Cardiac Heart Disease Prediction using Deep Learning-based Ensemble Classifier

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ABSTRACT

Cardiac heart disease (CHD) is the most fatal cause of death globally. Early detection of CHD helps to take preventive action to improve the lifestyle of the patient. This paper presents a hybrid ensemble classifier for the CHD prediction based on the Deep Convolution Neural Network (DCNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) layer. The DCNN enhances the spatial characteristics, LSTM provides long-term dependency, and GRU depicts the temporal characteristics of the patient's healthcare attributes. Further, improved Synthetic Minority Oversampling Techniques (ISMOTE) are used for data augmentation to minimize the class imbalance problem and achieve stability in training. The effectiveness of the suggested system is evaluated on the Framingham dataset consisting of The EC provides a recall of 98.7%, a precision of 99.5%, a selectivity of 97.3%, an F1-score of 99.1%, a negative predictive value (NPV), and an accuracy of 98.5% for the original dataset. The EC-ISMOTE offers the improved recall of 99.8%, precision of 99.8%, selectivity of 99.8%, NPV of 99.8%, F1-score of 99.8% and accuracy of 99.8% which has shown a noteworthy boost over the performance of traditional CHD techniques.

Keywords: *Cardiac heart disease prediction, deep learning, Deep Convolution Neural Network, Data Augmentation, Long Short-Term Memory*

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1. INTRODUCTION

Globally, Disease X impacts more than 34 million individuals and remains a major contributor to death and disability [1]. Cardiovascular diseases (CVD) are the world's leading cause of mortality, and the lack of medical personnel in underdeveloped nations makes the situation even worse [2]. Preventing mortality in rural regions may be achieved with the automated and early identification of heart diseases. Clinical auscultation using a stethoscope is a simple, effective, and cost-effective method of physically examining the human heart; nonetheless, it necessitates the expertise of qualified medical professionals [3-5]. Without the assistance of qualified medical professionals, automated identification of cardiac problems might be facilitated by signal processing-based heart sound analysis. For the early detection and screening of cardiac diseases, primary health clinics may benefit considerably from heart sound analysis [6-8].

A poor diet, a family history, heavy alcohol use, high blood pressure (BP), smoking, high cholesterol, diabetes, obesity, and physical inactivity are the main factors of heart disease [9- 10]. Heart conditions can be broadly classified into the following: pulmonary embolism, rheumatic heart disease, heart failure, coronary heart disease, heart attack, stroke, and congenital heart disease. A healthy lifestyle, frequent exercise, and controlling diabetes and hypertension can all help avoid CVDs [11]. For the identification of cardiac disease, several machine learning and deep learning strategies have been proposed in the past ten years. A Support Vector Machine (SVM) was used by Tabassum and Islam [12] to identify cardiovascular diseases (CVD), and they were able to identify atrial fibrillation (AF), myocardial infarction (MI), ST-segment abnormalities, and apnea with an accuracy of 84.6%. Heart rate, heart rate interval, QRS complex, RR interval, PR interval, and ST elevation were among the ECG characteristics used to train their SVM model. On the Cleveland dataset, Mohan et al. [13] also employed a Hybrid Random Forest with a Linear Model (HRFLM) to identify heart disease, with an accuracy of 88.7%. They emphasized that feature selection is essential to system functionality. Several algorithms, including K-Nearest Neighbor (KNN), SVM, Naive Bayes (NB), and Deep Neural Network (DNN), were assessed by Sharma et al. [14] for the diagnosis of cardiac disease. SVM (86.2%) fared better on the Cleveland dataset than DNN (81.9%), NB (83.97%), and KNN (81.43%), indicating that generative models may be used to generate synthetic datasets for better results. Using the Cleveland dataset, Li et al. [15] developed a fast conditional mutual information (FCMIM) feature selection approach that reduced processing time by selecting important features and increased SVM's accuracy to

92.37%. This indicates that the quantity, kind, and originality of characteristics employed determine how successful machine learning models are. When Prajwal et al. [16] examined several classifiers for CVD diagnosis, they found that SVM had the highest accuracy at 72.68%, followed by GB (70.03%), HV (71.32%), KNN (66.14%), ANN (72.51%), and Gradient Boosting (GB), KNN, and Hybrid Voting (HV). In order to help diagnose CVD, they included characteristics linked to BMI. Using Radial Basis Function SVM (RBF-SVM) on ECG data, Fang et al. [17] extracted QRS characteristics using the Pan-Tompkins technique and chose them using K-means clustering in order to identify heart illness. Compared to normal samples (99.74%), the model's performance on aberrant samples was somewhat lower (97.53%), but overall it achieved 98.98% accuracy.

