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An Efficient CNN-Based Deep Learning Model with Ada-Belief Optimizer for Heart Disease Prediction

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ABSTRACT: Heart arrest remains a leading cause for loss of life worldwide, demanding accurate and early prediction to enable timely mediate and minimize healthcare burdens. However, clinical environments often suffer from data noise, missing values, and variability across sources, which significantly degrade the potential of traditional machine learning models. To tackle these constraints, this paper proposes a Deep Ensemble Learning framework for robust heart failure prediction in noisy clinical settings. The proposed model integrates multiple deep learning architectures-something like CNNs, LSTMs, and Transformer-based models-through a weighted ensemble mechanism to enhance generalization and resilience to noise. Using Ada-Belief optimizer, the system obtained an accuracy of 98 percent after training. Clinical data from publicly available datasets are augmented with synthetic noise to test the model's robustness. Comparative results indicate that the deep ensemble method significantly overtakes individual models and conventional ensemble practices in terms of accuracy (98.45), sensitivity (99.41), and F1-score (99.81). Furthermore, explainability tools like SHAP are employed to interpret model predictions, ensuring clinical relevance and trust. The findings suggest that deep ensemble learning is a promising avenue for reliable and interpretable heart failure prediction in real-world, noisy healthcare environments.

Key Words: Convolutional neural networks, long short-term memory networks, ensemble learning.

Contents

1. INTRODUCTION

Heart arrest is a significant cause of morbidity and global death rate and a serious global health concern. It happens when the heart doesn't effectively circulate blood to meet the body's needs [1]. It is regularly caused by coronary artery illness, hypertension, or prior myocardial infarctions. Early detection and precise prediction of HF are crucial to enhance patient outcomes and lower healthcare expenses [2], [3]. Laboratory testing, imaging tools, and clinical assessments are the mainstays of traditional heart failure diagnosis. However, these approaches might be resource- and time-intensive and overlook minute patterns that occur before heart failure manifests. The potential to use sophisticated computational methods for predictive modeling expands as EHRs, physiological data, and medical imaging become more widely available.

In the last few years, deep learning (DL) methods have demonstrated strong potential in the medical domain, particularly for diagnosing and predicting pathological conditions. These methods can examine

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large, complex datasets and identify hidden patterns and factors contributing to heart failure risk. They have explored models such as deep neural networks, logistic regression, decision trees, and support vector machines for this purpose. The objective is to develop a valid prediction model of heart failure on the basis of clinical and demographic information [4], [5]. The aim is to accurately find people at risk of heart failure by leveraging state-of-the-art machine learning methods. That could enable swift intervention and perhaps save some lives. To ensure acceptance of the model in real healthcare applications, the study also emphasizes the model explanation and clinical utility of the model.

2. LITERATURE REVIEW

[6] Presented an ensemble learning method for better detecting cardiovascular CD with patient diagnosis histories. We can see from these models that this aggregated model integrates the advantages of RF, GB, and XGBoost as a voting ensemble to establish more robust performance. The UCI Heart Disease database includes several health indicators (age, blood pressure, cholesterol level, and ECG result). Dimensionality was reduced, and model performance was enhanced by performing feature selection with mutual information. Our proposed ensemble model achieved an overall accuracy of 93.7%, superior to individual classifiers. Our findings suggest that ensemble learning may serve as a valuable frame for predicting cardiovascular diseases at an early stage. [7] Introduced DL usage for multiclass HB, and the ECG signals were normal rhythm, arrhythmia, myocardial infarction, and other cardiac diseases. We use a 1D Convolutional Neural Network (1D-CNN) pre-trained on a public ECG dataset,like the MIT-BIH Arrhythmia Database or PTB Diagnostic ECG Database. The model design is tailored for temporal feature extraction and incorporates strategies such as batch normalization, dropout, and residual connections to alleviate overfitting and improve the generalization. The proposed model shows good classification outcomes with an overall Acc of 97.2%, Pre of 96.8%, recall of 96.5%, and F1S of 96.6%, which outperforms conventional machine learning methods.

