Every feature extraction algorithms has a unique advantage. In the proposed system, several feature extraction techniques have been applied to determine the best of employed algorithms for health analytics classification. Feature extraction in the proposed NN extract the interesting features that can improve the quality from new added data. The features are tested on the proposed pre-trained classifier from scratch. Feature extraction, is evaluated here using a series of pooling and the convolution layers and finally connects with a classifier.

The complexity of big healthcare data leads to a rapid employment of AI techniques in smart healthcare sectors. Many different AI algorithms were previously employed by producers and consumers of smart care, and life sciences providers. Diagnosis and treatment

recommendations, patient engagement and adherence, and administrative activities are the most common service provided in intelligent healthcare systems. Although, many services where AI can improve healthcare services in a same quality or better than humans operated services.

Experimental Results

All experiments were carried out using Intel (R) Core i7 – 6820HQ Processor with CPU @ 2.70 GHz, the Memory is 8 GB, and the Operating system is Windows 10 PRO. The simulation platform is Waikato Environment for knowledge analysis (WEKA) Version 3.9.5

A. Model Evaluation Metrics

Many classification metrics are available for evaluating ML models. However, choosing among these metrics can be sometimes tricky as each one has its own upsides and downsides. A classification metric is a value (number) that measures how well a ML model performs when categorizing observations. A binary classification is a situation in which we only have two classes: positive (binary 1) and negative (binary 0). In this study having a heart attack could be referred as a positive or negative class.

Confusion Matrix (CM) is at the heart and core of any binary classification model. CM is a matrix representation of the sample counts according to their predicted and actual classification status.

A True Positive (TP) outcome is one in which the model predicts the positive class accurately. A True Negative (TN) is a result where the model predicts the negative class accurately. On other hand, a False Positive (FP) is a result where the model can not predicts the positive class correctly. A False Negative (FN) is a result where the model can not predicts the the negative class correctly. Based on the CM matrix, a variety of evaluation metrics can be defined. Accuracy, recall, and F1-score are examples of these. Accuracy is defined as the proportion of correctly classified records. Accuracy is given by

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (3)$$

Recall, can be called True Positive Rate (TPR) as well or sensitivity, it evaluates the model's capability to predict a positive outcome. Recall is given by

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

Precision, can be called Positive Predictive Value (PPV) as well, it is the proportion of predicting positive classes (binary 1) that are actually positive classes. It measures how many of the positive observations predicted are actually positive. Precision is give by

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

Specificity, can be called True Negative Rate (TNR) as well, it evaluates the model's capability to predict a negative outcome. Specificity is given by

$$Specificity = \frac{TN}{TN + FP} \quad (6)$$

The harmonic mean of precision and recall is defined as the F1-score. It is used to rate performance statistically. F1-score is given by

$$F1 - score = \frac{2 * (Recall * Precision)}{Recall + Precision} \quad (7)$$

Receiver Operating Characteristics (ROC) demonstrates the tradeoff between recall and specificity Essentially, we calculate recall and specificity for each probability threshold and plot them on a single chart. Recall is plotted on the vertical axis (y-axis) and specificity on the horizontal axis (x-axis). However, the ROC curve can be used to calculate the area under the curve (AUC). The greater the AUC value, the more effective the classifier. An AUC of 1 indicates a perfect classifier.

B. Experiments

Many experiments have been carried out at this stage using ML algorithms, yielding numerous results that we can compare and select the best of these algorithms to be applied to the recommended model for heart disease prediction in the proposed intelligent healthcare system. To have accurate results data was split to train and test in several distributions.

To improve the handling of the dataset's features, data preprocessing was performed. The data was divided into different groups to provide more accurate and efficient results, and we calculated the probabilities of having heart disease or not for each section of this data separately. Figure 4 depicts the distribution of the probabilities that were reached from these data. Table 1 presents the achieved results after training the proposed algorithms in several training and testing procedures on a non-suffering heart disease data set

As a result of the machine learning analysis of this study, the problem-detected cardiology data set was processed until it was properly used in the algorithms and used in a range of different classification algorithms, including (KNN, DT, NB, MLP classifier, feed forward ANN, and CNN). These comprehensive classification algorithms were used to determine the best algorithms that can be used to classify heart disease. Other cross-validation evaluation variables were tested to conclude the best accomplishment algorithm for expecting the occurrence of heart disease.