For the detection of cardiac disease, machine learning (ML) approaches are simpler to apply than deep learning (DL) models; however, ML models typically perform poorly on larger datasets, and characteristics like data modality, feature extraction, normalization, and selection have a substantial impact on their outcomes [33–36]. However, DL-based frameworks have decreased preprocessing needs, enhanced noise immunity, greater correlations between local and global ECG properties, enhanced feature discrimination, and the capacity to handle bigger datasets. A Daubechies-6 mother wavelet function was used to reduce noise in an 11-layer Deep Convolutional Neural Network (DCNN) for myocardial infarction (MI) diagnosis by Acharya et al. [18]. 95.22% accuracy with noise reduction and 93.53% accuracy without it were reported. Although training required significantly more data and increased computing costs, they found that the DCNN without noise reduction outperformed the model with noise reduction. By effectively identifying heartbeats using local and global ECG characteristics, Zubair et al. [19] demonstrated how DCNNs can automatically extract ECG features. Using many convolutional layers made it possible to create more distinctive ECG characteristics than was possible with manual feature extraction. Computationally, 1-D DCNNs were more straightforward for multiclass cardiac arrhythmia identification [20–21]. Premature ventricular contractions (PVC), atrial premature beats (APB), and regular beats were all diagnosed with 98.335% accuracy by a 4-layer DCNN created by Avanzato and Francesco [22], exceeding algorithms even in the absence of data pre-processing. Ahmed et al. [23] proposed various machine learning classifiers for heart failure classification in the Framingham dataset. The random forest (RF) achieves an overall accuracy of 87.03%, outperforming the support vector machine (SVM) (67.24%), KNN (60.34%), and logistic regression (82.76%). Krishnan et al. [24] suggested a recurrent neural network for heart disease prediction that considers SMOTE for data augmentation. The multiple gated recurrent unit (GRU) is utilized to tackle the problem of vanishing gradients in RNNs that arises due to the learning of long sequence categorical data. Data augmentation helps alleviate the class imbalance problem by generating synthetic samples from the Framingham dataset. The GRU-RNN provides an accuracy of 81.43% whereas GRU- RNN-SMOTE achieves an overall accuracy of 98.78% in predicting heart disease.

Based on the thorough study, it is found that the HDD is difficult due to specific research gaps, which are summed up as follows:

- Inadequate feature representation, discriminating capacity, and connectivity
- Instability in training and low accuracy during testing due to class imbalance caused by uneven dataset size
- Limited generalization capability of the model;
- Complicated structures of DL frameworks and transfer learning models increase computation burden and restrict their deployment on standalone devices with limited resources;
- Poor accuracy due to an imbalance in the variability of features between and within classes
- The characteristics have poor correlation and long-term dependency.

This paper presents a deep learning based CHD prediction to improve the feature distinctiveness and CHD prediction rate. The major contributions of the proposed system are summarized as follows:

- Development of the ensemble classifier based on DCNN, LSTM, and GRU, where DCNN helps to offer spatial correlation; LSTM depicts long-term dependency, and GRU provides the temporal depiction of the healthcare data.
- Development of improved SMOTE to enhance the variability in the synthetic dataset to minimize the class imbalance problem and achieve stability in training.
- To evaluate the performance of the proposed system on the Framingham dataset based on accuracy, precision, recall, NPV, selectivity, and F1-score.

The rest of the article is summarized as follows: Section 2 offers the details about the proposed methodology and ISMOTE. Section 3 delivers the experimental results and their discussions. Section 4 offers the conclusions and future scopes.

2. METHODOLOGY

The flow diagram of the proposed EC classifier is shown in Fig. 1, which consists of data preprocessing, feature representation using EC, and CHD prediction using a softmax classifier. The pre-processing stage consists of data augmentation using improved SMOTE, feature normalization, and removal of missing values. Data augmentation helps to minimize the data augmentation issue, and normalization and missing value removal help to standardize the data and remove abnormal values in the dataset. The DCNN helps to provide the spatial correlation and connectivity between the healthcare attributes that comprise the behaviour, demographics, and health data. The LSTM provides the long-term dependency and temporal depiction between the healthcare attributes. The GRU helps to achieve multilevel long-term dependency in medical attributes.

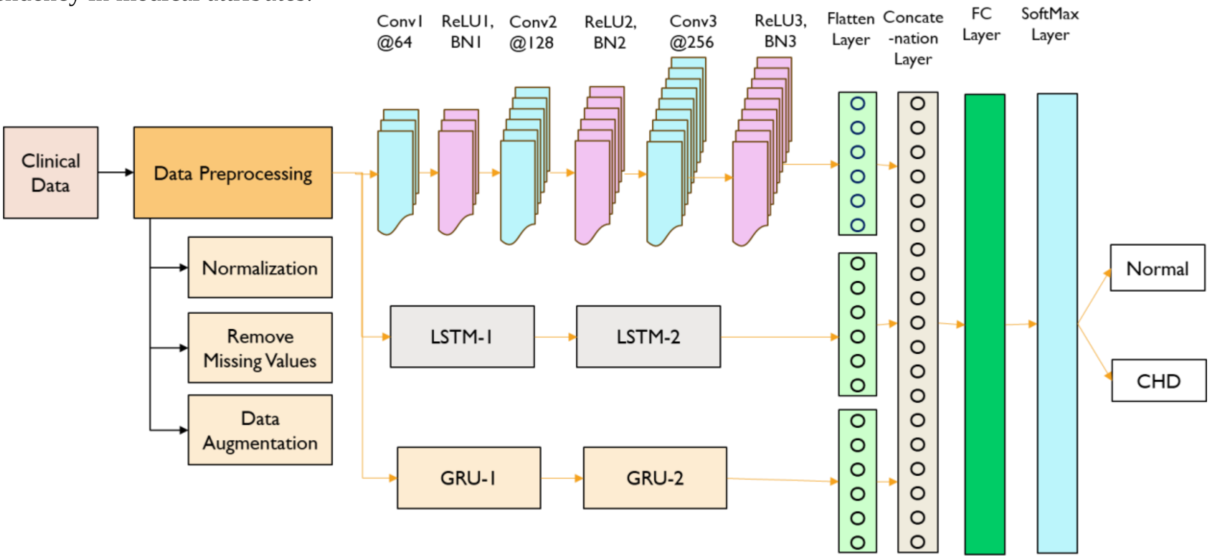


Fig. 1 Process flow of proposed algorithm

2.1 ISMOTE

SMOTE is utilized to minimize the class imbalance problem by creating synthetic samples. The larger training data helps to improve the training stability and accuracy, which leads to a significant boost in testing accuracy. The traditional SMOTE generator generates the synthetic data by duplicating the minority class samples, which may be poorly separated or sparse. The first step in ISMOTE is to extract the minority class samples from the dataset to generate the synthetic dataset. The minority class samples are represented using equation 1.