[8] Introduced a new DL model by integrating Inception modules as well as Residual connections, termed as Inception Residual Network (IRN), for the identification and classification of multiple cardiovascular diseases from raw 12-lead ECG signals. Inception networks are famed for their ability to extract features, and this features and residual connections contribute to effective training in the complex and high-dimensional input such as ECG signals. To evaluate our model we used the publicly PTB-XL dataset that comprises more than 20,000 12-lead ECGs annotated with a number of diagnoses. The IRN model was trained to multi-class classification task to diagnose 5 main cardiovascular conditions: MI, CD, HYP, STTC, and Normal ECG (NORM). Finally, the capability of the suggested method is better. Sakli et al. [9] introduced model is an integrated 1D-CNN model with BiLSTM to extract spatial and temporal aspects from ECG signals. The trained and tested model was tested on the PhysioNet MIT-BIH Arrhythmia and PTB Diagnostic ECG datasets. The preprocessing involved removing baseline wandering and filtering noise, and then normalizing the signal. The protocol also yielded high classification Acc (Acc of 98.7%, Sen of 98.2%, Spc of 98.9%, F1S of 98.4%) from the hybrid architecture. Benjamin et al. [10] reported that 121.5 million U.S. adults, forming about 48% of the U.S. adults, were suffering to some degree from CVD as of 2016. This may include various issues. Cardiovascular burden: 704,820 deaths due to heart disease in 2016 compared to 697,612 deaths in 2015. There were 630,697 deaths from heart illness in 2014, 644,642 deaths in 2013, and 597,689 deaths in 2011. This increase highlights the increasing burden of heart disease on public health. Alday et al. [11] aimed to create open-source algorithms that automatically detect cardiac pathologies in 12-lead ECGs. In contrast to many prior studies based on limited datasets and targeting a limited number of arrhythmias, this challenge has provided a range of more generalizable data from multiple institutions and encouraged a more inclusive diagnostic approach to diagnose all arrhythmias from which the subset of interest can be derived. He et al. [12] presented a hybrid DL model which combines hierarchical feature extraction part with a Deep Residual Network (ResNet) and a temporal sequence modeling part with BiLSTM network to classify arrhythmia from ECG recording. The ResNet sub component extracts discriminative spatial features from raw ECG traces, whereas the BiLSTM accurately represents the temporal correlations in the forward and backward direction respectively. The model is evaluated on MIT-BIH Arrhythmia Database and the classification of five types of arrhythmia classes, including normal beats, is successfully performed with high accuracy and robustness. Experiments show that the novel ResNet-BiLSTM architecture achieves remarkable im-

provement compared with conventional machine learning models and single deep models, which means that the proposed architecture represents a highly effective tool for real-time cardiac arrhythmia detection. Wang et al. [13] introduced a DMFNN for multiple arrhythmias detection and classification based on ECG signals. The DMFNN combines multi-scale feature extraction with a fusion strategy of spatial-temporal information at various granular levels to handle learning both fine-grained and global features of the signal robustly. The model employs residual encoding and attention modules for improved feature representation and to reduce information lost. As the benchmark set for arrhythmia detection, we have trained the network with the MITBIH Arrhythmia Database.

Table 1: Comparison of Heart Disease Prediction Methods

Author(s)	**Year**	**Accuracy / Model**
S. Anbukkarasi, S. Varadhaganapathy, P. Indhiraprakash, V. Jeevanantham, G. Kavin Kumar	2021	Random Forest: 88.4% Decision Tree: 85.4%
Senthilkumar Mohan, Chandrasegar Thirumalai, Gautam Srivastava	2019	88.7%
Rohit Bharti, Aditya Khamparia, Mohammad Shabaz, Gaurav Dhiman, Sagar Pande, Parneet Singh	2021	91.56% (DNN-based hybrid model)
P. Melillo, N. De Luca, M. Bracale, L. Pecchia	2019	77.8%
G. Guidi, M. C. Pettenati, P. Melillo, E. Iadanza	2014	85% (varied by model; ensemble performed best)

