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RESEARCH PAPER

Early Prediction of Heart Failure via Supervised Machine Learning Models: A Performance Analysis

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***Abstract*—Heart disease is one of the most important illnesses face today, and most of its victims die. Diagnosing and treating heart disease is no easy task. Being precise and efficient is essential for this difficult diagnostic procedure. Prevention of mortality was achieved with the early diagnosis of cardiac illness. The rising incidence of cardiac problems has made the prediction of their onset one of the most difficult medical jobs to date. The Cleveland Heart sickness dataset is utilized in this study to develop a Convolutional Neural Network (CNN) based model for the prediction of cardiovascular sickness. The dataset is split into two parts, with a ratio of 80:20, after undergoing essential preprocessing operations such as handling missing values, feature selection by correlation analysis, Min-Max normalization, and categorical encoding.6 Convolutional neural networks (CNNs) are designed to automatically extract hierarchical information for correct classification using their pooling, fully connected, and convolutional layers. With an AUC close to 1.0, a recall of 99.97%, a precision of 99.98%, and an F1-score of 99.96%, the CNN model demonstrates outstanding discriminative power in experimental assessments. Compared to more conventional models like Multi-Layer Perceptron, Logistic Regression, and Random Forest. Findings demonstrate CNN's dependability and robustness in identifying patterns of cardiac disease, lowering the rate of incorrect predictions, and bolstering clinical diagnosis; hence, CNN is a scalable option for practical healthcare applications.**

Keywords—Heart Failure Prediction, CNN Model, Cleveland Heart Disease Dataset, Machine Learning, Deep Learning.

I. INTRODUCTION

A major contributor to death and disability on a global scale, cardiovascular disease (CVD) poses a significant threat to public health around the world. Particularly among men and women, heart disease has become a major killer, with coronary heart disease being the most common form. Statistics reveal that approximately 630,000 individuals die from heart disease annually, accounting for nearly one in every four deaths [1][2]. Heart failure, often representing a late-stage manifestation of various cardiovascular disorders, results in insufficient cardiac ejection and carries a high mortality rate while also imposing substantial healthcare costs [3]. Diabetes, excessive blood pressure, abnormal heart rate, abnormal cholesterol levels, and lifestyle variables all contribute to its multifactorial nature, making its detection difficult. Moreover, emerging evidence highlights that conditions such as Coronavirus infection may exacerbate cardiovascular health, and it is reported that cardiac injury is observed in close to one over five patients regardless of respiratory symptoms [4]. Early prediction and early identification of heart failure are thus essential in curbing mortality and enhancing patient outcome. Traditional methods of diagnosis, based on the history of the medical history, physical examination and laboratory tests are frequently unable to predict the development of the disease at the early stages with adequate accuracy [5][6][7]. This drawback highlights the necessity of sophisticated computational technology that can find the sophisticated trends in the large-scale health data [8]. ML and DL approaches have demonstrated great potential in this area, enabling earlier and more precise prediction of the progression of cardiac disease. As an example, a recent study has indicated prediction accuracy of 90-93 per cent with the use of ML and DL-based models in cardiovascular risks assessment.

Supervised machine learning models are the most promising AI-based methods to predict heart diseases, as they use labeled clinical data to project patient characteristics to disease outcomes [9][10]. Such models are not only able to offer predictive accuracy, but also allow the establishment of cost effective and proactive healthcare systems. Supervised ML based on early prediction can therefore transform the paradigm of curative treatment to preventive one, and reduce the global heart failure burden [11]. This study compares various methods of early heart failure prediction using supervised machine learning models in an effort to improve diagnostic accuracy and patient care.