$$x_{min} = \{x_i | y_i = C_{min}\} \tag{1}$$

Here, denotes the features, depicts the class labels, and symbolizes the class label of the minority class. Further, the dataset is divided into k clusters using k-mean clustering algorithm to deal with the sparse data samples. The samples are augmented by considering the other samples from the same cluster. The synthetic samples for sample x are generated using randomly selected neighbors ( ) from Neighbors and mean value of attributes (of the cluster as given in equation 2. Here, and are two random numbers lies between 0 and 1.

$$x_{syn} = x + \lambda_1 * \{x_{nn} - x) + \lambda_2 * \{x_{avg} - x) + \tag{2}$$

2.2 Ensemble Classifier

The parallel combination of the DCNN, LSTNM, and GRU enhances the feature distinctiveness of medical data and facilitates feature connectivity, thereby improving CHD prediction. The proposed ensemble classifier uses the parallel combination of DCNN, LSTM, and GRU. The first parallel arm consists of a DCNN with three convolution layers having 64, 128, and 256

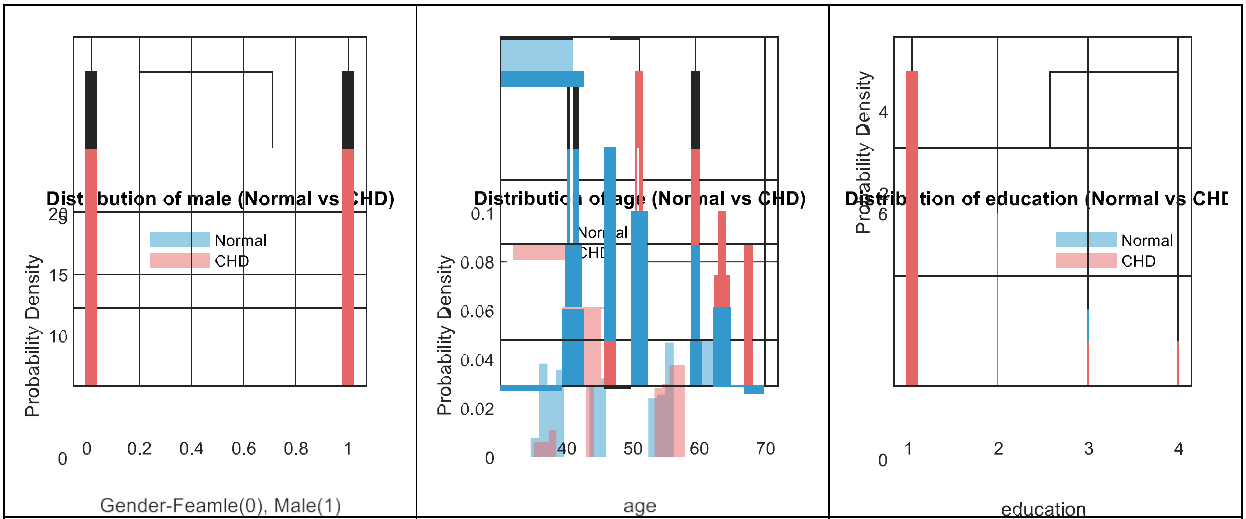
filters at the first, second, and third layers. The convolution layers are followed by a rectified linear unit (ReLU) layer and a batch normalization layer (BN). The ReLU layer improves the non-linear features of the attributes, and the BN layer standardizes the output of the ReLU layer to speed up the training process and avoid overfitting. The second parallel arm uses two LSTM layers with 50 hidden neurons, and the third parallel layer uses two GRU layers with 50 neurons in each layer. The outputs of the three arms are concatenated together, which are further given to the FC layer to enhance the connectivity in features obtained from DCNN, LSTM, and GRU. Finally, the softmax layer is utilized to classify the input features into standard and CHD labels.

3. EXPERIMENTAL RESULTS AND DISCUSSIONS

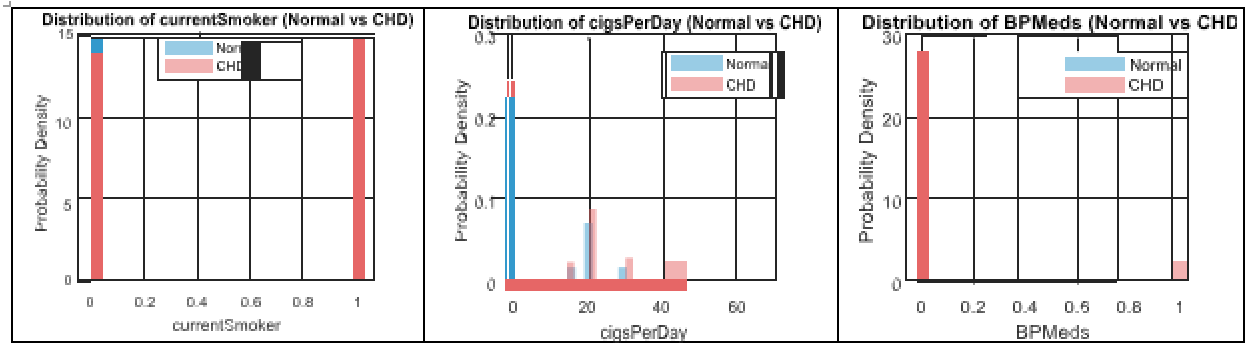
The proposed system is implemented using MATLAB programming language on a personal computer system with 16 GB of RAM, a Core i7 processor, 8 GB of graphics, and a Windows operating environment.