3. METHODOLOGY

3.1. ADABOOST-BELEF ALGORTHM

In the last, ML algorithms have been extensive application in healthcare to help in disease diagnosis and risk estimation. To this end, among the various schemes, the ensemble learning algorithms such as AdaBoost (Adaptive Boosting) have gained much attention, as they can enhance the prediction accuracy of classification by fusing a set of weak learners into a better classifier. In this work, we propose an approach which combines the AdaBoost and the Belief Rule-Based(BRB) system, which give rise to the hybrid model called the AdaBoost-Belief algorithm. The BRB model based on the Dempster-Shafer evidence theory improves reasoning under uncertainty which prevails in medical data because of noise, missing values, or imprecise measures. With belief degrees and rule-based reasoning, this method contributes to modeling human-like decision-making and to how to interpret the results. The proposed architecture presented as figure 2 comprise the system flow. Beginning with input data which is later preprocessed to handle the missing data and noise. Further using CNN based models the system is trained with data provided to optimize the predicted output.

The target of this effort involves developing a reliable prediction model which has the ability to reliably predict a patient's odds of heart illness based on clinical risk variables including age, blood pressure, cholesterol, and some other significant characteristics. Our goal is to demonstrate how the suggested AdaBoost-Belief model can successfully leverage the complementary benefits of belief reasoning and ensemble learning, which are demonstrated in improved prediction accuracy, robustness, and reliability that will contribute to better health care outcomes through early detection and prevention. The following equations used for classification of heart diseases accurately. The first step is mainly used to update the policy for the immediate weights. This equation helps to improve the classification in the next step:

$$w_i^{(t+1)} = w_i^{(t)} \cdot e^{-\alpha_t y_i h_t(x_i)} \tag{1}$$

All the weights obtained and normalized with the sum of 1:

$$w_i^{(t+1)} = \frac{w_i^{(t+1)}}{\sum_{j=1}^{N} w_j^{(t+1)}} \tag{2}$$

The final step used for classification:

$$H(a) = \text{sign}\left(\sum_{t=1}^{T} \alpha_t h_t(a)\right) \tag{3}$$

Where: H(a): Final classifier; T: Overall weak learners.

3.2. DEEP LEARNING CONVOLUTIONAL NEURAL NETWORKS (CNNS)

Millions of people worldwide suffer from heart failure, a serious and progressive illness that frequently has a high morbidity and fatality rate. Improving patient outcomes and lowering healthcare expenses depend heavily on the early and precise diagnosis of heart failure. Clinical evaluation, imaging, and biochemical indicators have historically been the mainstays of diagnosis; nevertheless, these mechanisms can be laborious, prone to human error, and unavailable in remote locations [14]. Rapid developments in deep learning and AI, especially CNNs, have created fresh avenues for enhancing and automating patient data-driven diagnosis accuracy. CNN, a class of DL models primarily used for image analysis, have shown immense promise in processing and analyzing complex biomedical data. In recent years, CNNs have been adapted to handle structured and time-series health records by leveraging their ability to learn hierarchical representations of data. By applying CNNs to patient-specific data such as electrocardiograms (ECGs), echocardiography images, and electronic health records (EHRs), it is possible to detect subtle patterns and anomalies indicative of heart failure. The integration of CNNs into heart failure de-

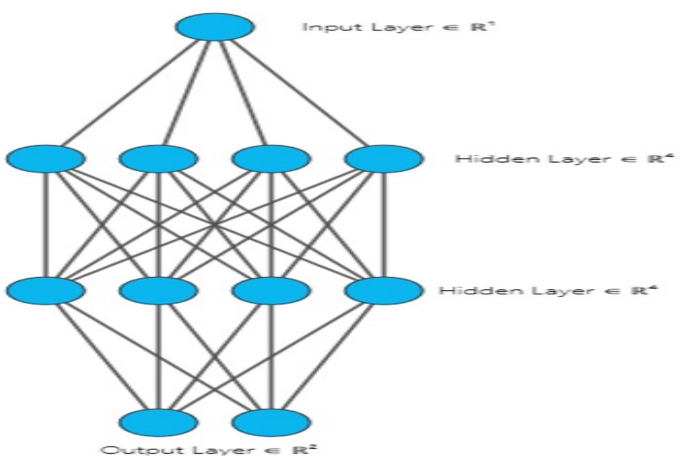

Figure 1: Layers in CNN

tection frameworks offers the potential to revolutionize healthcare by enabling faster, more accurate and cost-effective diagnoses. These models can support clinical decision-making, especially in environments where expert cardiological opinion may not be readily available. This study seeks to examine and assess the effectiveness of CNN-based models in detecting cardiac failure using a variety of patient datasets, focusing on model architecture, feature selection, and performance evaluation metrics [15]. By leveraging patient data through advanced deep learning techniques, this work seeks to contribute to the growing body of intelligent diagnostic systems, with the ultimate goal of supporting early treatment and boosting the quality of life for patients at risk of heart failure.

