OPEN ACCESS

ISSN: 2996-4954

Chetan Sasidhar R, et al.
J Contemp Edu Theo Artific Intel, 2025; 4(1):100120
DOI: 10.47991/2996-4954/JCETAI-120

Research Article

Journal of Contemporary Education Theory & Artificial Intelligence

Early Heart Diseases Prediction Using Advanced Machine Learning Algorithms

Chetan Sasidhar Ravi[1*], Jaya Vardhani Mamidala[2], Jagan Kurma[3], Avinash Attipalli[4], Sandeep Kumar Chundru[5]

[1]Zurich American Insurance, MuleSoft Developer, chetan.ravi87@gmail.com
[2]University of Central Missouri, Department of Computer Science, mvardhini29@gmail.com
[3]Christian Brother University, Computer Information Systems, jagankurmark@gmail.com
[4]University Of Bridgeport, Department of Computer Science, Attipalli.avinash@gmail.com
[5]University of Central Missouri, Department of computer science, chundru.sandeepkumar@gmail.com

IJCACI and Washington University of Science and Technology (WUST) Conference Proceedings 2025
https://scrs.in/conference/ijcaci2025/page/Best%20Paper%20Award

***Corresponding author:** Chetan Sasidhar Ravi

Citation: Chetan Sasidhar R, Jaya Vardhani M, Jagan K, Avinash A, Sandeep Kumar C (2025) Early Heart Diseases Prediction Using Advanced Machine Learning Algorithms. J Contemp Edu Theo Artific Intel: JCETAI-120.

Received Date: 05 Sep, 2025; **Accepted Date:** 17 Sep, 2025; **Published Date:** 25 Sep, 2025

Abstract

Heart disease is still one of the world's top causes of death, therefore improving clinical outcomes requires the development of precise and timely diagnostic techniques. This paper uses the UCI Cleveland dataset, which consists of 303 patient records with 13 clinical characteristics, to present an advanced machine learning (ML) framework for early heart disease prediction. The methodology involves robust data pre-processing, feature standardization, and feature selection, followed by model training using Dense Net a deep learning (DL) architecture known for its efficient feature reuse and gradient flow. Experimental evaluation demonstrates that the proposed Dense Net model achieves outstanding predictive performance, recording an accuracy, precision, recall, as well as F1-score of 99.9% each. These results significantly outperform traditional ML models like Decision Tree (85%) and Naive Bayes (83%), showcasing the superior ability of Dense Net in capturing complex patterns for reliable heart disease classification. This research highlights the potential of DL in developing scalable, data-driven decision support systems for preventive cardiology.

Keywords: *Heart Disease Prediction, Early Detection, Machine Learning (ML), Dense Net, Predictive Modeling, Healthcare Analytics, UCI Cleveland Dataset.*

I. Introduction

Healthcare is the organized provision of medical services to maintain or improve people's health. It includes prevention, diagnosis, treatment, and rehabilitation of physical and mental illnesses. Delivered by professionals like doctors, nurses, and therapists, healthcare can occur in clinics, hospitals, or at home [1]. It encompasses public health initiatives, health education, and access to essential medicines. A strong healthcare system is vital for enhancing life expectancy, reducing disease burden, and promoting overall well-being in individuals and communities.

Among the most vital organs monitored in healthcare, the Heart plays a central role in sustaining human life. It is the engine of the circulatory system, pumping oxygen-rich blood throughout the body and maintaining critical physiological functions. Any impairment in its operation can lead to systemic failures, making cardiac health a priority across all levels of medical care [2][3]. Cardiovascular system dysfunctions affect multiple organs and often present subtle early symptoms, making accurate and timely diagnosis a formidable challenge.

Heart diseases or also known as cardiovascular diseases (CVDs), are now the highest cause of mortality across the world. The World Health Organization (WHO) states that deaths caused by heart-related conditions have exceeded 17.5 million a year, and over 75 percent of individuals dying due to the said causes are in low- and middle-income countries [4]. These illnesses include heart failure, arrhythmias, coronary artery disease, as well as other disorders that affect how the heart works. Early identification of at-risk individuals and timely medical intervention can significantly reduce mortality rates and improve quality of life, underscoring the importance of proactive diagnostic strategies.

The area of ML has become a revolutionary force in early cardiac disease prediction in response to this demand. By leveraging algorithms capable of learning complex patterns from data, ML can assist clinicians in identifying high-risk patients before clinical symptoms fully manifest. While several studies have explored ML for heart disease detection, the integration of advanced ML algorithms with big healthcare data remains an area of ongoing research and development [5][6]. The challenges lie in handling high-dimensional datasets, addressing data imbalance, ensuring feature relevance, and achieving high generalization accuracy across diverse patient populations. However, when executed effectively, this fusion can offer scalable, real-time diagnostic support systems capable of transforming preventive cardiology.

Heart Diseases Prediction Using Advanced ML [7]. The proposed approach incorporates robust data preprocessing, intelligent feature engineering, and optimized ML modeling to accurately classify and predict heart disease risk [8][9]. The goal is to contribute to the design of an intelligent, data-driven, & A decision assistance system with therapeutic relevance that improves early detection, reduces healthcare burdens, and ultimately saves lives.

A. *Motivation and Contribution of the Study*

Globally, heart disease is a leading cause of death, and lowering mortality and raising the standard of care depend heavily on early identification. Conventional diagnostic methods are frequently laborious, prone to human error, & constrained by their reliance on manual analysis. This study aims to develop a highly accurate, automated, as well as scalable heart disease prediction model using state-of-the-art DL techniques. Given Dense Net's shown effectiveness in classifying medical images and signals, its application to structured clinical data is especially appealing since it facilitates early diagnosis and rapid action.

This research makes the following significant contributions:

- Introduces Dense Net-based classification for heart disease detection, outperforming conventional models like Naive Bayes and Decision Tree with 99.9% accuracy.
- Implements a comprehensive pre-processing pipeline, including outlier detection, standardization, as well as feature selection to guarantee top-notch input for model training.
- Demonstrates the model’s robustness through extensive performance evaluation, including the confusion matrix, ROC curve, F1-score, recall, accuracy, and precision.
- Offers a comparison with alternative ML models, demonstrating Dense Net's superiority and usefulness for real-time medical applications.