3.1 Dataset

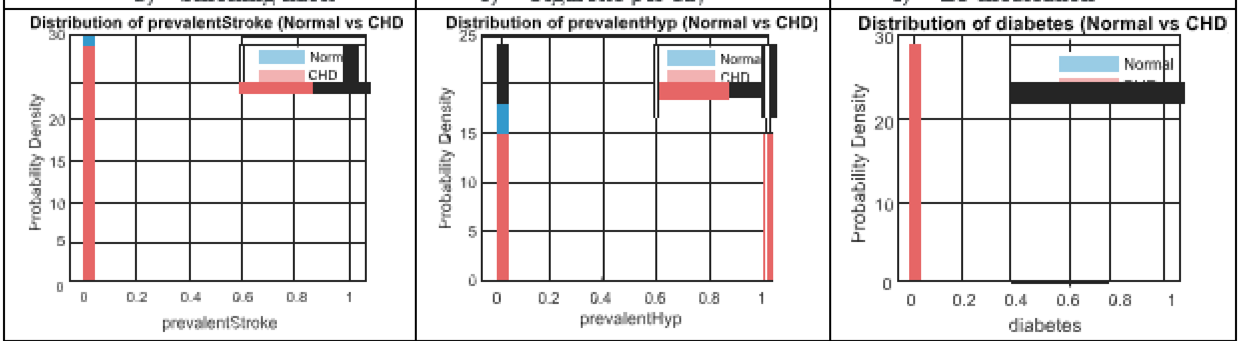
The "Framingham" dataset consists of 4240 samples having 15 attributes. The attributes include behavioural, physiological, pre-existing conditions, and demographic data of patients that are used to predict the 10-year risk of CHD. The behavioural attributes indicate the smoking habit (currentSmoker), cigarettes per day (cigsPerDay), and blood pressure medication (BPMeds); the demographics attributes contain gender, age, and education; the physiological attribute encompasses the systolic BP (sysBP), heart rate (HR), diastolic BP (diaBP), and glucose level. The pre-existing conditions consist of diabetes, stroke (prevalentStroke) and hypertension (prevalentHyp). The analysis of the dataset for various attributes providing the probability density of normal and CHD are visualized in Fig. 2 (a-o) respectively.