A. Motivation and Contribution of Study

Cardiovascular disease (CVD), especially heart failure, is the number one cause of death globally, and its diagnosis has been hampered by the multifactorial nature of its risk factors including diabetes, hypertension, cholesterol imbalance, and lifestyle factors. Conventional diagnostic approaches, including clinical examination and laboratory tests, are limited in their ability to detect disease onset at an early stage, resulting in delayed interventions and high mortality rates. The challenge lies in accurately identifying complex, non-linear relationships within clinical data that traditional methods often fail to capture. This necessitates the adoption of advanced computational approaches that can process large-scale health datasets, extract hidden patterns, and deliver precise predictions. Motivated by the potential of DL, this study explores the use of CNNs for heart disease prediction, aiming to provide a robust, scalable, and automated framework that enhances diagnostic accuracy, supports early detection, and ultimately contributes to reducing the global burden of cardiovascular diseases. The key contribution ae as follows:

- Utilizes the widely recognized Cleveland Heart Disease dataset, ensuring reproducibility and allowing comparison with existing methods.
- A robust preprocessing pipeline including missing value handling, feature selection, normalization, and categorical encoding ensures clean, well-prepared input for optimal model performance.
- The development of a CNN architecture for early prediction of cardiac illness makes use of automatic hierarchical feature extraction to improve diagnostic accuracy.
- Maintains recall, accuracy, and precision levels comparable to those of popular ml models like as LR and RF.

B. *Justification and Novelty*

Heart failure is a major cause of death globally, and standard diagnostic approaches have their limitations when it comes to capturing the complexity of cardiovascular risk factors. Therefore, work is justified by the need of early and accurate detection of heart failure. Unique to this work is the use of a CNN trained on structured clinical data; normally, CNNs are trained on picture data. The research outperforms more traditional models, such as RF and LR, with an astonishing accuracy of 99.99% by modifying CNN architecture to appropriately assess tabular health records from the Cleveland Heart Disease dataset. A major step forward in AI-driven healthcare, this novel application of deep learning to structured medical data demonstrates the model's possible for real-time, high-precision prediction of cardiac disease.

C. *Structure of Paper*

The following is the outline of the paper: Section II discusses previous research on heart failure prediction, Section III lays out the methodology that is to be used, Section IV shows the results and analysis, and Section V finishes with a discussion of potential future study.

II. LITERATURE REVIEW

The research presented in this section focuses on heart failure prediction platforms that use various machine learning approaches. Table I provides a summary of these investigations.

Prajapati et al. (2025) the predictive modelling used is SVM method that can easily handle a very high quotient of complex health data. Heart failure is when the heart is not really pumping along any more in its usual way. SVM is something that figures out who and when bad things might happen to, which is to say, who really might have quite serious vascular issues. The high percentage of 79% accuracy of the classification capabilities in the SVM is applicable to a broad spectrum of clinical indications and risk factors [12].

Kaur et al. (2024) the overwhelming majority of the people nowadays are of busy lives, so more people never really had weak hearts in the past. Heart failure is the one where the heart does not pump as it must. There are 12 characteristics in the data that can be used to predict cardiac failure. The SVM's outstanding 88% accuracy rate for classification fits several clinical criteria and risk factors. This paper is laying much stress on the necessity of intelligent, knowledgeable computer strategies as an imperative to become truly good at diagnosing and treating heart failure early and on the path to superior thoughts on tracking health [13].

Rani (2024) investigation into the potential of supervised learning approaches, including SVM models, for the prediction of heart failure. This work demonstrates that SVMs are effective in predicting cardiac events using a large dataset of clinical variables (87.53% classification rate). The study emphasizes the need to incorporate multimodal data (such as clinical biomarkers, imaging, lifestyle, and demographic information) to improve the effectiveness of prediction and provide preventive healthcare solutions. Wearable devices, the Internet of Things, and EHRs contribute to the availability of rich, longitudinal data streams for real-time monitoring and prediction [14].

Andari et al. (2023) explores the future of heart failure, a possibly fatal complication of cardiovascular diseases, which are the world's leading cause of death. The 299 samples and 12 attributes in this real-world dataset are utilized by this solution. Following feature analysis, the MLP ANN was integrated using the backpropagation methodology with three machine learning methods: LR, k-NN, and NB. Every algorithm's hyper-parameters were evaluated with varying values to determine accuracy and optimal performance. Accuracy rates of 84%, 77%, 76%, and 74% for the ANN, NB, and K-NN algorithms, respectively, were reported [15].

Pandey and Kaur (2022) This paper's model was developed using five different ML algorithms: GB, RF, KNN, LR, and SVM. Among the ML approaches tested, SVMs had the highest efficiency level of 94.56% in predicting whether or not subjects would have cardiovascular disease [16].

