International Journal of Core Engineering & Management
Volume-6, Issue-12, 2021 ISSN No: 2348-9510

# SURVIVAL ANALYSIS IN HEART FAILURE PATIENTS BASED ON CLINICAL DATA USING AI-DRIVEN STATISTICAL

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*Abstract*

***The heart has to be protected and informed of its damage since it controls human life, among other functions. All coronary illnesses culminate in cardiovascular collapse. A survival prediction tool is necessary to address the issue of the high mortality rate caused by heart failure. This study investigates the use of several classification models for forecasting heart failure outcomes using the Heart-failure-clinical-records dataset by the UCI ML Repository. The research compares several ML models, including Random Forests (RF), KNN, DT, and NB, with a DL-based CNN. Data preprocessing techniques such as standard scaling and SMOTE are applied to address data imbalance and ensure accurate predictions. Our evaluation criteria for each model include their F1 score, precision, recall, and accuracy. The CNN model outperforms traditional ML models in terms of accuracy (99.95%), precision (99.93%), recall (99.96%), and F1-scor (99.97%). In contrast, the highest-performing ML model, Naive Bayes, achieves 87% accuracy. The results suggest that deep learning, particularly CNN, offers superior predictive capabilities for heart failure, making it an effective tool for early detection and improved patient care.***

***Keywords: Heart failure prediction, clinical data analysis, Heart Failure Clinical Records dataset, disease, machine learning.***

## I. INTRODUCTION

Constantly functioning organs are inseparable from the continuance of human existence. The heart is the most important organ because it carries oxygen-rich blood to every part of the body via its pumping action. The body subsequently receives the oxygen and nutrition it needs via blood. In addition to the brain, the heart is the body's final line of defence against harmful substances. Nobody can stop this heartbeat. How many beats per minute is the common definition of heart rate [1].

The leading cause of death globally is heart disease. Every year, heart disease and stroke claim the lives of over 2 million Americans. Problems with the heart and blood circulation are symptoms of heart disease, which is an illness of the system of big blood vessels [2]. Heart problems such as rheumatic heart disease, CHD, and heart failure are among the many disorders that impact the cardiovascular system [3][4]. Patients with heart disease are at higher risk of death and morbidity due to heart failure, the last stage of the illness. Heart failure is becoming more common as a result of future life expectancy rises and improvements in myocardial infarction treatment treatments that extend the lives of people with compromised heart function.
A complete assessment of symptoms, medical history, physical exam findings, and diagnostic

International Journal of Core Engineering & Management
Volume-6, Issue-12, 2021 ISSN No: 2348-9510

procedures is necessary to diagnose heart failure. Nonetheless, ML techniques may bolster the diagnosis and prognosis of this illness as technology advances and computers get better at processing data. Recently, there has been a lot of buzz in the medical profession about how ML methods may help detect and forecast heart diseases [5][6]. ML algorithms have the ability to go through vast amounts of patient information in pursuit of patterns and associations that healthcare providers may miss [7][8].

### A. Motivation and Contributions of the Study

As a leading cause of mortality globally, heart failure impacts millions of individuals every year. Predicting heart failure episodes early on is critical for better patient outcomes and lower death rates. This study adds to a growing body of knowledge in predictive healthcare by tackling the challenge of heart failure prediction using ML and DL methods. The key contributions of this research include:

- Training models and conducting analyses using the Heart Failure Clinical Records Dataset, which provides a solid basis.
- Addressing data quality and class imbalance using standard scaling and SMOTE.
- Implementing and comparing multiple ML models (Random Forest, K-NN, Decision Trees, Naive Bayes) with a CNN model.
- Assessing model performance using F1-score, recall, accuracy, and precision.
- Making progress on a predictive paradigm for the early diagnosis and treatment of heart failure.

### B. Organization of the paper

Here is how the paper is organised: Sections I and II include the most recent findings from studies involving heart failure patients. Section III subsequently lays out the process for this. Section IV follows with the findings and discussion, followed by Section V with a conclusion and future scope. Finally, the section concludes and discusses potential future endeavours.