a) Gender | b) Age | c) Education



d) Smoking habit | e) Cigarette per day | f) BP medication



g) Prevalent stroke | h) Prevalent hypertension | i) Prevalent diabetes

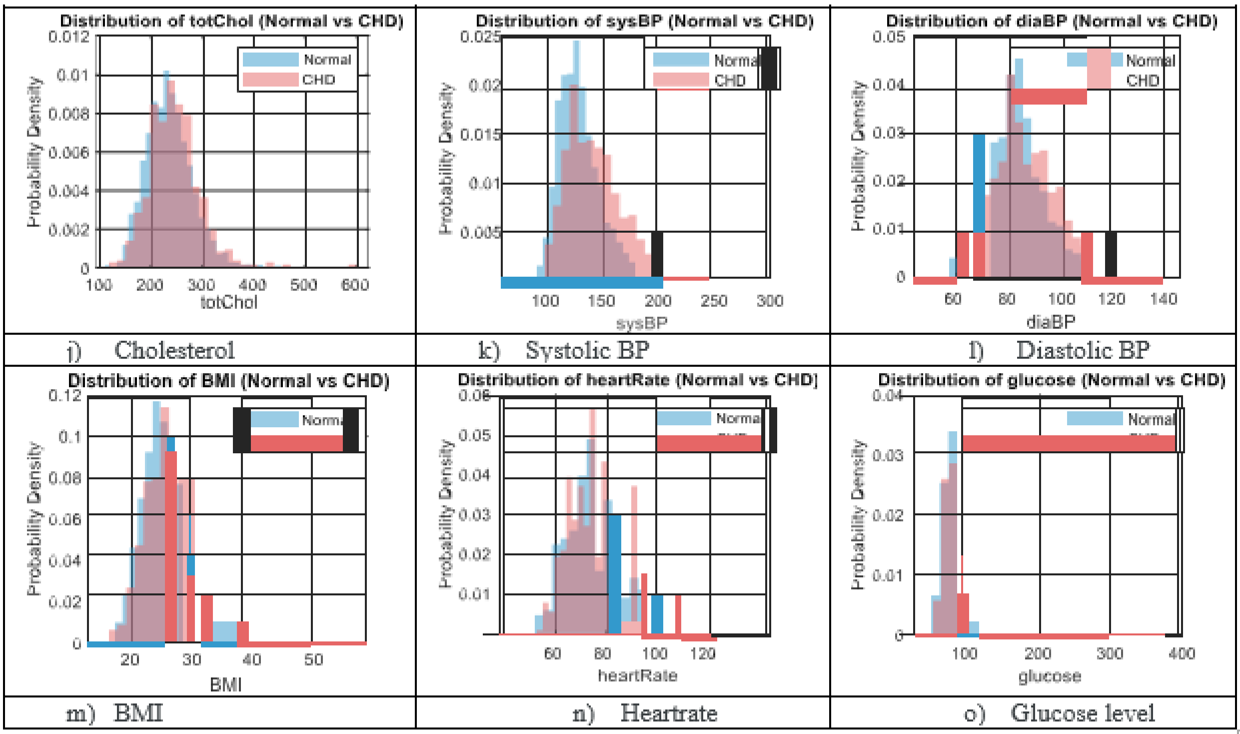
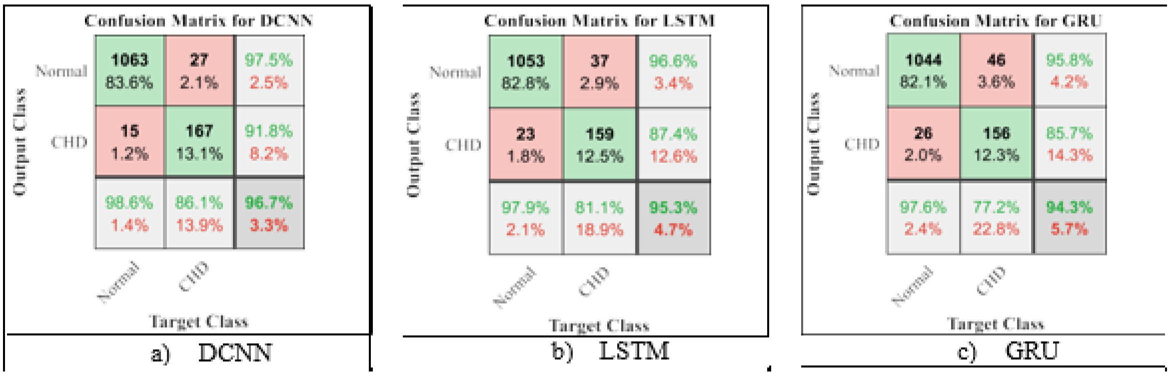


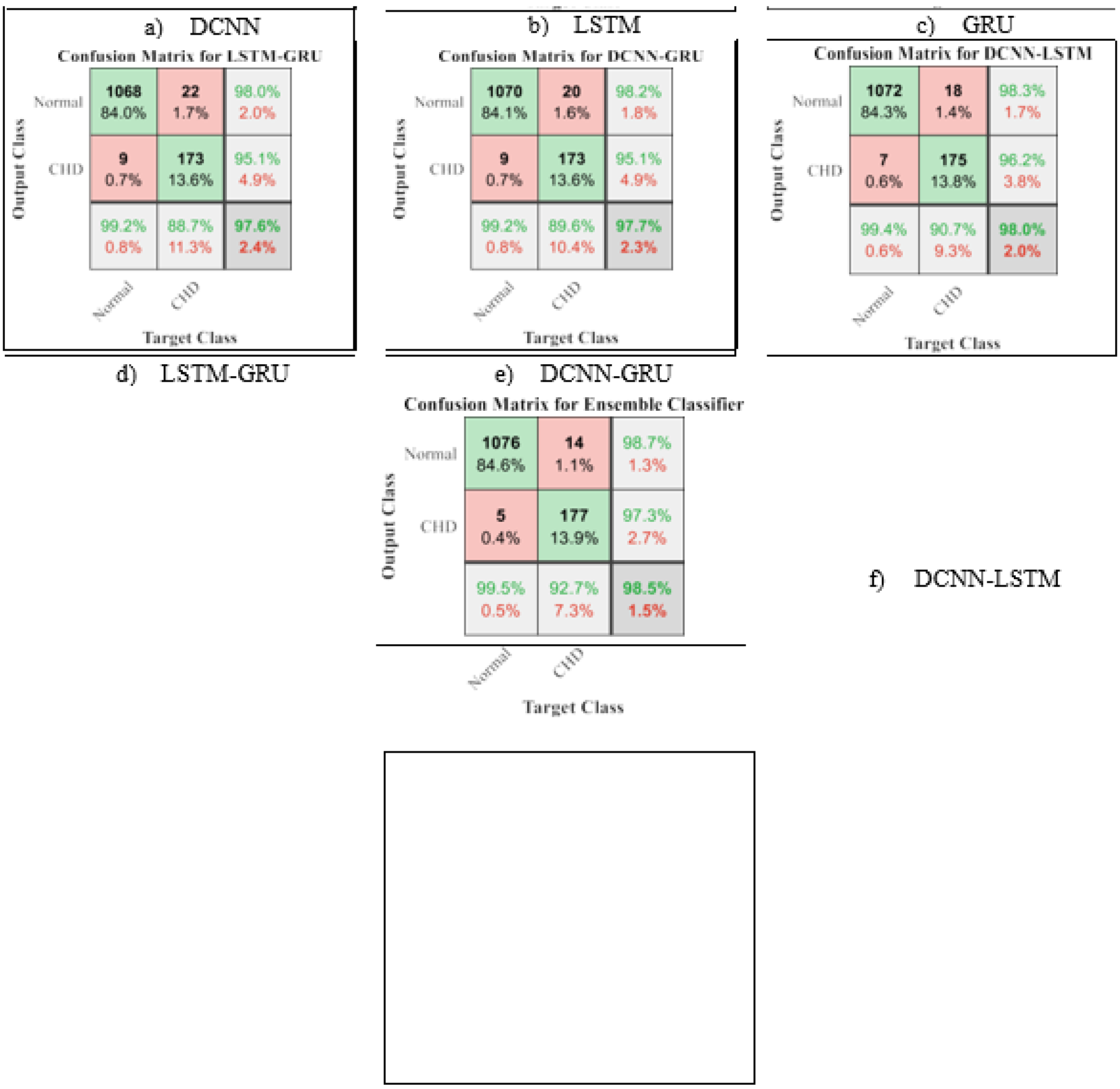
Fig. 2 Visualizations of the attributes of Framingham dataset