Battula et al. (2021) identify the early warning signs of heart disease, people can take steps to reduce their risk, and they can start treatment right away if they can. The model was trained to predict the occurrence of cardiac disease on the training dataset using multiple approaches, such as LR, kNN, DT, and RF. The accuracy of the model was then evaluated using the testing dataset. When compared to the other three algorithms, RF comes out on top. The RF technique offers the most accurate data match at 88.16% [17].

Previous research has demonstrated accuracies ranging from 76% to 94% when predicting heart failure using several ML models, such as SVM, LR, RF, k-NN, and MLP. Though these models have potential, their utilization is typically limited by dependency on manual feature engineering, sensitivity to high-dimensional data, and restricted capacity to learn complex, non-linear correlations in clinical data. Further, the majority of previous studies use the conventional ML methods with small to moderate datasets and, therefore, limited scalability and generalization to populations of diverse patients. The suggested research would employ a CNN with the Cleveland Heart Disease dataset to get around these predictability issues. Automatic learning of hierarchical and discriminative features by CNNs eliminates the need for manual preprocessing in many cases. This improves predicted accuracy and robustness while reducing the number of manual preprocessing steps.

TABLE I. COMPARATIVE ANALYSIS OF MACHINE LEARNING TECHNIQUES FOR PREDICTION OF HEART FAILURE

Methodology	Data	Key Findings	Limitation	Future Work
SVM	Clinical data with complex health attributes	Achieved 79% accuracy; suitable for handling complex health data and predicting vascular issues	Did not discuss interpretability or comparison with other methods	Expand model generalization and test with larger datasets
Support Vector Machine (SVM)	Dataset with 12 features for cardiac failure prediction	Achieved 88% accuracy; emphasizes early diagnosis using smart ML techniques	Limited feature set; lacks integration of external real-time data	Promote intelligent diagnostic tools and use real-time monitoring for health care
Support Vector Machine (SVM), multimodal data integration	Large dataset with clinical, lifestyle, and demographic data	87.53% accuracy; highlights the role of IoT, wearables, and EHRs in prediction	Model interpretability and generalization challenges remain	Achieve better accuracy, interpretability, and integration with real-time, multi-modal data.
ANN with backpropagation; compared with LR, KNN, Naïve Bayes	Real dataset: 12 features, 299 samples	ANN achieved highest accuracy (84%); comparison with other ML methods	Small dataset size; basic feature set	Explore deep learning improvements and use larger, balanced datasets
ML algorithms: GB, RF, KNN, LR, SVM	Clinical dataset for cardiovascular prediction	SVM achieved best performance (94.56%) among all models	No discussion of feature importance or interpretability	Focus on explainability, real-time deployment, and clinical integration
ML methods: LR, k-NN, DT, RF	Medical data; Python-based model implementation	Random Forest gave best performance (88.16% accuracy)	Lack of SVM comparison; only traditional ML methods evaluated	Use more advanced models (e.g., deep learning), expand dataset, explore time-series health prediction

III. METHODOLOGY

This methodology paper describes a stepwise approach to the prediction of heart diseases with the help of CNN model. The Cleveland Heart Disease dataset contains vital clinical information such age, sex, kind of chest pain, cholesterol, and electrocardiogram (ECG) readings; collecting this data is the initial stage. Feature and value restrictions: all through data preparation. To prepare the data for modelling, use Min-Max scaling to normalize it and code the categorical variables. The data is divided between the training and testing sets in an 80:20 ratio. The recommended architecture for a convolutional neural network (CNN) model incorporates pooling, convolutional, and full-connected layers to automatically recognize and learn hierarchical features for classification. Metrics used to evaluate the efficacy of models include accuracy, precision, recall, F1-score, and area under the curve (AUC-ROC). The results reveal that this model can accurately identify patterns of cardiac sickness and assists with early diagnosis. It also has good categorization capabilities. A heart failure prediction flow diagram is shown in Figure 1.