## II. LITERATURE REVIEW

The literature on the topic of heart failure forecasting employing ML and DL methods is presented in this section.

In this work, Tripoliti et al. (2017) predict whether heart failure patients will take their medicine as prescribed by mining a dataset that includes biomarkers measured in their breath and saliva. The second phase involves feeding an output of a classification model with information by breath and saliva biomarkers to ascertain if the patient is following their medication schedule. An evaluation of the approach using a dataset consisting of 29 patients reveals an impressive attained accuracy of 96%[9].

In this paper, Tiwaskar et al. (2018) offer a comparative evaluation of statistical, ML, and data mining approaches to the problem of heart failure risk prediction. They test and compare the performance of several classifiers, such as CNN, DT, and RF. The corresponding model accuracies are 85%, 80.1%, 85.38 percent, and 93 percent. This enhances the validity of our empirical analysis, as CNN has never been used on the Cleveland dataset before [10].

In, Liu et al. (2019) to construct CNN-based deep learning models. Subsequently, make use of the models that have been built to identify and forecast admissions or patients that may pose a high risk. To assess their performance, we trained CNNs using MIMIC III's discharge summary notes. On prediction tasks, DL models seem to be superior to their normal counterparts. The CNN approach only manages F1 scores of 0.674 and 0.656 in 30-day readmission prediction, whereas the CNN technique obtains 0.756 and 0.733 in general readmission prediction, respectively [11].

In the study, Zhang et al. (2018) a database of 54 healthy individuals and 15 patients with CHF was used from Physio Net. The signals were sorted into several evaluation duration categories. Using classifiers from RNNs, RFs, and SVMs, we compared raw R-R intervals, R-R interval means and standard deviations (STDs), and clinically standard features of short-term (5-minute) HRV. Based on testing databases, the results revealed that selecting all HRV variables may produce a particular 30-minute period with a sensitivity of 88.55% and a specificity of 94.81%[12].

This paper, Sang et al. (2020) created an SVM model for heart failure prediction; this model addresses the issue of linear separability of nonlinear data in high-dimensional feature spaces by using crossover kernel functions and radial basis. By the end of the testing phase, the built SVM prediction model had an accuracy of 87.50% when applied to a heart failure clinical data set. Findings of an experiment demonstrate that the model's classification accuracy has been significantly enhanced, as measured by the model assessment indicators of accuracy, recall rate, and F value [13].

Table I shows prior studies on Evaluating ML Approaches for Heart Failure Patients using deep learning and machine learning methods, comparing their effectiveness.

TABLE I. Summary of the Related Work On Comparative Analysis And Forecasting

| Ref | Methodology | Dataset | Performance | Limitations & Future Work |
|---|---|---|---|---|
| [9] | Two-stage data mining approach: Anamnestic and instrumental data model in stage 1. | 29 patients (saliva and breath biomarkers) | Accuracy: 96% | Small dataset (only 29 patients); needs validation with larger cohorts to generalise findings. |
| [10] | Comparative study of statistical and ML techniques: DT, RF, CNN | Cleveland dataset | Accuracy: Statistical (85%), DT (80.1%), RF (85.38%), CNN (93%) | CNN applied for the first time to the Cleveland dataset; future work suggested exploring other neural network architectures. |
| [11] | Deep learning approach using CNNs trained on unstructured clinical notes (MIMIC III); Random Forest models used for comparison | MIMIC III clinical notes | CNN: F1 Score (General: 0.756, 30-day readmission: 0.733); RF: F1 Score (General: 0.674, 30-day: 0.656) | Limited to discharge summary notes; suggests leveraging other unstructured sources like physician notes for better predictions. |
| [12] | RNN, Random Forest, and SVM classifiers applied on HRV data with LOOCV technique; HRV features used over various time durations | PhysioNet dataset (54 normal subjects, 15 CHF patients) | Sensitivity: 88.55%; Specificity: 94.81% | Limited subject pool; recommends further experiments with larger datasets and additional clinical features. |
| [13] | SVM with radial basis kernel; grid search and cross-validation for hyperparameter tuning | Clinical heart failure dataset | Accuracy: 87.50%; Evaluation metrics: Accuracy, Recall, F1 Score | Limited to linear/nonlinear SVMs; suggests exploring ensemble methods and hybrid models for improved performance. |