Table 1: Results of Non-Predicted Heart Disease at Several Training and Testing Subsets

Train to Test %	Method	Precision	Recall	F1-score
90 to 10	NB	0.95	0.87	0.91
	KNN	0.92	0.99	0.95
	DT	0.95	0.57	0.71
	MLP Classifier	0.92	0.99	0.95
	Feed forward ANN	0.92	0.98	0.95
	CNN	0.92	0.99	0.95
80 to 20	NB	0.94	0.87	0.91
	KNN	0.92	0.99	0.95
	DT	0.93	0.59	0.72
	MLP Classifier	0.92	0.99	0.95
	Feed forward ANN	0.92	0.98	0.95
	CNN	0.91	0.99	0.95
	NB	0.94	0.87	0.91

	KNN	0.92	0.99	0.95
	DT	0.94	0.48	0.63
	MLP Classifier	0.92	0.99	0.95
	Feed forward ANN	0.92	0.98	0.95
	CNN	0.91	1.00	0.95
60 to 40	NB	0.94	0.87	0.91
	KNN	0.92	0.99	0.95
	DT	0.94	0.48	0.63
	MLP Classifier	0.92	1.00	0.95
	Feed forward ANN	0.92	0.98	0.95
	CNN	0.91	1.00	0.95

Figure 5 and Figure 6 illustrate the performance outcome parameters of the classification algorithms used (loss and accuracy respectively) in each segment of the segmented data and the algorithms applied to them. These algorithms showed good results, providing the classification criteria KNN, MLP, CNN, and Feed forward ANN with the highest accuracy and lowest degree of loss where the ratios were close, followed by the feed forward ANN that performed better than DT and NB. The loss using DT is skipped from Figure 6 as it is out layered, and makes the other ML losses un-noticed. Tables 3 and 4 show the detailed accuracy and loss respectively

According to the results presented in Tables 3 and 4 for all stages of data segmentation, MLP classification is the best performing than KNN and CNN which are the best performers and show the highest accuracy.

Briefly, we compiled the cardiology data set, pre-processed it as necessary, then ran it to better understand the data set, then applied six algorithms (KNN, NB, TD, MLP classification, feed forward ANN, CNN), and evaluated the accuracy of the existing predictions. We found good performance for all implemented algorithms as shown by KNN, MLP rated the best performing up to 91.27% indicating that these are the most efficient in predicting heart disease. These analyzes identified highly predictive features of heart disease screening that show potential benefit for clinicians seeking to predict the occurrence of heart disease. It is noteworthy that the amount of data on heart disease provided by this data set is rather large to adequately address all problems. In the future, we hope to implement more of these algorithms so that we can predict with high accuracy heart disease and related conditions using machine learning approaches.

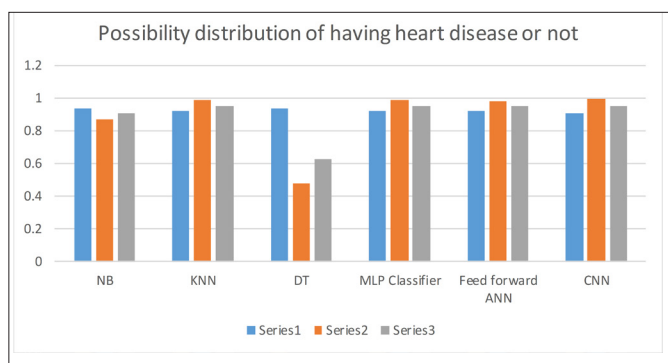


Figure 4: Possibility Distribution of having Heart Disease or Not

Table 2: Results of Predicted Heart Disease Patients at Several Training and Testing Subsets

Train-to-Test %	Method	Precision	Recall	F1-score
90 to 10	NB	0.27	0.49	0.35
	KNN	0.49	0.09	0.16
	DT	0.13	0.67	0.22
	MLP Classifier	0.55	0.08	0.15
	Feed forward ANN	0.46	0.14	0.22
	CNN	0.55	0.10	0.17
80 to 20	NB	0.27	0.48	0.35
	KNN	0.50	0.09	0.15
	DT	0.12	0.58	0.20
	MLP Classifier	0.57	0.10	0.17
	Feed forward ANN	0.45	0.14	0.22
	CNN	0.56	0.06	0.12
70 to 30	NB	0.28	0.48	0.35
	KNN	0.49	0.09	0.15
	DT	0.12	0.70	0.20
	MLP Classifier	0.55	0.11	0.19
	Feed forward ANN	0.45	0.17	0.25
	CNN	0.61	0.06	0.11
60 to 40	NB	0.28	0.48	0.35
	KNN	0.49	0.09	0.15
	DT	0.12	0.70	0.20
	MLP Classifier	0.60	0.08	0.13
	Feed forward ANN	0.45	0.15	0.23
	CNN	0.58	0.07	0.12