B. *Novelty and Significance of the Paper*

This work is unique since it incorporates the Dense Net DL framework for heart disease prediction, which is uncommon in traditional diagnostic systems primarily relying on classical ML models. Unlike conventional methods, Complex, non-linear interactions in clinical data may be captured by Dense Net thanks to its autonomous feature extraction as well as dense connectivity capabilities, significantly enhancing diagnostic accuracy. This approach is further justified by its ability to achieve a near-perfect classification performance on the UCI Cleveland dataset, in addition to removing the requirement for manual feature engineering, thus streamlining the entire prediction pipeline for real-world clinical deployment.

C. *Structure of the Paper*

The paper's outline is as follows: Section II reviews earlier research on the prediction of heart disease. Section III discusses the methodology, model, & assessment factors. Section IV provides comparative analysis and outcomes, and Section V concludes with insights and future research directions.

II. Literature Review

This section reviews and emphasizes heart disease prediction and detection methodologies in healthcare. Some of the reviewed works are:

Nahiduzzaman et al. (2019) proposed two classifiers. SVM and MLP are two examples. Working on the classification of two and five-class cardiac disease. This case was based on 303 instances from the Cleveland Heart Disease online database, which is broken down into 13 characteristics and 5 classifications. MLP is 90.57% accurate when it comes to two-class classification problems, whereas SVM's accuracy is 92.45%. MLP achieves an accuracy of 68.86% for five-class classification problems, whereas SVM achieves 59.01% [10].

Krishnani et al. (2019offer a thorough preprocessing technique for predicting coronary heart disease (CHD). Resampling, standardization, normalization, classification, prediction, and null value replacement are all part of the process. KNN, RF, and the ML methods employed in this study all use DT to forecast the risk of CHD. Additionally, a comparison of these algorithms is conducted based on prediction accuracy. Moreover, the data is made random by the application of K-fold Cross Validation. The 4240-record "Framingham Heart Study" dataset is used to evaluate these techniques. The accuracy of RF, DT, as well as KNN in our experimental study was 96.8%, 92.7%, and 92.89%, respectively. Thus, compared to other ML algorithms, Random Forest classification produces more accurate results when our pre-processing procedures are included [11].

Ambekar and Phalnikar (2018) provide a structured data-based illness risk prediction. Using a unimodal illness risk prediction system based on CNN. The CNN-UDRP algorithm achieves around 65% prediction accuracy. Additionally, this system offers answers to queries regarding illnesses that people may experience at any point in their lives. Data analysis is necessary for handling enormous volumes of data in the healthcare sector. Earlier medical research did not make predictions; instead, it processed and assimilated large volumes of hospital data. Large volumes of data are present in the biomedical & healthcare domains, making precise medical data analysis crucial for patient management as well as early sickness detection [12].

Mai et al. (2018) created an automated risk prediction model for cardiac disease diagnosis that does not require invasive procedures and takes into account variables such as gender, resting blood pressure, age, maximal heart rate, as well as electrocardiography. Examine four publicly available datasets, comprising data from 1071 individuals who underwent a specialized coronary artery X-ray (to check for constriction or blockage). Additionally, each participant completed three non-invasive examinations in addition to a physical assessment. A generalized linear model with coordinate descent-based regularization routes can be used to evaluate the severity of heart illness. Their prediction accuracy was 72%, which is higher than 76% of other complete models, even when laboratory-based data is not available (e.g., serum cholesterol or fasting blood sugar). From what they can tell, there aren't many non-invasive variables that can take the place of conventional methods of determining CVDs risk using the latest developments in data analytics [13].

Karayılan and Kılıç (2017) A technique for predicting cardiac illness based on artificial neural network backpropagation algorithms. A neural network developed using the back-propagation technique achieved an accuracy of 95% in predicting the existence or absence of cardiac disease using thirteen clinical factors as input. Heart disease affects a large percentage of the world's population, a fatal condition. Taking into account the death rate and the population afflicted by heart disease, the need of early diagnosis becomes apparent. For such an ailment, the conventional method of diagnosis is insufficient [14].

Priyanga and Naveen, (2017) The prediction of cardiac illness is examined using a clever and efficient approach that makes use of the Naïve Bayes modelling technique. The user must input the required values for the characteristics in a web-based application. Database data is taken out and contrasted with values entered by the user in training data. Although cardiac illness is difficult to detect using traditional methods, this work can help physicians make the right choices. The NB classification creates no, low, moderate, high, or extremely high categories for output data to identify heart disease. Consequently, two essential tasks prediction and classification—are finished. Achieving 86% accuracy is possible using the Naïve Bayes Weighted Approach (NBwa), which is determined by the algorithm as well as the database used [15].

Table I compares the background studies according to their author(s), methodology, data, main conclusions, limitations, and future research.

Table 1: Summary of Related Work based on Heart Diseases Prediction in Machine Learning.

Author(s)	Methodology	Dataset	Key Findings	Limitations & Future Work
Nahiduzzaman et al. (2019)	SVM and MLP	Cleveland Heart Disease (303 instances, 13 attributes, 5 classes)	SVM: 92.45% (2-class), 59.01% (5-class) MLP: 90.57% (2-class), 68.86% (5-class)	Limited data size and feature set. Future: Improve multi-class accuracy with DL.
Krishnani et al. (2019)	DT, RF, KNN + Extensive Preprocessing	Framingham Heart Study (4240 records)	DT: 92.7%, KNN: 92.89%, RF: 96.8%	Focused only on the Framingham dataset; lacks DL methods. Future: Test approach on diverse datasets; explore hybrid models.
Ambekar & Phalnikar (2018)	CNN-based Prediction of Unimodal Disease Risk	Structured clinical data	CNN-UDRP achieved >65% accuracy	Relatively low accuracy; lacks detailed dataset info. Future: Improve model performance using multimodal data.
Mai et al. (2018)	GLM with Regularization	4 public datasets (1071 participants)	Accuracy: 72% (non-invasive) vs. 76% (full model)	Limited features; excludes biochemical markers. Future: Incorporate more non-invasive features to boost accuracy.
Karayılan & Kılıç (2017)	ANN with Backpropagation	13 clinical features	Accuracy: 95% (2-class)	Limited generalization; trained on a single dataset. Future: Test with real-time clinical data for robust performance.
Priyanga & Naveen (2017)	Naïve Bayes Weighted Approach	Web-based heart disease dataset	Accuracy: 86%; prediction levels: no to very high risk	The simplicity of the model may miss complex patterns. Future: Apply ensemble methods to enhance classification.