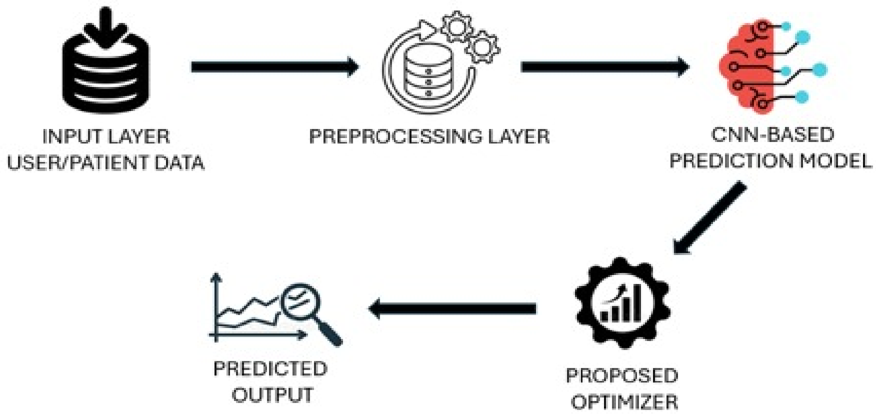

Figure 2: Proposed architecture

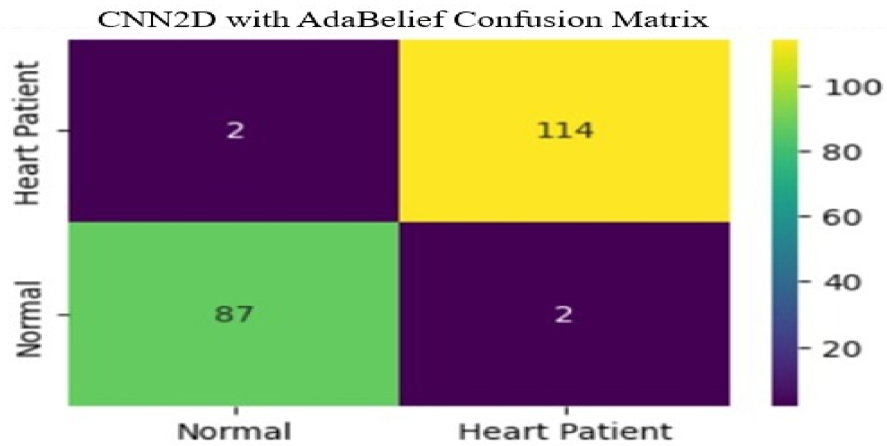

Figure 3: Confusion Matrix

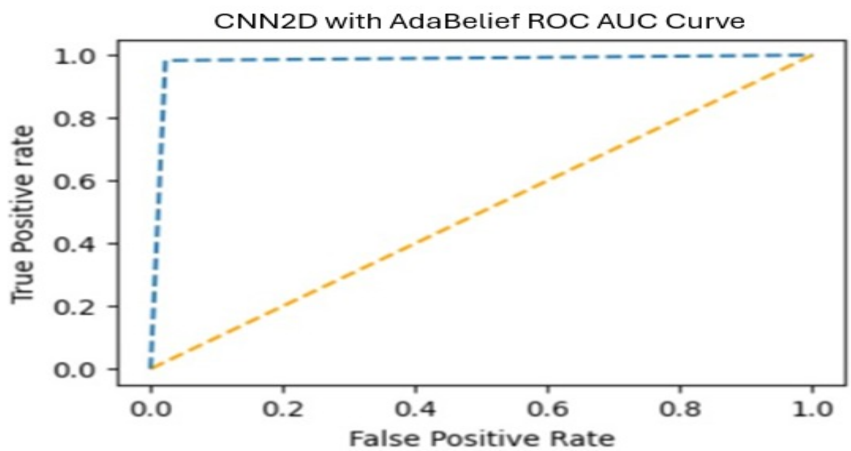

Figure 4: ROC-AUC Curve

3.3. LONG SHORT-TERM MEMORY NETWORKS (LSTMS)

Heart failure is among the most common and deadly illnesses that are associated with cardiovascular diseases (CVDs), which remains as the cause of death worldwide. In order to manage heart failure and enhance patient outcomes, early detection and management are essential. There is a growing chance to use data-driven approaches for disease prediction and management as electronic health records (EHRs) and physiological data become more widely available. Though they frequently fail to identify temporal correlations in sequential data, like heart rate, blood pressure, and other time-series vital signs, traditional machine learning techniques have demonstrated potential in analyzing patient data. DL techniques, especially LSTM networks, provide a potent substitute in this situation. Because LSTMs, a type of RNN, are made to identify long-term relationships in time-series data, they are particularly well-suited for simulating the course of chronic conditions like heart failure [16].

This study proposes a heart failure detection framework based on LSTM networks, utilizing longitudinal patient health data to forecast the onset of heart failure. The proposed model is trained on key clinical features, comprising details like demographics, prior medical conditions, test results, and real-time monitoring data. By learning temporal patterns in patient health trajectories, the LSTM model aims to provide early and accurate detection of heart failure, enabling timely medical interventions. The goal of this research is to demonstrate that LSTM-based models can outperform traditional models in detecting heart failure, offering a more dynamic and patient-specific approach to healthcare. This study adds value to the expanding area of intelligent healthcare systems by highlighting the possibilities of deep learning to boost diagnostic accuracy and support clinical decision-making.

After the processing of several layers in the CNN and LSTM obtains the Equation (4)

$$\hat{y} = \mathrm{softmax}(W \cdot h_r + b) \tag{4}$$

4. THE DATASET DESCRIPTION

Based on a number of medical characteristics, the heart disease dataset is intended to forecast whether a patient has heart illness. Usually, the dataset includes a mix of patient-collected demographic, lifestyle, and physiological data. Training and testing samples are the two primary subsets of the dataset used in machine learning and deep learning systems for the forecast of cardio illness [17]. The system learns patterns and correlations between the