International Journal of Core Engineering & Management
Volume-6, Issue-12, 2021 ISSN No: 2348-9510

## III. METHODOLOGY

Since heart failure is a leading cause of mortality worldwide, it is critical to predict when patients will have episodes so that medical intervention may be initiated promptly and patient outcomes can be improved. This project uses the Heart Failure Clinical Records dataset, which is maintained in the UCI ML repository, to predict the chance of heart failure based on a patient's medical records. It does this by employing models from ML and DL. By applying a combination of data pre-processing techniques, such as standard scaling and SMOTE for balancing, the study addresses challenges related to data quality and class imbalance. The methodology includes training various ML models—RF, KNN, DT, and NB—and comparing them with a DL-CNN model. After model training, evaluate the model performance with key performance matrices like f1-score, recall, accuracy, and precision. Figure 1 is a flow diagram showing the general procedure of the study design for predicting heart failure.

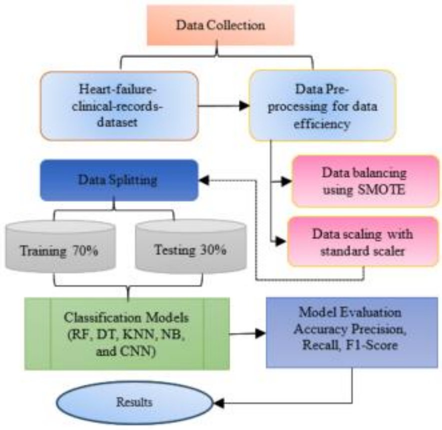


Fig. 1. Flowchart for Methodology for Heart Failure Prediction

The following steps of methodology for heart failure prediction are detailed below:

### *A. Data Collection*

We obtained the dataset of cardiac failure clinical records by the UCI ML repository. All of the patients' medical records that include cardiac problems make up the dataset. The data collected throughout the follow-up period includes thirteen clinical characteristics. Among the 299 patient records, 105 are female and 194 are male. Following Table II shows the description of the data.

TABLE II. DESCRIPTION OF DATASET

| Features | Description |
|---|---|
| Age | patient age (years) |
| Anaemia | decline in haemoglobin and red blood cell levels |
| Creatinine | Blood concentrations of the CPK enzyme (mcg/L) |
| Diabetes | while dealing with a diabetic patient |
| ejection_fraction | the portion of blood that is eliminated from the body as a result of heart contractions |
| high_blood_pressure | people afflicted with hypertension |

International Journal of Core Engineering & Management
Volume-6, Issue-12, 2021 ISSN No: 2348-9510

| | |
|---|---|
| Platelets | components of blood plasma (kilo platelet / mL) |
| Serum_creatinine | amount of creatinine in the blood serum (mg /dL) |
| Serum_sodium | blood sodium concentration in the serum (mEq/L) |
| Sex | Gender: female or male |
| Smoking | disregarding whether or not the patient smokes |
| Time | follow-up period (days) |
| Death_event | at completion of the follow-up |