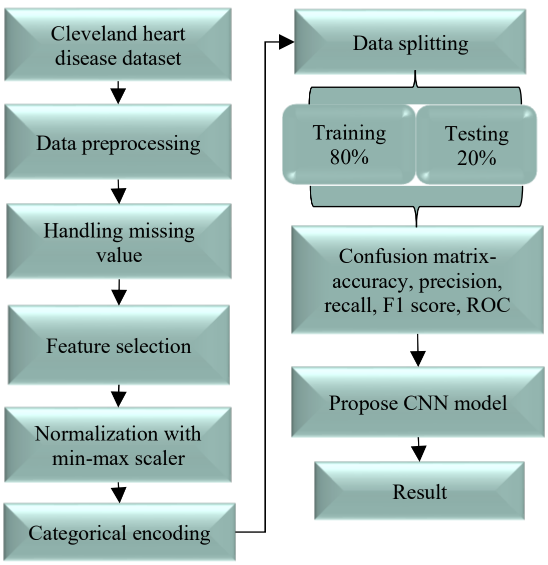

Fig. 1. Flowchart of the Prediction of Heart Failure

The following sections provide each step description that also shows in methodology and proposed flowchart:

A. Data Collection

The Cleveland Heart Disease dataset was obtained from the UCI Machine Learning Repository. Information that can aid in the diagnosis of cardiac disease is included in the patient data collection, which includes age, sex, kind of chest discomfort, cholesterol levels, blood pressure, and electrocardiogram (ECG) readings. Although it's a great starting point for comparing and building machine learning models, the results might not apply to larger or more varied populations due to its modest size (303 records). What follows is a graph representing this dataset's visualization.

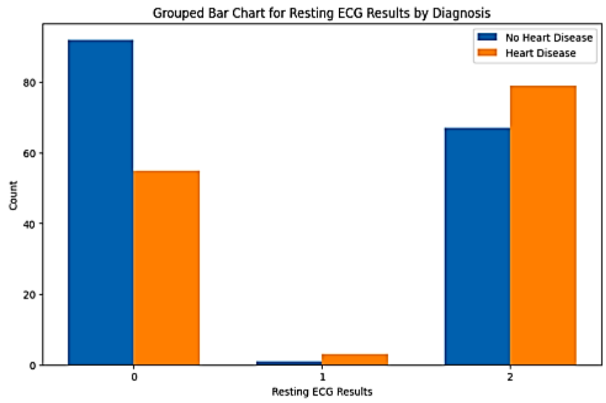

Fig. 2. Grouped bar chart for resting ECG Results by Diagnosis

Figure 2 shows, as a grouped bar chart, the distribution of resting electrocardiogram readings according to the presence or absence of heart disease. There are three possible ECG outcomes (0, 1, and 2), and the overall patient count is shown on the y-axis. Categorization 0 shows that there are many more patients without heart disease than those with the condition, whereas Categorization 2 shows that there are somewhat more patients with the condition than without. Both groups display an extremely low count in Category 1. This graphic shows how resting electrocardiogram results differ between patients with and without cardiac disease, which may be useful for diagnosis.

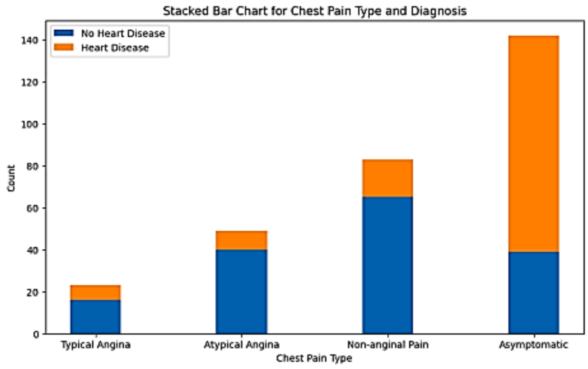

Fig. 3. Stacked Bar Charts for Chest Pain Type and Diagnosis

Figure 3 shows a stacked bar chart that shows the correlation between several indications of chest pain and the identification of heart disease. The picture graphically depicts four distinct types of chest pain: traditional angina, non-anginal pain, asymptomatic chest pain, and atypical angina. As the big orange section in this category indicates, it is clear that those labelled as Asymptomatic demonstrate the highest relationship with heart disease. Although non-anginal pain, atypical angina, and typical angina are more common in the general population, it can occasionally manifest in the heart disease group.