III. Methodology

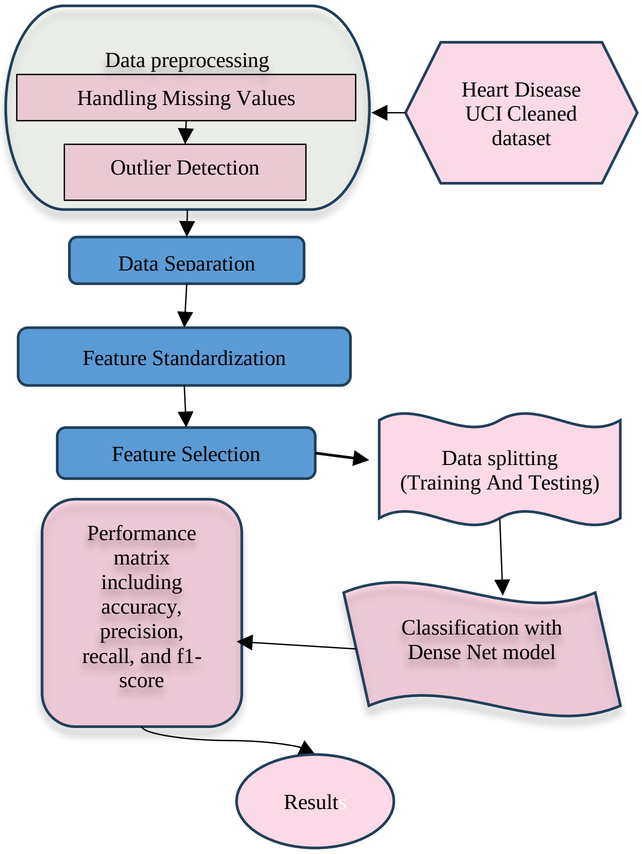

Fig. 1. Data Flowchart Diagram for Heart Diseases in Healthcare.

The ML algorithms methodology for heart disease employs a methodical approach, as seen in Figure 1. The Heart Disease UCI Cleveland dataset is initially queried for 303 patient information. This dataset contains 13 clinical variables, including age, cholesterol levels, blood pressure, and more. First, data preparation is applied to the raw dataset, which involves addressing missing values by deleting records that are incomplete and detecting outliers to get rid of anomalous data points that can affect model performance. The raw dataset is first subjected to data preparation, which includes removing incomplete records to fill in missing values and identifying outliers to eliminate unusual data points that can impair model performance. Dense Net models may be trained and evaluated by dividing the cleaned-up dataset into a training set as well as a test set. A DL framework called a Dense Net model minimizes the number of parameters while guaranteeing the effective spread of features. Lastly, the technology may be applied therapeutically to detect cardiac problems in patients early and take timely action to improve patient outcomes and lower care costs.

D. Data Collection

The Heart Disease data from UCI Cleveland was utilized in the research, which was obtained from the UCI ML repository. 303 patient records with 13 clinical characteristics, including blood pressure, cholesterol, age, and more. Because of its extensive feature collection and well-labeled results, this dataset is frequently used for heart disease prediction research and may be utilized to train and assess ML models. Some visualization is here.

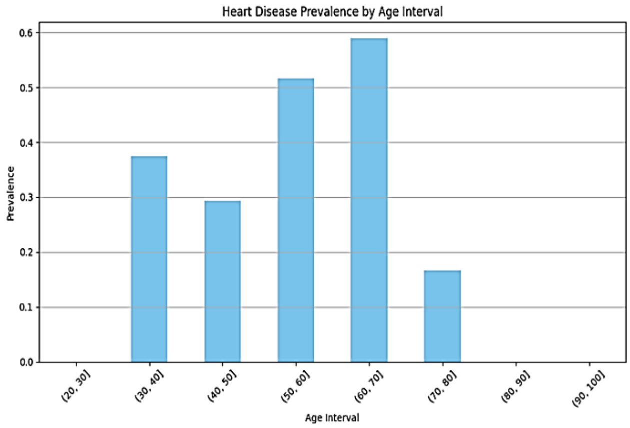

Fig. 2. Heart Disease Prevalence Across Age Intervals.

The frequency of heart disease with time and at various age intervals is shown in Figure 2. The highest prevalence is observed in the 50–60 and 60–70 age groups, indicating increased risk with age. Prevalence is lower in younger (<40) and older (>70) groups, showing a bell-shaped distribution trend.

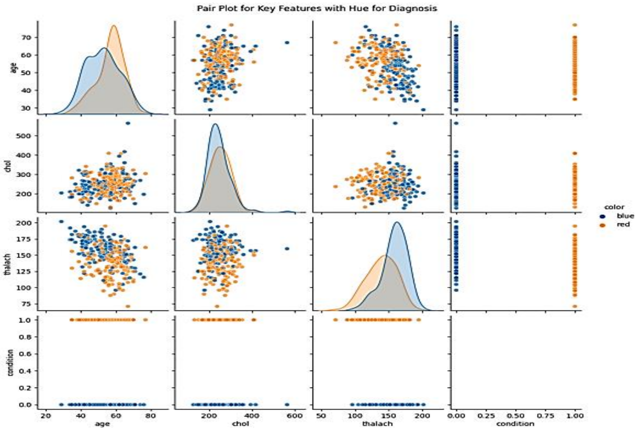

Fig. 3. Temporal Analysis of Heart Disease Prevalence.

Figure 3 presents a pair plot showing relationships between key heart disease features (age, chol, trestbps, thalach) with hue based on diagnosis. The plot reveals visible clustering patterns between patients with and without disease. Notably, lower maximum heart rate (thalach) and higher cholesterol (chol) are associated with heart disease.