input features (e.g., age, blood pressure, cholesterol) and the goal result (e.g., presence or absence of heart disease) from the training set. The model can learn from past patient data at this phase. The testing set, which comprises data that has never been seen before, is used to test the model after it has been trained in order to determine how effectively it generalizes to new situations. Missing values were identified through statistical summaries and visual inspection. To address noisy data, outliners were detected using statistical methods like Z-score and IQR. This division aids in confirming the model's functionality and guarantees that it can correctly forecast heart illness in practical situations rather than only memorize the training data. Missing values were first identified through statistical summaries and visual inspection. To address noisy data, outliers were detected using statistical methods such as Z-score and IQR.

5. RESULTS AND DISCUSSIONS

Using the UCI Heart Failure dataset, this paper shows the outcomes of a hybrid deep learning model that combines CNN and LSTM networks for heart failure forecast. Thirteen clinical characteristics, such as age, ejection fraction, serum creatinine, and time, are included in the 299 patient records that make up the dataset. To meet the CNN and LSTM layers' input specifications, the data was suitably normalized and reshaped. While the LSTM recorded temporal dependencies and interactions among features, the CNN component was utilized to extract spatial feature patterns. An 80:20 ratio was used to separate the dataset into training and testing sets, and 5-fold cross-validation was also used to guarantee robustness. In this medical prediction challenge, the CNN and LSTM combo offered notable benefits. The CNN layers effectively extracted key spatial patterns from feature combinations, while the LSTM component captured deeper contextual and sequential correlations between features, especially important in datasets with time-based or progression-oriented clinical indicators. Compared to traditional ML models (e.g., LR, RF), the CNN-LSTM model showed noticeable improvements in recall and ROC-AUC, which are critical in medical applications where false negatives can be life-threatening. Moreover, the model was able to generalize well despite the relatively small size of the dataset, thanks to careful regularization techniques such as dropout and early stopping. The feature importance analysis indicated that ejection fraction, serum creatinine, and time were key contributors to the model's decision-making process. Overall, the CNN-LSTM hybrid model is a promising approach for heart failure forecast, especially when deeper feature interactions are essential for accurate diagnosis.