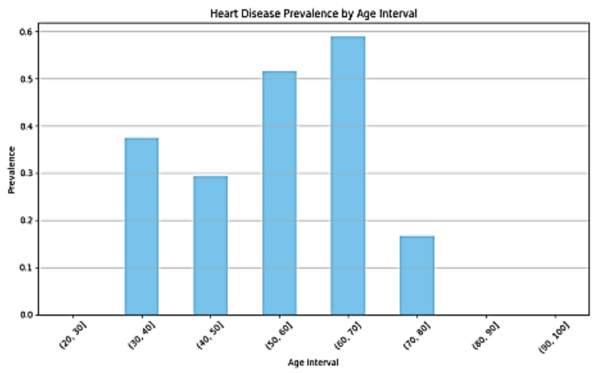

Fig. 4. Temporal Analysis of Heart Disease Prevalence

The patterns of risk linked with ageing are illuminated by Figure 4, which displays the historical analysis of the prevalence of heart disease across different age intervals. People in their 60s and 70s are second most at risk for cardiovascular disease, followed by those in their 50s and 60s, according to the bar chart. Those in their middle years and those in their later years are the most vulnerable. The 30–40 and 40–50 age brackets show moderate prevalence, while prevalence drops significantly after age 70, possibly due to lower sample sizes or survivor bias. Minimal to no cases are observed in the extreme age groups of 20–30 and 80–100. This analysis underscores the importance of early screening and intervention for individuals aged 50 to 70, when the risk appears to be at its peak.

B. Data Preprocessing

In the preprocessing phases, dealt with missing values by either eliminating or imputing null entries. Then, used a correlation heatmap to pick features, and found that age and thalach were important predictors. For data normalization to the [0,1] range, utilized Min-Max scaling. To convert non-numerical data to numeric data, employed categorical encoding. These procedures guaranteed clean, scaled, and model ready data to make heart disease prediction effective.

C. Handling Missing Value

The first step involves handling missing or inconsistent values within the dataset. Records with null entries are either removed or imputed using statistical techniques to maintain data integrity and consistency, ensuring the model is trained on reliable inputs.

D. Feature Selection

A correlation heatmap is a statistical tool for finding and selecting the most relevant features by displaying the correlations between them and the target variable. This increases the model's prediction performance, streamlines training, and decreases noise.

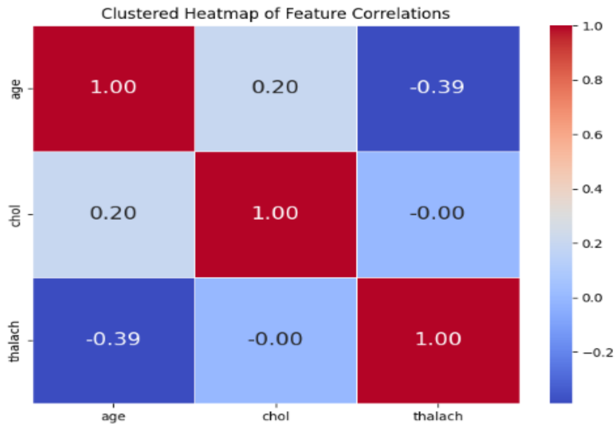

Fig. 5. Heatmap of Feature Correlations.

The correlation coefficient between age, cholesterol, and maximum heart rate is shown in Figure 5. Using a cool warm color map, and see that a strong negative correlation is represented by blue and a strong positive correlation by red. All of the diagonal elements are 1, which means that the feature is perfectly correlated with itself. According to the heatmap, there is a moderate negative correlation of -0.39 between age and maximum heart rate, a weak positive correlation of 0.20 between age and cholesterol, and no linear link between cholesterol and maximum heart rate at -0.00. One of the best ways to quickly grasp the interrelationships of a dataset's variables is with this visual representation.