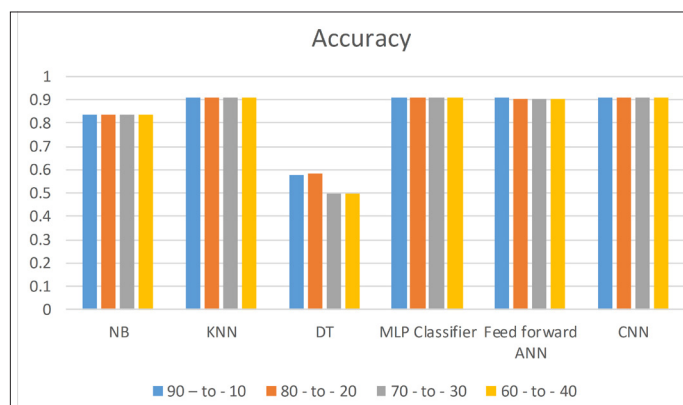


Figure 5: The Accuracy of the Classification Algorithms Used

C. Analysis and Discussion

In this study, we propose a healthcare framework for predicting cardiovascular disease based on a set of ML algorithms. The framework starts off by collecting a variety of patient-specific data, which is then fed into these algorithms, which classify the likelihood of heart disease or not. The data is pre-processed, debugged and dimensionality reduction techniques are applied at the beginning so that it can be used correctly in the existing algorithms. The dataset is then trained in several stages to detect differences in accuracy. Finally, it is fed into the chosen algorithms, and the accuracy/error ratio is calculated, proving whether or not the algorithm is effective in diagnosis.

This process can be used for a variety of medical purposes, including diagnosing different types of cancer and diseases based on images using these algorithms. We hope to expand on this work in the future by applying as many different machine learning algorithms as possible that can be used in our proposed system and comparing them so that we can arrive at the most appropriate algorithm to use in the system based on the percentage of accuracy that is achieved. We can also increase the size of the database to achieve higher data quality in heart disease prediction, and we can use various types of data pre-processing methods until we achieve error-free data to make good use of these algorithms and achieve true accuracy.

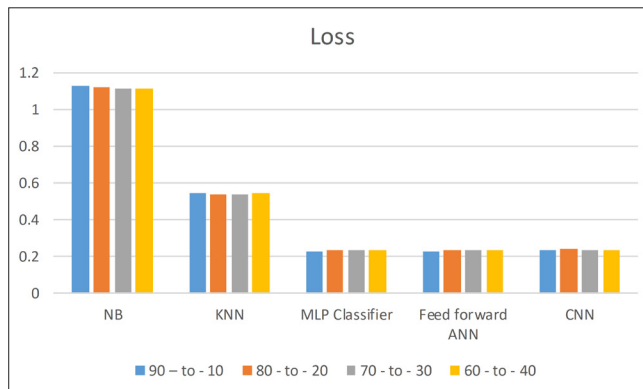


Figure 6: The Loss from the Classification Algorithms Used

Table 3: The Detailed Accuracy Results

Method	90 to 10	80 to 20	70 to 30	60 to 40
NB	0.8383	0.8376	0.83919	0.83919
KNN	0.91099	0.9095	0.9095	0.9088
DT	0.5791	0.5854	0.4968	0.4972
MLP Classifier	0.9127	0.9116	0.9112	0.9115
Feed forward ANN	0.9091	0.9066	0.9058	0.9066
CNN	0.9128	0.9107	0.9111	0.9108

Conclusions and Road Map of Future Work

Reasonable awareness of the heart disease risks precision can have an insightful consequence on humanity. In the long term, early-stage diagnosing is an essential phase for achieving this goal. Previous research has already conducted to predict cardiovascular disease using ML, and this what we did in this research, but by employing an improved and novel way with a bigger data set for training the proposed model. That's it, the research shows that a deep learning feature extraction and selection algorithms can deliver a strongly interrelated feature set that can be then employed with numerous AI algorithms. Furthermore, this work proved that the employed algorithms (NB, DT, KNN, MLP Classification Neural Networks, Feed forward ANN, and CNN) work well.

With the features of high impact and precise production, superior to related business. Accuracy was achieved (91.099%, 57%, 83%, 91.27%, 90.91%, 91.08%) for each of them, respectively. For future work, we aim to oversimplify the proposed model furthermore to make it work with additional feature selection / extraction algorithms, and to be forceful against data sets which have a huge missing data or data loss. Applying upcoming DL and pretrained Transfer Learning (TL) techniques is another futuristic approach. The main objective of this research was to expand the existing work using state-of-the-art AI techniques to make the

model useful and easy to implement in everyday environments.