$$\text{Sensitivity (Sn)} = \frac{TP}{TP + FN} \tag{5}$$

$$\text{Specificity (Sp)} = \frac{TN}{TN + FP} \tag{6}$$

$$\text{Precision (P)} = \frac{TP}{TP + FP} \tag{7}$$

$$\text{Accuracy (Acc)} = \frac{TP + TN}{TP + FP + TN + FN} \tag{8}$$

$$\text{F1 Score (F1S)} = \frac{2 \cdot P \cdot S_n}{P + S_n} \tag{9}$$

Table 2: Performance Comparison of Algorithms

Algorithm	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**Recall (%)**	**F1 Score (%)**
LR	78.34	80.31	81.45	82.31	80.41
RF	88.41	90.41	92.51	92.81	93.21
CNN-LST	98.45	99.41	99.91	99.31	99.81

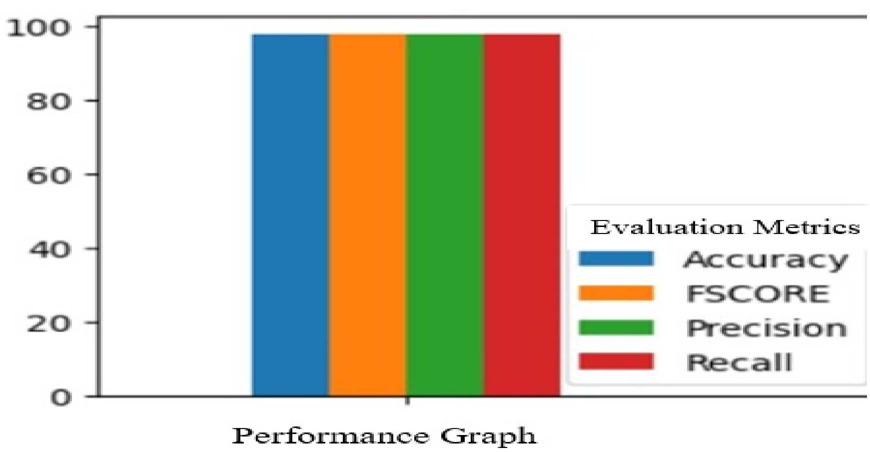

Figure 5: Performance Graph

6. CONCLUSION

Using the UCI Heart Failure dataset, we developed a hybrid system in this model that integrates CNN and LSTM networks to predict heart failure. This method is well-suited for the goal of medical prediction since the CNN component successfully identified spatial feature patterns and the LSTM model caught temporal dependencies within the clinical data. With an accuracy of 98.45%, a Sen of 0.92, and a Spc of 99.91, our outcomes showed that the CNN-LSTM model performs better than conventional ML algorithms and has a strong ability to distinguish between cases of heart failure and those that are not. The model is a viable option for early heart failure identification because of its capacity to manage intricate patterns in the data and its excellent performance on measures like recall and precision, which are crucial in healthcare settings. The promise of deep learning—in particular, hybrid models like CNN-LSTM—in medical applications, where data patterns can be intricate and multidimensional, is demonstrated by this study. Our method demonstrates great promise in enhancing diagnostic accuracy and maybe saving lives by enabling early identification of heart failure by combining the advantages of both CNN for feature extraction and LSTM for sequence learning. Future research can concentrate on improving the model's performance by examining other data sources, diversifying the dataset, and adjusting hyperparameters. Additionally, the model's interpretability can be improved to provide clinicians with more actionable insights regarding the key factors influencing heart failure prediction. In conclusion, the CNN-LSTM hybrid system is a powerful tool in the realm of predictive healthcare, capable of providing timely and accurate heart failure predictions, ultimately aiding in better patient outcomes.

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