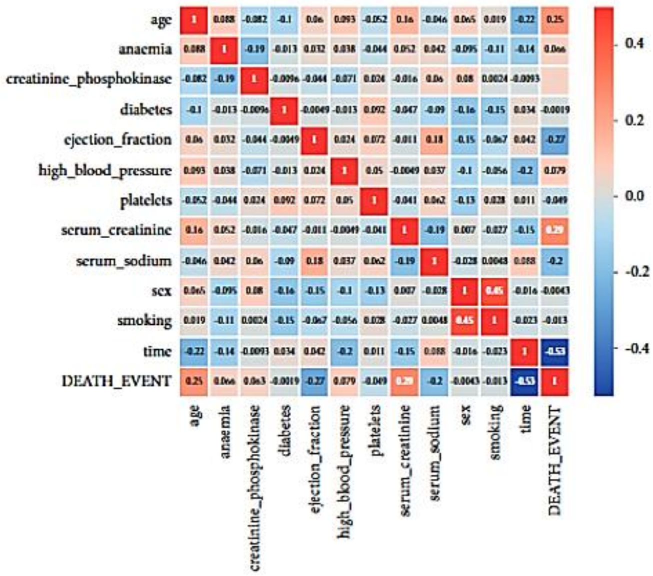


Fig. 2. Correlation heat map of data

Figure 2 displays a correlation heat map that depicts the associations between characteristics in a dataset, including the target variable, DEATH_EVENT. Red means there is a positive connection and blue means there is a negative correlation, and each column displays the correlation coefficient among two variables. Darker colours correspond to stronger connections, with values ranging from -0.4 to 0.4. Notably, time exhibits a moderate negative correlation with DEATH_EVENT, indicating that a longer time period is linked with a lower risk of a fatal event.

International Journal of Core Engineering & Management
Volume-6, Issue-12, 2021 ISSN No: 2348-9510

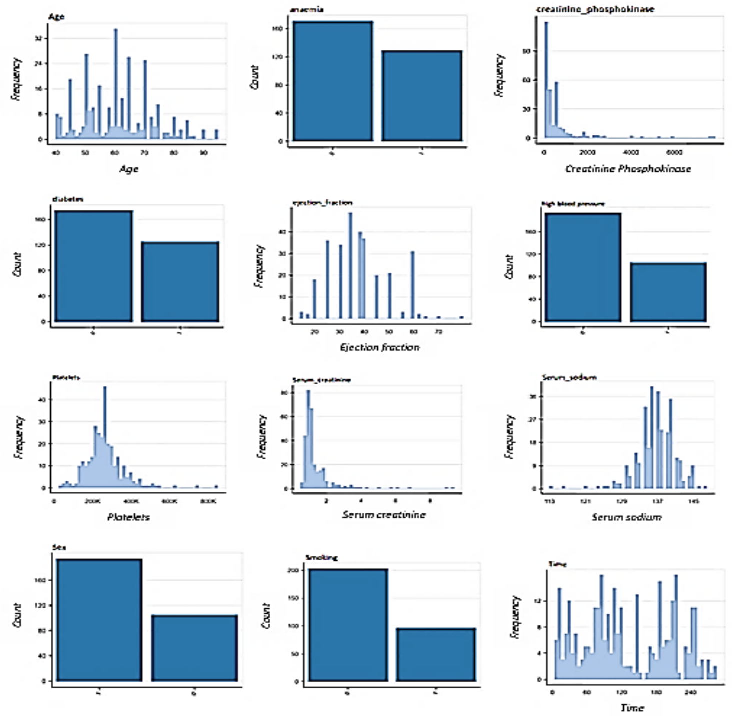


Fig. 3. Univariate distributions across key parameters

### B. *Data scaling with Standard scaler*

When working with datasets, data scaling is used to make sure that feature values fall inside a certain range, such 0 to 1 or -1 to 1. Regular scalar should be used for data scaling. When using the Standard Scaler approach, which is based on the Z-score normalisation, characteristics are standardised by dividing the sum of their standard deviations by their means. The result is a normally distributed set of numbers with zero mean and one unit variance [14]. A mean of the x variable, denoted as ¯x, is used in Equation 1 to scale a value xi into x 0 i.

$$x_j' = \frac{x_i - \bar{x}}{s}$$
(1)

The property's standard deviation acts as a scaling factor in this case, while the sample mean acts as the translational term. A technique's transformability is one of its advantages.

### C. *Data balancing with SMOTE*

SMOTE is an up-sampling technique that creates additional samples for under-represented groups by combining neighbouring samples. In order for it to function, it first generates a new sample at a location along a line connecting nearby samples in the feature space, which it draws between the samples. The first step is to randomly choose a subset of the minority class to serve as a target sample. The next step is to choose one neighbour at random from the set of k neighbours. Then, a synthetic sample is generated at random along the line in the feature space that connects the target point to this neighbour. A large number of synthetic samples representative of the minority group may be generated using this method.