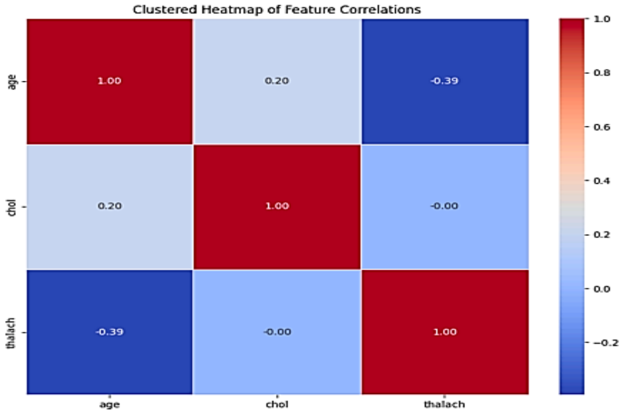

Fig. 4. Clustered Heatmap of Feature Correlations.

Figure 4 displays a clustered heatmap of feature correlations among age, cholesterol (chol), as well as maximum heart rate (thalach). The weak negative correlation between age and thalach (-0.39) indicates that cardiac output declines with advancing years. Age and cholesterol have a weakly positive association (0.20), whereas thalach and cholesterol have a very poor link.

E. Data Preprocessing

Data preparation is crucial to the performance of ML techniques, particularly those used to predict cardiac illness. Its relevance cannot be overstated, since it directly determines the quality and dependability of the outputs. The details of the preprocessing processes are given below.

- **Handling Missing Values:** Identifying and correcting any missing data points to produce a comprehensive dataset for analysis.
- **Outlier Detection and Removal:** Detecting & deleting outliers that may skew the findings to improve data quality.

F. Data Separation

The data was first divided into features and labels. The input variables that are used to predict the outcome are the features, whereas the label (target values) indicates if cardiac disease is present in each sample.

G. Feature Standardization

The values of features were standardized with the help of Standard Scaler (Scikit-learn). Each feature is given an equal chance to train the model by rescaling the data utilizing the specified technique until the mean is zero and the standard deviation is one, as well as the features with bigger numerical ranges do not prevail. It is presented as in Equation 1.

$$z = \frac{x-\mu}{\sigma} \qquad (1)$$

The transformation of a feature value x to a standardized value z is done using the equation $z = \frac{x-\mu}{\sigma}$. A feature's standard deviation (σ) and mean (μ) are the standardization features. Standardization centers the data around zero and accelerates to a unit variance. Standardizing the value of each feature ensures that each contributes equally during training of the model.

H. Feature Selection

Feature selection aims to increase model accuracy by emphasising the most significant data features, reducing complexity and improving the speed of prediction of cardiac disease. To increase the accuracy of heart problem detection, the recommended technique employs a robust feature selection procedure. Using a range of approaches, the model determines the most significant information, resulting in more accurate categorisation.

I. Data Splitting

The Scikit-learn toolkit's train_test_split function has to be used to separate the training as well as testing datasets. A 95:5 split ratio was discovered, with 5% going to testing data and 95% going to training data.

J. Implementation with the Dense Net Model

Dense Net or Densely Connected Convolutional Network is a DL architecture that aims to improve the flow of information and gradient between the layers. Every layer in the same block is directly linked to every subsequent layer, creating a unique connection pattern. This contrasts with conventional CNNs, in which just the layer directly before it provides input to each subsequent layer.

Dense Net (Densely Connected Convolutional Networks) introduces dense connections to enhance gradient flow and information: The feature maps of every layer before it is fed into each layer. Instead of summing feature maps (as in Res Nets), Dense Net concatenates them. This leads to feature reuse, parameter efficiency, and mitigation of the vanishing gradient problem [16]. Let X_{last} be the final feature map from the last dense block. It is calculated by Equation (2) and (3).

$$\hat{y} = w^T \cdot G(X_{last}) + b \qquad (2)$$

If it's a classification problem, we apply SoftMax:

$$p = softmax(\hat{y}) \qquad (3)$$

To compute the final Dense Net prediction, we use the weight matrix w^T with the globally averaged features $G(X_{last})$, and we add the bias term b to obtain the output logits $\hat{y}$.

K. Performance Matrix

Performance metrics are an important part of the ML process, particularly in assessing predictive models. These criteria help evaluate how well a model predicts cardiac disease. F1-score, recall, accuracy, as well as precision are more objective metrics. To assess a model accurately, both measures need to be included. The parameters to evaluate the effectiveness of the ML methods for classification are provided by the confusion matrix. The terms used to evaluate model performance are provided:

- **True Positive (TP):** TP is the number of samples that are positively identified by the classifier.
- **True Negative (TN):** The number of negative samples that the classifier identified.
- **False Positive (FP):** The number of samples that the classifier predicts would be positive but are negative.
- **False Negative (FN):** Those samples which fall into the positive class, but are mapped as negative by the classifier are called samples.

1) Accuracy

Accuracy refers to the fraction of accurately predicted observations in a dataset. It is calculated by dividing the number of accurate estimations by the total number of projections. Equation (4) shows the provided formula.

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (4)$$

2) Precision

One of the most important characteristics of the recovered instances is precision. Equation (5) for accuracy is shown below:

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

3) Recall

Recall is a tiny proportion of appropriate examples that are recovered from the overall number of relevant instances. Equation (6) for recall is shown below:

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \qquad (6)$$

4) F1 Score

The F1-score consists of two primary components: accuracy as well as recall. The F1-score compensates for categorized data with FP and FN. The F1 score is expressed by the following Equation (7):

$$\text{F1} = \frac{2*(\text{precision}*\text{recall})}{\text{precision+recall}} \qquad (7)$$

5) ROC

The receiver operating characteristic, or ROC, is the region under the curve that represents the relationship between the transfer product rate and the feed rate.

The model's efficacy as well as comparative analysis are assessed using these performance metrics.

IV. Results and Discussion

This paper investigates the outcomes of the proposed model used to forecast heart disease. Python 3 with TensorFlow and Scikit-Learn were used for the tests on a 64-bit Windows 10 PC powered by an Intel i7 processor (3.60 GHz, four cores) as well as 16 GB of random-access memory. The Dense Net model's performance, shown in Table II, achieved remarkable results in classifying heart disease cases. It recorded an accuracy of 99.9%, ensuring precise overall classification. While the recall of 99.9% demonstrates its efficacy in identifying real heart disease cases, the accuracy of 99.9% suggests that there are few false positives. Its robustness is indicated by the F1-score of 99.9 percent which balances precision and recall. In terms of medical practice, these findings show that the model is successful in accurately and consistently detecting heart disease.