3.2 Comparative Results for EC for Original Dataset

The confusion matrices for various classifiers for the original Framingham dataset are shown in Fig. 3. The comparative analysis of the different classifiers for the CHDP without data augmentation is given in Table 1. The EC provides the improved accuracy of 98.5% which shows a noteworthy boost over the DCNN-LSTM (98%), DCNN-GRU (97.7%), LSTM-GRU

(97.6%), DCNN (96.7%), LSTM (95.3%), and GRU (94.3%) by combining the advantages of DCNN, GRU, and LSTM. The imbalance in the training data results in poor NPVs of 92.7% for EC, 90.7% for DCNN-LSTM, 89.6% for DCNN-GRU, 88.7% for LSTM-GRU, 86.1% for DCNN, 81.1% for LSTM, and 77.2% for GRU. The lower samples of the CHD class result in a lower prediction rate, which limits the system's reliability for real-time implementation. The lower training samples also result in lower selectivity compared to the precision and recall of the CHDP. Among the individual classifiers, DCNN provides improved outcomes compared to LSTM and GRU, achieving an accuracy of 96.7%, a recall of 97.5%, a precision of 98.6%, a specificity of 91.8%, an F1-score of 98.5%, and an NPV of 86.1%. When two classifiers are combined, DCNN-LSTM offers improved recall of 98.2%, precision of 99.4%, selectivity of 96.2%, F1-score of 98.85%, NPV of 90.7%, and accuracy of 98% compared to LSTM-GRU and DCNN-GRU. The EC offers an improved recall of 98.7%, a precision of 99.5%, a selectivity of 97.3%, an accuracy of 98.5%, an NPV of 92.7%, and an F1-score of 99.10%.





g) EC

Fig. 3 Visualizations of the confusion matrices for various classifiers for the original dataset

Table 1: Comparison of EC for original dataset for CHD prediction

Algorithm	Recall	Selectivity	Precision	F1-score	NPV	Accuracy
GRU	95.9	85.7	97.6	96.74	77.2	94.3
LSTM	96.6	87.4	97.9	97.25	81.1	95.3
DCNN	97.5	91.8	98.6	98.05	86.1	96.7
LSTM-GRU	98.0	95.1	99.2	98.60	88.7	97.6
DCNN-GRU	98.2	95.1	99.2	98.70	89.6	97.7
DCNN-LSTM	98.3	96.2	99.4	98.85	90.7	98.0
EC	98.7	97.3	99.5	99.10	92.7	98.5

3.3 Comparative Results for EC-ISMOTE for the Augmented Dataset

The effectiveness of the proposed CHDP method for the augmented dataset is given in Table 2 for different algorithms. The Ensemble Classifier (EC) achieves the highest accuracy of 99.8%, showing a notable improvement over all other models, including DCNN-LSTM (99.7%), DCNN-GRU (99.5%), LSTM-GRU (99.4%), DCNN (98.3%), LSTM

(98.5%), and GRU (99.0%). The augmentation strategy significantly enhances classification performance by increasing the diversity and representativeness of training samples. The EC also provides the best performance across all other metrics, with a recall, precision, F1-score, selectivity, and NPV of 99.8%, demonstrating its strong generalization ability and robustness. Specifically, DCNN achieves a recall of 98.2%, precision of 98.4%, F1-score of 98.4%, NPV of 98.2%, and accuracy of 98.3%, indicating that while it performs reasonably well, it lacks the comprehensive balance achieved by hybrid or ensemble models. Among the hybrid models, DCNN-LSTM achieves a recall of 99.7%, precision of 99.6%, selectivity of 99.6%, F1-score of 99.6%, NPV of 99.7%, and an accuracy of 99.7%, showcasing a strong performance very close to the ensemble. Similarly, DCNN-GRU and LSTM-GRU also benefit significantly from data augmentation, reporting accuracies of 99.5% and 99.4%, respectively, with consistently high values in other performance metrics.