### *D. Data Splitting*

The data was divided into training and test sets in a 70:30 ratio to establish the performance of ML and DL models for heart failure prediction.

### *E. Classification Models*

Predicting data classes and validating ML and DL model performance for heart failure are both accomplished via classification. What follows is an explanation of the following models:

**1) Random Forest**

The many DT that make up a RF work together as an ensemble. The model's forecast is based on the highest-ranked class after collecting predictions from all of the random forest trees. Even when faced with missing values, a RFC can preserve the accuracy of a wide range of data points [15].

**2) K-Nearest Neighbor (KNN)**

KNN is a lightning-fast algorithm. A non-parametric method, it operates on train-test sets without making any assumptions. The fact that it can generalise without any training data points gives rise to the name "lazy algorithm." [16]. As a result, the algorithm is able to quickly process input during training while storing all of that information for testing. Here It may see k-instances running training datasets.

**3) Naïve Bayes (NB)**

Among the many ML algorithms used for classification, the NB classifier stands out for its simplicity and power [17]. The Bayes theorem provides the foundation for this, stating that given a set of circumstances, the product of the conditional probabilities of each attribute subject to that event may be used to compute the likelihood of a specific event happening.

**4) Decision tree (DT)**

The building blocks of a decision tree are the nodes that are added to each branch until the tree reaches a terminal node. An attribute test is represented by every node in a decision tree, which has a class label. Decision tree algorithms' strengths lie in their simplicity of interpretation and their robustness against noise. A number of recent studies have utilised DT to forecast customer churn [18][19].

**5) Convolutional Neural Networks (CNN)**

The four primary layers of a CNN, which is a kind of feedforward neural network, are the input, convolutional, pooling, and output layers. Its unique network architecture gives it a leg up when it comes to learning and feature extraction, which is particularly useful for image recognition.

The convolution kernel establishes a connection between the CNN and the input layer. The convolution kernel accomplishes multi-scale feature extraction by means of dot multiplication via a sliding window [20]. In addition to drastically lowering the amount of free variables that need to be learnt, the convolution layer's weight-sharing technique makes it more efficient for feature extraction. We then minimise the feature matrix and network complexity by adding a pooling layer after the convolutional layer. Due to the one-dimensional nature of the ECG signals used as input, the convolution layer employs one-dimensional convolution[21].

International Journal of Core Engineering & Management
Volume-6, Issue-12, 2021 ISSN No: 2348-9510

Data normalisation was done prior to data training. The initial input is used by the 1econvolutional layer to extract features. Equation 2 displays the output of the a-th neurone in the one-dimensional convolutional layer.

$$O_a = \delta\left(\sum_{j=1}^{n} W_j X_{a-j+n} + b\right)$$
(2)

A weight coefficient matrix W, an offset coefficient b, and a number of convolution kernels n make up the input sequence X_1(l = 1, 2,...,n). The next step is to feed the output of the convolution layer back into the pooling layer after it has been entered into an activation function δ (here, ReLU) [22].

### *F. Model Evaluation*

This section introduces the evaluation metrics that will be used to analyse the method's outcomes. four assessment criteria to evaluate the strategy. The following definitions apply to the four metrics of accuracy, precision, recall, and F1-measure:

**Accuracy:** The accuracy score, which is short for "classification accuracy rating," is calculated by dividing the total number of forecasts by the number of correct predictions. Accuracy (A) is defined by Equation (3).

$$A = \frac{(True\ Positive + True\ Negative)}{(Total\ Number\ of\ Predictions)}$$
(3)

Where,

- **True Positive (TP):** This is the sum of all the observables that were anticipated to have a good outcome.
- **True Negative (TN):** This is the total of all favourable findings subtracted from all unfavourable forecasts.
- **False Positive (FP):** This is the amount of unfavourable findings that were expected to be favourable.
- **False Negative (FN):** Counting all the favourable observations that ended up being negative, this is the total.