Table 2: Performance of Heart Diseases in Healthcare.

Performance Metric	DenseNet model
Accuracy	99.9
precision	99.9
Recall	99.9
F1-score	99.9

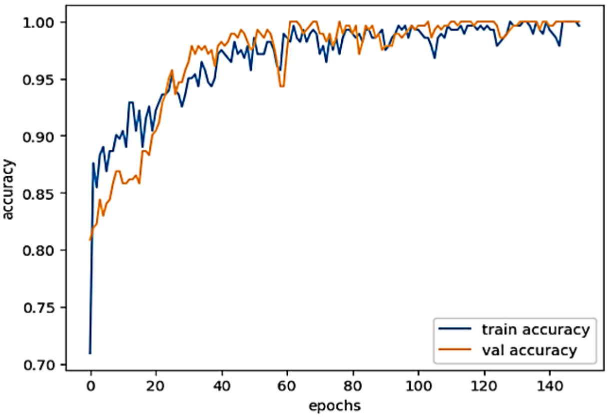

Fig. 5. Training and validation Accuracy of Dense Net Model.

Figure 5 shows the accuracy of training and validation of a Dense Net model during the 150 epochs. Both measures indicate an upward trend that is very sharp at the beginning and later levels off between 98 and 99 percent. This pattern indicates that the model is effectively learning and adapting to fresh data with minimal instances of over fitting or under fitting.

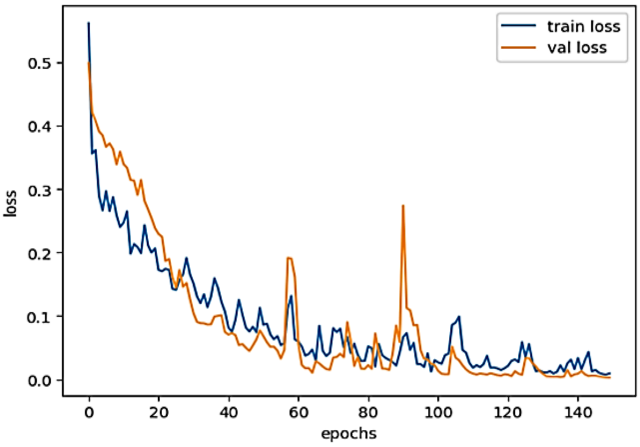

Fig. 6. Training and validation Loss of DenseNet Model.

Training and validation loss of a Dense Net model across 150 epochs is shown in Figure 6. Both loss curves generally decrease, indicating the model is learning. Although validation loss varies and spikes sometimes, the general lower trend indicates the model is successfully reducing mistakes and enhancing performance.

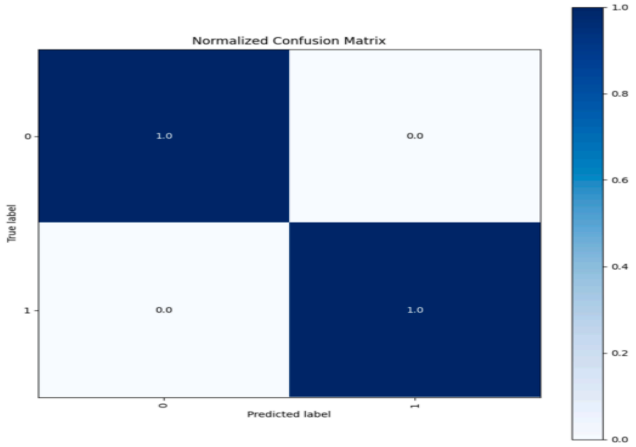

Fig. 7. Confusion Matrix of Dense Net Model.

The Dense Net model's normalized confusion matrix is displayed in Figure 7. It achieved perfect classification, with all true positives and true negatives correctly predicted (values of 1.0 along the diagonal). No FP or FN were recorded.

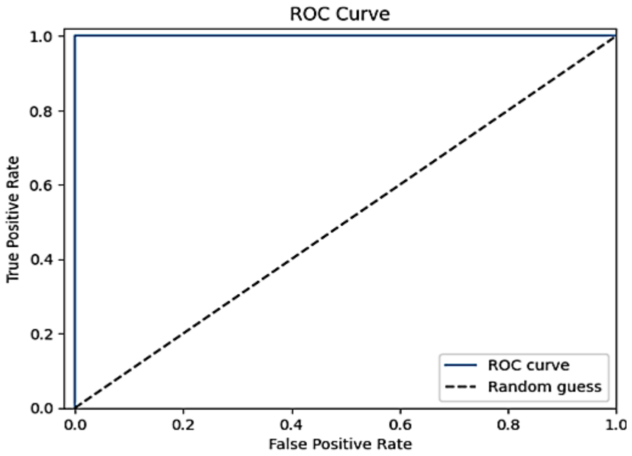

Fig. 8. ROC curve of Dense Net Model.

Figure 8 shows the Dense Net model's ROC curve. A very low FP rate across all thresholds and an unusually high genuine positive rate are indicated by the curve's hugging of the top-left corner. This indicates exceptional discriminating strength, proving that the Dense Net model can differentiate between the classes almost flawlessly.

L. Comparative Analysis

The many ML models used to predict cardiac disease are compared in this section. Table III uses the Heart Disease UCI Cleveland dataset to examine the accuracy of several models in identifying heart disease. At 85% accuracy, the Decision Tree model demonstrated a small increase over the 83% accuracy of the Naive Bayes model. Nevertheless, Dense Net considerably outcompeted these models with the amazing accuracy of 99.9%, This suggests that it is more adept at identifying intricate patterns to forecast cardiac conditions.

Table 3: Comparative Accuracy of ML Models for Heart Diseases in Healthcare.

Performance Metric	**Naive Bayes[17]**	**Decision Tree[18]**	**DenseNet**
Accuracy	83	85	99.9

The suggested approach for early cardiac disease detection and prediction has a number of potential benefits. The use of a Dense Net model can result in a high accuracy (99.9% accuracy), which is significantly better than older methods of ML for purpose of classification of disease. The advantage of the automated feature extraction is that there is no longer a need to manually engineer the features, which will lessen the action required. By removing any outliers, we can also improve on data quality to ensure the model has the best chance to execute robustly. Furthermore, the generalisation of the model with a small amount of overfitting is beneficial for real-time monitoring of patient data and, in turn, would allow for early prediction and intervention to reduce medical expenses while enhancing overall patient outcomes as well as care quality.