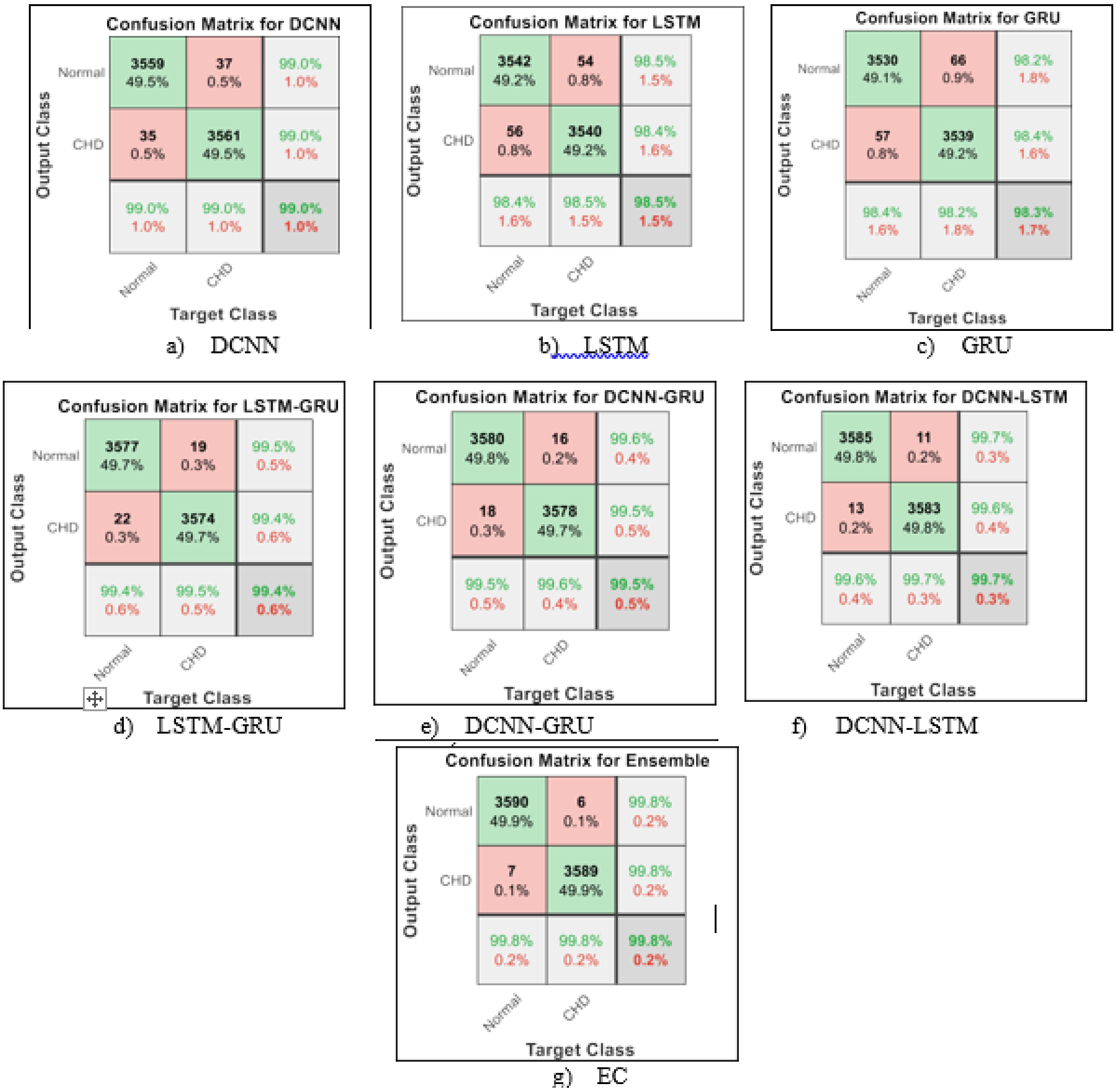


Fig. 4 Visualizations of the confusion matrices for various classifiers for the ISMOTE augmented dataset

Table 2: Comparison of EC-ISMOTE for the original dataset for CHD prediction

Algorithm	Recall	Selectivity	Precision	F1-score	NPV	Accuracy
GRU	99.0	99.0	99.0	99.0	99.0	99.0
LSTM	98.5	98.4	98.4	98.4	98.5	98.5
DCNN	98.2	98.4	98.4	98.4	98.2	98.3
LSTM-GRU	99.5	99.4	99.4	99.4	99.5	99.4

DCNN-GRU	99.6	99.5	99.5	99.5	99.6	99.5
DCNN-LSTM	99.7	99.6	99.6	99.6	99.7	99.7
EC	99.8	99.8	99.8	99.8	99.8	99.8

The comparison of various algorithms for CHD detection for EC, EC-SMOTE, and EC- ISMOTE is shown in Fig. 5- -10. A comparative analysis of the results reveals that the EC combined with ISMOTE significantly outperforms both its performance on original data and on data augmented using standard SMOTE, across all key evaluation metrics in heart disease prediction. In terms of accuracy, EC achieves 99.8% with ISMOTE, compared to 99.0% with SMOTE and 98.5% on the original data—a clear gain of 1.3 percentage points over the original. For recall, EC-ISMOTE scores 99.8%, surpassing 99.1% with SMOTE and 98.7% without augmentation. Precision remains consistently high for EC, reaching 99.8% with ISMOTE, 99.8% with SMOTE, and 99.5% on the original dataset. The F1-score also peaks at 99.8% with ISMOTE, a gain from 99.5% with SMOTE and 99.1% initially. Selectivity improves from 97.3% (original) to 97.7% (SMOTE) and sharply to 99.8% with ISMOTE, highlighting the reduction in false alarms. The most significant improvement is seen in NPV, which jumps from

92.7% on the original dataset to 93.2% with SMOTE and further to 99.8% with ISMOTE, reflecting vastly improved confidence in negative predictions. Overall, the EC-ISMOTE combination consistently achieves the highest scores across all metrics, showing improvements of up to 7.1 % in NPV and 2.5% in recall compared to the original dataset, validating its superiority in both sensitivity and reliability for heart disease prediction.