**Precision:** The number of positive results (including those owing to misdiagnosis) divided by the number of true positive findings is used to calculate precision (P). In order to determine P, we must use Equation (4):

$$P = \frac{True\ Positive}{(True\ Positive + False\ Positive)}$$
(4)

**Recall:** The percentage of false positives relative to the number of TP is the recall. The recall is computed using Equation (5):

$$R = \frac{TP}{(TP + FN)}$$
(5)

**F1 Score:** The F1 score is used to measure an accuracy of a model for each class. It is common practice to use the F1-score measure when dealing with an imbalanced dataset. This is when the F1 score comes into play as a measure of the plan's efficacy. We use Equation (6) to calculate the F1-

International Journal of Core Engineering & Management
Volume-6, Issue-12, 2021 ISSN No: 2348-9510

score:

$$F1 = 2 \times \frac{precision \times recall}{(precision + recall)} \quad (6)$$

The following matrix explained in above is used to access the model efficiency.

## IV. RESULT ANALYSIS AND DISCUSSION

This section pertains to an examination and interpretation of the results, as well as the subsequent discussion. This section presents the CNN model, as summarized in Table III, indicating impressive performance across key classification metrics. This section also provides the comparative analysis of different models like RF [23], KNN [24], DT [25], NB[26], and CNN with performance matrix. When developing algorithms to enhance heart failure prediction, the Heart Failure Clinical Records collection is used for training purposes nationwide.

TABLE III. RESULTS OF THE CNN MODEL FOR HEART FAILURE PREDICTION ON HEART-FAILURE-CLINICAL-RECORDS-DATASET

| Matrix | Convolutional neural network |
|---|---|
| Accuracy | 99.95 |
| Precision | 99.93 |
| Recall | 99.96 |
| F1-score | 99.97 |

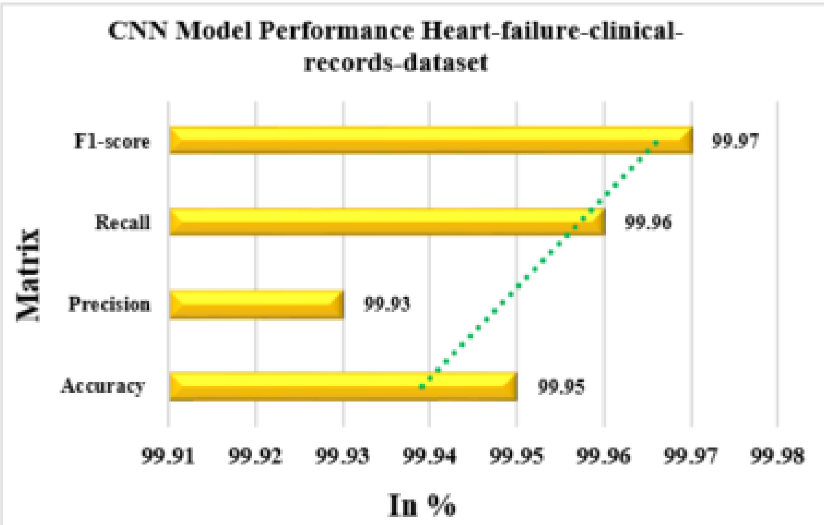


Fig. 4. CNN model Performance on Heart-failure-clinical-records-dataset

The CNN model demonstrates exceptional performance across all evaluation metrics, with an accuracy of 99.95%, precision of 99.93%, recall of 99.96%, and F1-Score of 99.977%. These high values show that the model has a balanced and strong classification skill, effectively recognising TP with little FP and FN. This performance suggests that the CNN is well-suited for the task, achieving near-perfect results.