V. Conclusion and Future Scope

In healthcare, heart disease is one of the conditions where early detection is crucial to the outcome of a patient and the reduction of healthcare expenditure. Predictive modelling has been helpful in these situations because to advanced ML algorithms, which correctly predict whether heart disease would occur or not depending on the presence or absence of particular dataset features. With a 99.9 percent accuracy rate in patient categorisation, the Dense Net model whose performance is evaluated by recall, precision, accuracy, and F1-score has shown great results in this article. The superiority of Dense Net in representing non-linear and complicated patterns in the clinical data was also proven through comparative analysis with the classical models, like Naive Bayes and Decision Trees. Nonetheless, this model demonstrated some misclassifications, especially on the instances with overlapping clinical presentation, and the fact that the model is dependent on a single dataset has its drawbacks in wider clinical practice.

The restrictions will be addressed in future studies by investigating ensemble learning strategies as well as performing cross-validation and testing on the diverse, multi-source clinical data to improve the model's stability and generalizability. More useful clinical characteristics will be used in the future to explain predictive accuracy improvement and reduced misclassification of borderline cases. These enhancements are aimed at increasing the robustness of the model and its applicability in the reality of the diversity of healthcare contexts.

References

1. G. Velmurugan, R. Subashini, N. SaravanaBhavan, and V. Selvam, “A Study on Service Quality of a Health Care Organization,” *Int. J. Online Biomed. Eng.*, vol. 15, no. 10, pp. 91–106, Jun. 2019, doi: 10.3991/ijoe.v15i10.10906.
2. S. Nashif, M. R. Raihan, M. R. Islam, and M. H. Imam, “Heart Disease Detection by Using Machine Learning Algorithms and a Real-Time Cardiovascular Health Monitoring System,” *World J. Eng. Technol.*, vol. 06, no. 04, pp. 854–873, 2018, doi: 10.4236/wjet.2018.64057.

3. S. Garg, “Predictive Analytics and Auto Remediation using Artificial Inteligence and Machine learning in Cloud Computing Operations,” *Int. J. Innov. Res. Eng. Multidiscip. Phys. Sci.*, vol. 7, no. 2, 2019.
4. M. Marimuthu, M. Abinaya, K. S., K. Madhankumar, and V. Pavithra, “A Review on Heart Disease Prediction using Machine Learning and Data Analytics Approach,” *Int. J. Comput. Appl.*, vol. 181, no. 18, pp. 20–25, Sep. 2018, doi: 10.5120/ijca2018917863.
5. A. L. Beam and I. S. Kohane, “Big Data and Machine Learning in Health Care,” *JAMA*, vol. 319, no. 13, p. 1317, Apr. 2018, doi: 10.1001/jama.2017.18391.
6. V. Kolluri, “A Comprehensive Analysis On Explainable And Ethical Machine: Demystifying Advances In Artificial Intelligence,” *TIJER - Int. Res. Journals*, vol. 2, no. 7, 2015.
7. M. Padmanabhan, P. Yuan, G. Chada, and H. Van Nguyen, “Physician-Friendly Machine Learning: A Case Study with Cardiovascular Disease Risk Prediction,” *J. Clin. Med.*, vol. 8, no. 7, p. 1050, Jul. 2019, doi: 10.3390/jcm8071050.
8. L. Ali, A. Rahman, A. Khan, M. Zhou, A. Javeed, and J. A. Khan, “An Automated Diagnostic System for Heart Disease Prediction Based on χ2 Statistical Model and Optimally Configured Deep Neural Network,” *IEEE Access*, vol. 7, no. c, pp. 34938–34945, 2019, doi: 10.1109/ACCESS.2019.2904800.
9. V. Kolluri, “Machine Learning in Managing Healthcare Supply Chains: How Machine Learning Optimizes Supply Chains, Ensuring the Timely Availability of Medical Supplies,” *J. Emerg. Technol. Innov. Res.*, vol. 3, no. 6, 2016.
10. M. Nahiduzzaman, M. J. Nayeem, M. T. Ahmed, and M. S. U. Zaman, “Prediction of Heart Disease Using Multi-Layer Perceptron Neural Network and Support Vector Machine,” in *2019 4th International Conference on Electrical Information and Communication Technology (EICT)*, IEEE, Dec. 2019, pp. 1–6. doi: 10.1109/EICT48899.2019.9068755.
11. D. Krishnani, A. Kumari, A. Dewangan, A. Singh, and N. S. Naik, “Prediction of Coronary Heart Disease using Supervised Machine Learning Algorithms,” in *TENCON 2019 - 2019 IEEE Region 10 Conference (TENCON)*, 2019, pp. 367–372. doi: 10.1109/TENCON.2019.8929434.
12. S. Ambekar and R. Phalnikar, “Disease Risk Prediction by Using Convolutional Neural Network,” in *2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA)*, IEEE, Aug. 2018, pp. 1–5. doi: 10.1109/ICCUBEA.2018.8697423.
13. H. Mai, T. T. Pham, D. N. Nguyen, and E. Dutkiewicz, “Non-Laboratory-Based Risk Factors for Automated Heart Disease Detection,” in *2018 12th International Symposium on Medical Information and Communication Technology (ISMICT)*, 2018, pp. 1–6. doi: 10.1109/ISMICT.2018.8573706.
14. T. Karayılan and Ö. Kılıç, “Prediction of heart disease using neural network,” in *2017 International Conference on Computer Science and Engineering (UBMK)*, 2017, pp. 719–723. doi: 10.1109/UBMK.2017.8093512.
15. P. Priyanga and N. C. Naveen, “Web Analytics Support System for Prediction of Heart Disease Using Naive Bayes Weighted Approach (NBwa),” in *2017 Asia Modelling Symposium (AMS)*, 2017, pp. 21–26. doi: 10.1109/AMS.2017.12.
16. A. M. Rafi *et al.*, “Application of DenseNet in Camera Model Identification and Post-processing Detection,” pp. 19–28, 2018.
17. A. U. Haq, J. P. Li, M. H. Memon, S. Nazir, R. Sun, and I. Garciá-Magarinõ, “A hybrid intelligent system framework for the prediction of heart disease using machine learning algorithms,” *Mob. Inf. Syst.*, 2018, doi: 10.1155/2018/3860146.
18. S. Mohan, C. Thirumalai, and G. Srivastava, “Effective heart disease prediction using hybrid machine learning techniques,” *IEEE Access*, 2019, doi: 10.1109/ACCESS.2019.2923707.
19. *Chundru, S. K., Vangala, S. R., Polam, R. M., Kamarthapu, B., Kakani, A. B., & Nandiraju, S. K. K. (2024). A Machine Learning-Based Framework for Predicting and Improving Student Outcomes Using Big Educational Data (Approved by ICITET 2024 Conference Proceedings). Available at SSRN 5315635.*
20. *Nandiraju, S. K. K., Chundru, S. K., Vangala, S. R., Polam, R. M., Kamarthapu, B., & Kakani, A. B. (2025). Towards Early Forecast of Diabetes Mellitus via Machine Learning Systems in Healthcare. European Journal of Technology, 9(1), 35-50.*
21. Krutthika H. K. & Rajashekhara R. (2019). Network-on-chip: A survey on router design and algorithms. *International Journal of Recent Technology and Engineering, 7*(6), 1687–1691. https://doi.org/10.35940/ijrte.F2131.037619
22. *Chalasani, R., Gangineni, V. N., Pabbineedi, S., Penmetsa, M., Bhumireddy, J. R., & Tyagadurgam, M. S. V. (2025). Big Data-Driven Approach for Lung Cancer Identification via Advanced Deep Transfer Learning Models. European Journal of Technology, 9(1), 51-67.*
23. *Vattikonda, N., Gupta, A. K., Polu, A. R., Narra, B., Buddula, D. V. K. R., & Patchipulusu, H. H. S. (2024). Machine Learning-Based Approaches for Detecting and Mitigating Distributed Denial of Service (DDoS) Attacks to Improved Cloud Security. European Journal of Technology, 8(6), 28-48.*
24. Krutthika H. K. & A.R. Aswatha. (2020). FPGA-based design and architecture of network-on-chip router for efficient data propagation. *IIOAB Journal, 11*(S2), 7–25.
25. *Polu, A. R., Narra, B., Buddula, D. V. K. R., Hara, H., Patchipulusu, S., Vattikonda, N., & Gupta, A. K. Analyzing the Role of Analytics in Insurance Risk Management: A Systematic Review of Process Improvement and Business Agility.*
26. *Madhura, R., Varshitha, P., Nikitha, S., Niveditha, K. M., & Bhat, M. (2024, December). RTL design of 16-bit RISC Processor Using Vedic Mathematics. In 2024 IEEE 33rd Asian Test Symposium (ATS) (pp. 1-4). IEEE.*
27. Krutthika H. K. & A.R. Aswatha (2020). Design of efficient FSM-based 3D network-on-chip architecture. *International Journal of Engineering Trends and Technology, 68*(10), 67–73. https://doi.org/10.14445/22315381/IJETT-V68I10P212
28. *Harinandan, R., Kumar, M., Vamshi, P., Padma, C. R., Krishnappa, K. H., & Raghunandan, J. R. (2024, August). Design and Development of a Real-time Monitoring System for ACL Injury Prevention. In 2024 2nd International Conference on Networking, Embedded and Wireless Systems (ICNEWS) (pp. 1-6). IEEE.*