E. Data Normalization with min-max Scaler

There are models that are sensitive to features in a dataset that have a wide range of values. To address this issue, used the following normalization techniques to scale the features. Flattens the data so that it falls within the interval [0, 1]. While it may not be as affected by outliers as the normal scaler, it is still susceptible to them. The formula for its calculation is as Equation (1):

$$n = \frac{n - minimum(n)}{maximum(n) - minimum(n)} \tag{1}$$

F. Categorical Encoding

The categorical data, such as the type of chest pain or sex, is converted into numerical form using encoding methods such as one-hot encoding and label encoding. In this way, know that ML models correctly understand certain properties that aren't numbers.

G. Data Splitting

Evaluation of a model's efficacy concludes with the generation of distinct data sets for training and testing. Typically, the two sets are 80:20. In doing so, evaluate the model's robustness to novel data and keep it from being "overfit".

H. CNN Model

CNNs are a specific kind of deep learning which was actually invented to operate and process grid-like input, such as image data. Because of the ability to detect hierarchies with raw pixel data, they have transformed the way images are classified and several other computer vision tasks. The convolutional, pooling, and fully linked layers make up a CNN. All of the layers are shown in Figure 6.

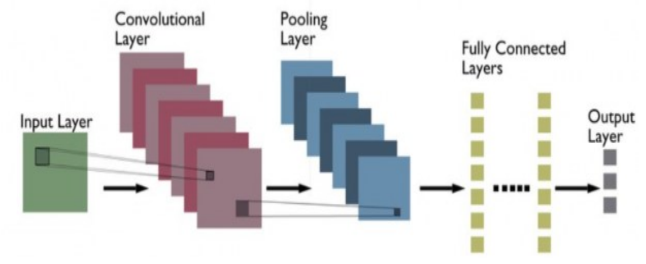

Fig. 6. CNN Architecture

Figure 6 depicts a CNN architecture that processes the input image through convolutional and pooling layers, flattens it, and then uses dense layers to get the final prediction. The following CNN layers are:

- **Convolutional layer:** produces an activation map using pixel-by-pixel filter scanning of the pictures.
- Pooling layer: reduces the amount of output produced by the convolutional layer, enabling more effective data storage.
- **Fully Connected Layer:** A fully linked input layer takes the "flattened" output of the preceding layers and uses it as an input to the level below. To make the right label prediction, the first fully connected layer takes feature analysis inputs with weights. Last linked layer - gives chance for every label.

I. Performance Matrix

The model's classification performance was assessed using validation accuracy, precision, F1-score, and recall, as these metrics are appropriate for evaluating models on a balanced dataset [18].

1) Accuracy

Accurately predicting cardiovascular disease risk variables is a key performance indicator. It demonstrates that the model's ability to predict whether heart disease risk variables are present or not is directly correlated with the percentage. Accuracy of Equation (2):

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{2}$$

2) Precision

The term "precision" describes the ratio of correct risk estimates to all risk projections. within the context of Equation (3):

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

3) Recall

One significant way to measure the model's efficiency is by looking at its recall. Comparing the overall actual risk to the expected risk incidents is what it does. It evaluates how well the model can identify each risk instance. It is evaluated. in Equation (4):

$$Recall = \frac{TP}{TP+FN} \tag{4}$$

4) F1_Score

The F1-score is a measure that encompasses both Precision and Recall. By integrating the Precision and recalls metrics, it assesses the Framework's ability to accurately predict risk indicators while minimizing errors. Equation (5) determines its value:

$$F1-score = 2 * \frac{(precision*recall}{(precision+recall)} \tag{5}$$

Where a True Positive (TP) accurately foretold a positive result. The TN correctly foretold a negative result. Incorrectly forecasting a positive result is known as FP. A FN is a prediction that was made with the wrong outcome in mind.

5) ROC

A ROC curve that divides the data into positive and negative categories. The graph summarizes the model's performance by showing the ratio of true positives to false positives at various classification thresholds, where 1-specificity and recall are the two variables. one way to gauge this capability is by calculating the AUC. High discriminatory power is shown by a value closer to 1.0, but performance comparable to random guessing is shown by an AUC near 0.5. In this case, the model's excellent classification capabilities and near-1 AUC demonstrate its high accuracy across all threshold levels. The curve follows the top-left border quite closely.