International Journal of Core Engineering & Management
Volume-6, Issue-12, 2021 ISSN No: 2348-9510

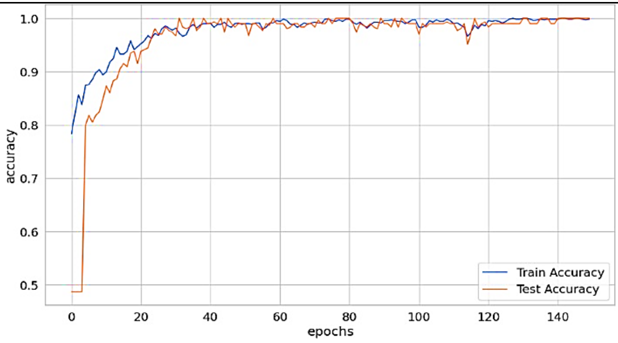


Fig. 5. Training and validation accuracy per epoch

Figure 5 displayed a CNN model's training and test accuracy over 150 epochs, with rapid improvement in the first 20 epochs and convergence around 99% accuracy. Both curves remain closely aligned, indicating strong generalisation with minimal overfitting. This shows that the model finds a strong middle ground between learning and generalisation, since it keeps performing well on validation data as well as training data.

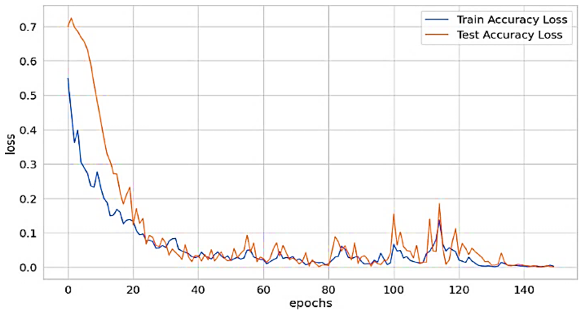


Fig. 6. Training and validation losses per epoch

Figure 6 displays the training and validation losses for each period. As the model gains confidence, a blue line shows a training loss, which lowers rapidly at the start but then levels out. The validation loss (orange line) also decreases initially but diverges from the training loss around epoch 30 and begins to increase after epoch 100, indicating overfitting. The model's performance on unknown data seems to be declining, indicating that it is beginning to memorise the training data instead of learning generalizable patterns.

TABLE IV. Comparison Between ML And DL Models for Heart Failure Prediction

| **MODELS** | **Accuracy** |
|---|---|
| Random forests**[23]** | 74 |
| KNN**[24]** | 75.09 |
| DT**[25]** | 80.60 |
| NB**[26]** | 87 |
| **CNN** | 99.95 |

The following Table IV shows the comparative analysis of model performance. In this comparison, CNN significantly outperforms the other models, achieving an impressive accuracy of 99.95%, which indicates its strong capability to capture complex patterns within the data. Among the traditional ML models, NB performs best with an accuracy of 87%, followed by DT at 80.60%, KNN at 75.09%, and RF at 74%. This suggests that while ML models like NB and DT can achieve reasonable accuracy, CNN's deep learning approach is far more effective for this task, making it the most suitable model for achieving high performance.

## V. CONCLUSION AND FUTURE SCOPE

Heart failure accounts for 8.5% of all heart disease fatalities and maybe 36% of CVD deaths worldwide, making it a major cause of mortality for individuals with diabetes and obesity. To improve patient outcomes via individualised treatment, decrease hospitalisations, alleviate symptoms, and intervene quickly, early identification is essential. Using ML and DL models, we presented a framework for forecasting the likelihood of cardiac failure in this research. The findings show that the CNN performs far better than the conventional ML models; it achieves an accuracy of 99.97%, a precision of 99.96%, and an F1-score of 99.97%. On the other hand, NB, the best ML model, achieved an accuracy87%. These findings highlight the superior capability of CNN in capturing complex patterns from clinical data, making it an ideal model for heart failure prediction. However, the study does have limitations. Despite being extensive, the dataset may not accurately reflect the variety of clinical data seen in the actual world, which might affect how well the model generalises. Further optimisation techniques, such as regularisation and dropout, can be applied to mitigate overfitting and enhance model performance on unseen data.

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