29. *Krishnappa, K. H. (2024). Traffic pattern analysis for malicious node detection in NoC design. Journal of Communications, 9, 12.*
30. *Mukund Sai Vikram Tyagadurgam, Venkataswamy Naidu Gangineni, Sriram Pabbineedi, Mitra Penmetsa, Jayakeshav Reddy Bhumireddy, et al. (2024) AI-Powered Cybersecurity Risk Scoring for Financial Institutions Using Machine Learning Techniques. Journal of Artificial Intelligence & Cloud Computing. SRC/JAICC-482. DOI: doi.org/10.47363/JAICC/2024(3)452.*
31. HK, K. (2020). Design of Efficient FSM Based 3D Network on Chip Architecture. *INTERNATIONAL JOURNAL OF ENGINEERING*, *68*(10), 67-73.
32. Krutthika, H. K. (2019, October). Modeling of Data Delivery Modes of Next Generation SOC-NOC Router. In *2019 Global Conference for Advancement in Technology (GCAT)* (pp. 1-6). IEEE.
33. Ajay, S., Satya Sai Krishna Mohan G, Rao, S. S., Shaunak, S. B., Krutthika, H. K., Ananda, Y. R., & Jose, J. (2018). Source Hotspot Management in a Mesh Network on Chip. In *VDAT* (pp. 619-630).
34. Nair, T. R., & Krutthika, H. K. (2010). An Architectural Approach for Decoding and Distributing Functions in FPUs in a Functional Processor System. *arXiv preprint arXiv:1001.3781*.
35. Gopalakrishnan Nair, T. R., & Krutthika, H. K. (2010). An Architectural Approach for Decoding and Distributing Functions in FPUs in a Functional Processor System. *arXiv e-prints*, arXiv-1001.
36. Krutthika H. K. & A.R. Aswatha. (2021). Implementation and analysis of congestion prevention and fault tolerance in network on chip. *Journal of Tianjin University Science and Technology*, *54*(11), 213–231. https://doi.org/10.5281/zenodo.5746712.
37. *Pabbineedi, S., Kakani, A. B., Nandiraju, S. K. K., Chundru, S. K., Tyagadurgam, M. S. V., & Gangineni, V. N. (2023). Scalable Deep Learning Algorithms with Big Data for Predictive Maintenance in Industrial IoT. International Journal of AI, BigData, Computational and Management Studies, 4(1), 88-97.*
38. *Chalasani, R., Vangala, S. R., Polam, R. M., Kamarthapu, B., Penmetsa, M., & Bhumireddy, J. R. (2023). Detecting Network Intrusions Using Big Data-Driven Artificial Intelligence Techniques in Cybersecurity. International Journal of AI, BigData, Computational and Management Studies, 4(3), 50-60.*
39. *Vangala, S. R., Polam, R. M., Kamarthapu, B., Penmetsa, M., Bhumireddy, J. R., & Chalasani, R. (2023). A Review of Machine Learning Techniques for Financial Stress Testing: Emerging Trends, Tools, and Challenges. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 4(1), 40-50.*
40. *Kakani, A. B., Nandiraju, S. K. K., Chundru, S. K., Tyagadurgam, M. S. V., Gangineni, V. N., & Pabbineedi, S. (2023). A Survey on Regulatory Compliance and AI-Based Risk Management in Financial Services. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 4(4), 46-53.*
41. *Bhumireddy, J. R., Chalasani, R., Vangala, S. R., Kamarthapu, B., Polam, R. M., & Penmetsa, M. (2023). Predictive Machine Learning Models for Financial Fraud Detection Leveraging Big Data Analysis. International Journal of Emerging Trends in Computer Science and Information Technology, 4(1), 34-43.*
42. *Gangineni, V. N., Pabbineedi, S., Kakani, A. B., Nandiraju, S. K. K., Chundru, S. K., & Tyagadurgam, M. S. V. (2023). AI-Enabled Big Data Analytics for Climate Change Prediction and Environmental Monitoring. International Journal of Emerging Trends in Computer Science and Information Technology, 4(3), 71-79.*
43. *Polam, R. M. (2023). Predictive Machine Learning Strategies and Clinical Diagnosis for Prognosis in Healthcare: Insights from MIMIC-III Dataset. Available at SSRN 5495028.*
44. *Narra, B., Gupta, A., Polu, A. R., Vattikonda, N., Buddula, D. V. K. R., & Patchipulusu, H. (2023). Predictive Analytics in E-Commerce: Effective Business Analysis through Machine Learning. Available at SSRN 5315532.*
45. *Narra, B., Buddula, D. V. K. R., Patchipulusu, H. H. S., Polu, A. R., Vattikonda, N., & Gupta, A. K. (2023). Advanced Edge Computing Frameworks for Optimizing Data Processing and Latency in IoT Networks. JOETSR-Journal of Emerging Trends in Scientific Research, 1(1).*
46. *Patchipulusu, H. H. S., Vattikonda, N., Gupta, A. K., Polu, A. R., Narra, B., & Buddula, D. V. K. R. (2023). Opportunities and Limitations of Using Artificial Intelligence to Personalize E-Learning Platforms. International Journal of AI, BigData, Computational and Management Studies, 4(1), 128-136.*
47. *Madhura, R., Krishnappa, K. H., Shashidhar, R., Shwetha, G., Yashaswini, K. P., & Sandya, G. R. (2023, December). UVM Methodology for ARINC 429 Transceiver in Loop Back Mode. In 2023 3rd International Conference on Mobile Networks and Wireless Communications (ICMNWC) (pp. 1-7). IEEE.*
48. *Shashidhar, R., Kadakol, P., Sreeniketh, D., Patil, P., Krishnappa, K. H., & Madhura, R. (2023, November). EEG data analysis for stress detection using k-nearest neighbor. In 2023 International Conference on Integrated Intelligence and Communication Systems (ICIICS) (pp. 1-7). IEEE.*
49. *KRISHNAPPA, K. H., & Trivedi, S. K. (2023). Efficient and Accurate Estimation of Pharmacokinetic Maps from DCE-MRI using Extended Tofts Model in Frequency Domain.*
50. *Krishnappa, K. H., Shashidhar, R., Shashank, M. P., & Roopa, M. (2023, November). Detecting Parkinson's disease with prediction: A novel SVM approach. In 2023 International Conference on Ambient Intelligence, Knowledge Informatics and Industrial Electronics (AIKIIE) (pp. 1-7). IEEE.*
51. *Shashidhar, R., Balivada, D., Shalini, D. N., Krishnappa, K. H., & Roopa, M. (2023, November). Music Emotion Recognition using Convolutional Neural Networks for Regional Languages. In 2023 International Conference on Ambient Intelligence, Knowledge Informatics and Industrial Electronics (AIKIIE) (pp. 1-7). IEEE.*
52. *Madhura, R., Krishnappa, K. H., Manasa, R., & Yashaswini, K. P. (2023, August). Slack Time Analysis for APB Timer Using Genus Synthesis Tool. In International Conference on ICT for Sustainable Development (pp. 207-217). Singapore: Springer Nature Singapore.*
53. *Krishnappa, K. H., & Gowda, N. V. N. (2023, August). Dictionary-Based PLS Approach to Pharmacokinetic Mapping in DCE-MRI Using Tofts Model. In International Conference on ICT for Sustainable Development (pp. 219-226). Singapore: Springer Nature Singapore.*