IV. Results and Discussion

The following are the computer programs and tools that were used for this study: Running on a 64-bit OS with 8 GB of RAM, Python is executed on Jupyter Notebook 6.0.3 with an Intel® CoreTM i7-4510U CPU@2.00 GHz 2.60 GHz. With an F1-score of 99.96%, an accuracy rate of 99.99%, a precision rate of 99.98%, and a recall rate of 99.97%, the CNN model proved to be quite reliable in predicting cases of heart illness on the Cleveland Heart illness dataset (Table II).

TABLE II. Parameters Performance for CNN Model on Cleveland

Measures	CNN
Accuracy	99.99
Precision	99.98
Recall	99.97
F1-score	99.96

TABLE III. Heart Disease Dataset

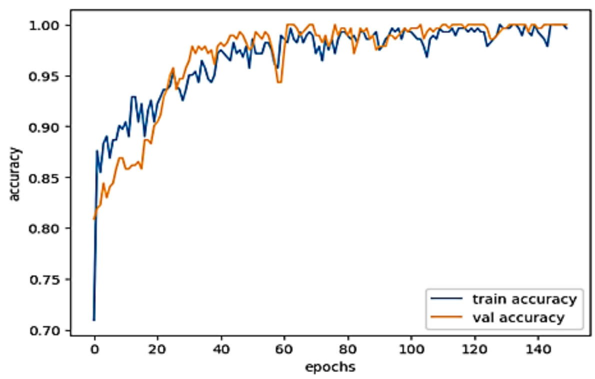

Fig. 7. Accuracy curve of CNN Model

Figure 7 shows the CNN model's accuracy curve, which compares training and validation accuracy over 150 training epochs. The plot indicates a steady improvement in both metrics during the early stages, with accuracy rapidly increasing from around 70 to over 90 within the first 30 epochs. The model has successfully learnt the underlying patterns when the training and validation curves converge near 100% as training continues. The validation accuracy remains consistently high and closely follows the training accuracy, demonstrating robust generalization and minimal overfitting.

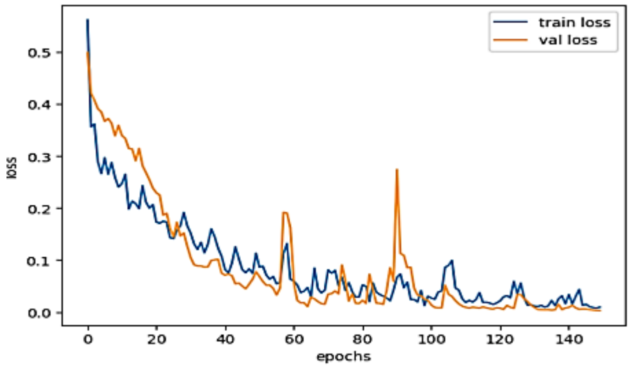

Fig. 8. Loss curve of CNN Model

Figure 8 shows the CNN model's loss curve across 150 epochs, showing how the validation loss and training loss have evolved. In the beginning, there is a significant drop in both loss values, which indicates that learning and optimization are going well. As long as it keeps going down, the training loss goes down, which means the model is fitting the data nicely. Although there are some discernible spikes around epochs 75 and 95 in the validation loss, which may be caused by batch variation or temporary overfitting, overall, it follows a similar downward pattern. Despite these fluctuations, both losses converge to values close to zero, demonstrating excellent model performance, high learning efficiency, and strong generalization capability with minimal signs of overfitting.

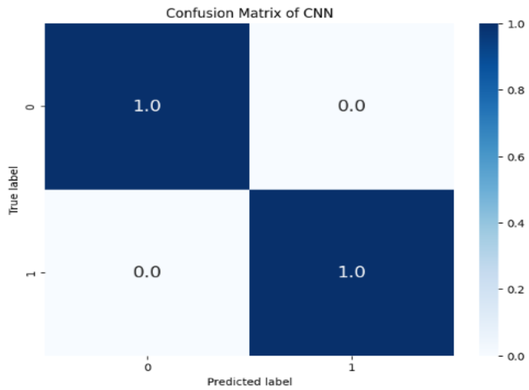

Fig. 9. Confusion matrix of CNN model

The CNN model's confusion matrix shows flawless classification performance, as illustrated in Figure 9. The diagonal elements, representing the number of correct predictions, are all equal to 1.0, while the off-diagonal elements, representing misclassifications, are 0.0. This indicates that the model achieved a 100% classification accuracy, correctly identifying all instances of both classes ('0' and '1') without any false positives or false negatives. This perfect result signifies that the model's precision and recall are also 1.0 for both classes.