Table 4: The Detailed Loss Results

Method	90 to 10	80 to 20	70 to 30	60 to 40
NB	1.1263	1.1225	1.1183	1.1183
KNN	0.5436	0.5404	0.5404	0.5442
DT	14.5303	14.3072	17.370	17.356
MLP Classifier	0.2294	0.2332	0.2338	0.2332
Feed forward ANN	0.2298	0.2322	0.2327	0.2327
CNN	0.2335	0.2397	0.2372	0.2364

References

1. Khan S, Ali S A (2017) Exploratory study into awareness of heart disease and health care seeking behavior among emirati women (uae)-cross sectional descriptive study. BMC women's health 17: 1-10.
2. Nugroho AS, Astutik E, Tama TD (2022) Risk factors for coronary heart disease in productive age group in Indonesia. Malaysian Journal of Medicine and Health Sciences 18: 99-105.
3. Reddy GT, Reddy M, Lakshmana K, Rajput DS, Kaluri R, et al. (2020) Hybrid genetic algorithm and a fuzzy logic classifier for heart disease diagnosis. Evolutionary Intelligence 13: 185-196.
4. Shah W, Aleem M, Iqbal MA, Islam MA, Ahmed U, et al. (2021) A machine-learning-based system for prediction of cardiovascular and chronic respiratory diseases. Journal of Healthcare Engineering 2021: 2621655.
5. Panch T, Szolovits P, Atun R (2018) Artificial intelligence, machine learning and health systems. Journal of global health 8: 2.
6. Ghosh P, Azam S, Jonkman M, Karim A, Shamrat FJM, et al. (2021) Efficient prediction of cardiovascular disease using machine learning algorithms with relief and lasso feature selection techniques. IEEE Access 9: 19304-19326.
7. AlZu'bi S, Jararweh Y, (2020) Data fusion in autonomous vehicles research, literature tracing from imaginary idea to smart surrounding community. Fifth International Conference on Fog and Mobile Edge Computing (FMEC) pp: 306-311.
8. Al-Zu'bi S, Hawashin B, Mughaid A, Baker T, (2021) Efficient 3d medical image segmentation algorithm over a secured multimedia network. Multimedia Tools and Applications 80: 16887-16905.
9. AlZu'bi S, Shehab M, Al-Ayyoub M, Jararweh Y, Gupta B (2020) Parallel implementation for 3d medical volume fuzzy segmentation. Pattern Recognition Letters 130: 312-318.
10. Shahwan MJ, Al-Qirim TM, Daradka H (2009) Effects of ballota undulata on blood biochemical parameters and insulin in albino rat. Asian Biomed 3: 171-3175.
11. AlZu'bi S, Aqel D, Lafi M (2022) An intelligent system for blood donation process optimization-smart techniques for minimizing blood wastages. Cluster Computing pp: 1-11.
12. AlZu'bi S, Hawashin B, Mujahed M, Jararweh Y, Gupta BB (2009) An efficient employment of internet of multimedia things in smart and future agriculture. Multimedia Tools and Applications 78: 29581-29605.
13. Bharti R, Khamparia A, Shabaz M, Dhiman G, Pande S, et al. (2021) Prediction of heart disease using a combination of machine learning and deep learning. Computational intelligence and neuroscience 2021: 8387680.
14. Mehmood A, Iqbal M, Mehmood Z, Irtaza A, Nawaz M, et al.

- (2021) Prediction of heart disease using deep convolutional neural networks,” Arabian Journal for Science and Engineering 46: 3409-3422.
15. Gao XY, Amin Ali A, Shaban Hassan H, Anwar EM (2021) Improving the accuracy for analyzing heart diseases prediction based on the ensemble method. Complexity 2021: 1-10.
 16. Rani P, Kumar R, Ahmed NM, Jain A, (2021) A decision support system for heart disease prediction based upon machine learning. Journal of Reliable Intelligent Environments 7: 263-275.
 17. Thanga Selvi R, Muthulakshmi I (2021) An optimal artificial neural network based big data application for heart disease diagnosis and classification model. Journal of Ambient Intelligence and Humanized Computing 12: 6129-6139.
 18. Abdel-Basset M, Gamal A, Manogaran G, Son LH, Long HV (2020) A novel group decision making model based on neutrosophic sets for heart disease diagnosis. Multimedia Tools and Applications 79: 9977-10002.
 19. Tuli S, Basumatary N, Gill SS, Kahani M, Arya RC, et al. (2020) Healthfog: An ensemble deep learning based smart healthcare system for automatic diagnosis of heart diseases in integrated iot and fog computing environments. Future Generation Computer Systems 104: 187-200.
 20. Elhoseny M, Mohammed MA, Mostafa SA, Abdulkareem KH, Maashi MS, et al. (2021) A new multi-agent feature wrapper machine learning approach for heart disease diagnosis. Comput Mater Contin 67: 51-71.