54. *Krishnappa, K. H., & Gowda, N. V. N. (2023, August). Dictionary-Based PLS Approach to Pharmacokinetic Mapping in DCE-MRI Using Tofts Model. In International Conference on ICT for Sustainable Development (pp. 219-226). Singapore: Springer Nature Singapore.*
55. *Madhura, R., Krutthika Hirebasur Krishnappa. et al., (2023). Slack time analysis for APB timer using Genus synthesis tool. 8th Edition ICT4SD International ICT Summit & Awards, Vol.3, 207–217. https://doi.org/10.1007/978-981-99-4932-8_20*
56. *Shashidhar, R., Aditya, V., Srihari, S., Subhash, M. H., & Krishnappa, K. H. (2023). Empowering investors: Insights from sentiment analysis, FFT, and regression in Indian stock markets. 2023 International Conference on Ambient Intelligence, Knowledge Informatics and Industrial Electronics (AIKIIE), 01–06. https://doi.org/10.1109/AIKIIE60097.2023.10390502*
57. *Jayakeshav Reddy Bhumireddy, Rajiv Chalasani, Mukund Sai Vikram Tyagadurgam, Venkataswamy Naidu Gangineni, Sriram Pabbineedi, Mitra Penmetsa. Predictive models for early detection of chronic diseases in elderly populations: A machine learning perspective. Int J Comput Artif Intell 2023;4(1):71-79. DOI: 10.33545/27076571.2023.v4.i1a.169*