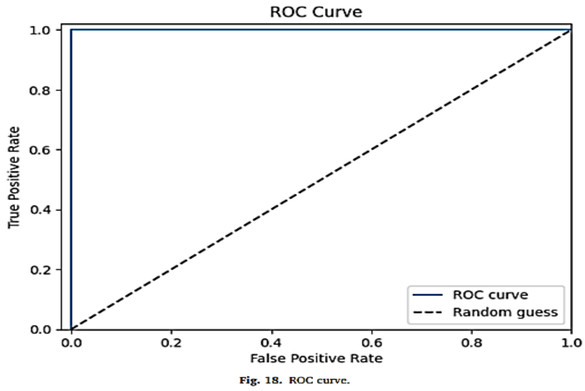

Fig. 10. AUC-ROC curve of CNN model

The area under the receiver operating characteristic (AUC-ROC) curve compares the true positive rate with the false positive rate at different threshold settings to evaluate the classification accuracy of the CNN model. This comparison is depicted in Figure 10. The ROC curve stubbornly holds onto the upper left corner of the graph, suggesting almost flawless class discrimination, in the picture. An AUC for the model close to 1.0 indicates good prediction accuracy.

TABLE III. COMPARISON BETWEEN MODELS FOR HEART FAILURE RISK PREDICTION

Matrix	**CNN**	**RF**[19]	**LR**[20]	**MLP**[21]
Accuracy	99.99	78.68	83	98.92
Precision	99.98	80	84	98.91
Recall	99.97	78	78	99
F1-score	99.96	79	81	99.45

Table III compares many models for predicting the likelihood of heart failure, including CNNs, RF, LR, and MLP. With scores of 99.98% for accuracy, 99.97% for precision, and 99.96% for F1-score, the CNN model clearly has the best predictive abilities. In contrast to MLP's 98.92% accuracy and 99.45% F1-score, LR and RF both show significantly lower scores across the board, at 83% and 76.68%, respectively. These findings show that CNN is a strong predictive tool to diagnose heart failure.

The suggested model of CNN in predicting heart failure risk shows excellent results with almost perfect scores in all measures of evaluation, thus, proving its firmness and consistency in clinical diagnosis. The main strength of the CNN is that it automatically derives complex features of input data without having to perform extensive manual feature engineering and, therefore, is capable of recognizing better patterns in cardiovascular data. Moreover, high accuracy and generalization are guaranteed in the model, reducing false predictions and maximizing the accuracy of diagnosis. These benefits render CNN an effective and scalable solution to the early detection and risk evaluation of heart failure in the clinical care contexts.

V. CONCLUSION AND FUTURE SCOPE

Globally, heart diseases are always the number one leading cause of death. According to the report of the WHO, 17.5 million people die annually across the world because of heart disease and stroke. More than three-quarters of deaths that are due to heart diseases are mainly in countries where the population is middle- and low-income. Excellent performance parameters of 99.99% accuracy, 99.98% precision, 99.97% recall, and 99.96% F1-score were achieved by this CNN model in heart failure prediction using the Cleveland Heart

Disease dataset. Its predictive success is contributed by the strong preprocessing pipeline and by the capability of the CNN to automatically extract hierarchical features. These findings indicate the possibility of the model to be used in practical clinical settings in the detection and risk evaluation of heart diseases. In terms of future scope, the research can be extended by incorporating larger and more diverse datasets, exploring multimodal data such as wearable sensor readings and electronic health records, and enhancing model interpretability to build trust among healthcare practitioners. Additionally, real-time deployment in healthcare monitoring systems could enable continuous patient assessment, paving the way for proactive and personalized cardiac care.

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