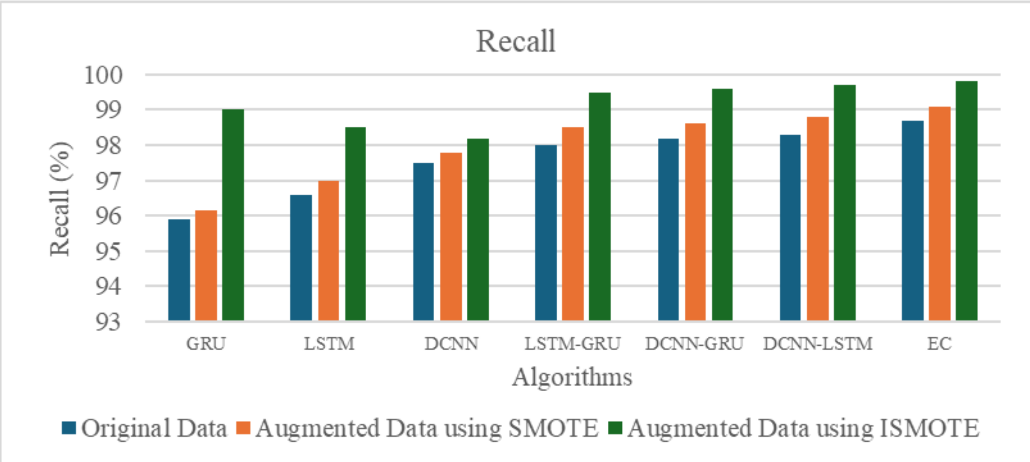


Fig.5 Recall comparison of various methods for CHD prediction

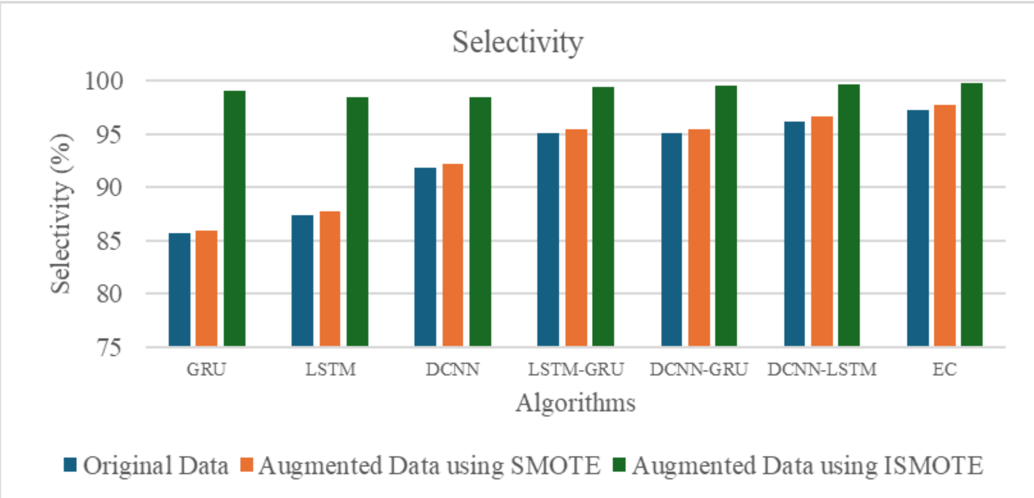


Fig. 6 Selectivity comparison of various methods for CHD prediction

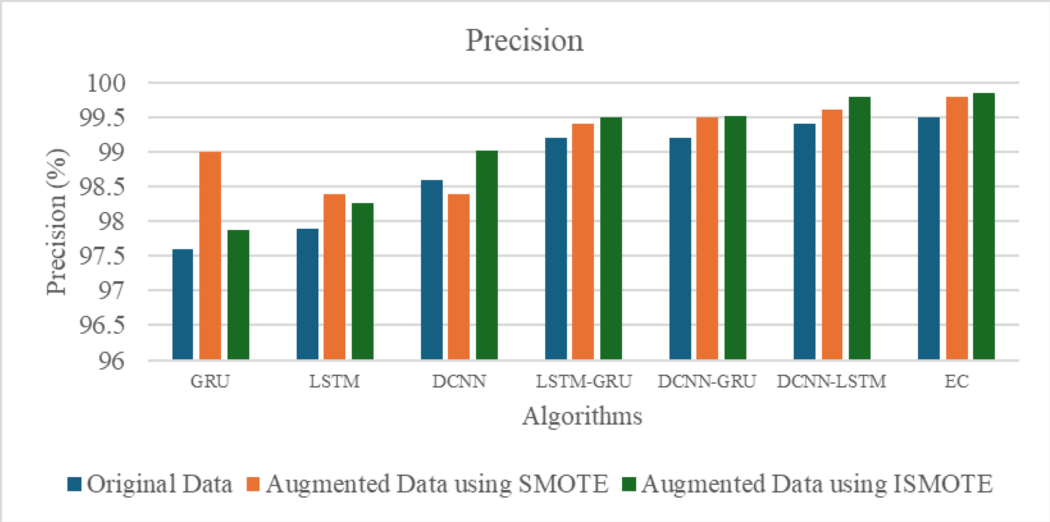


Fig. 7 Precision comparison of various methods for CHD prediction

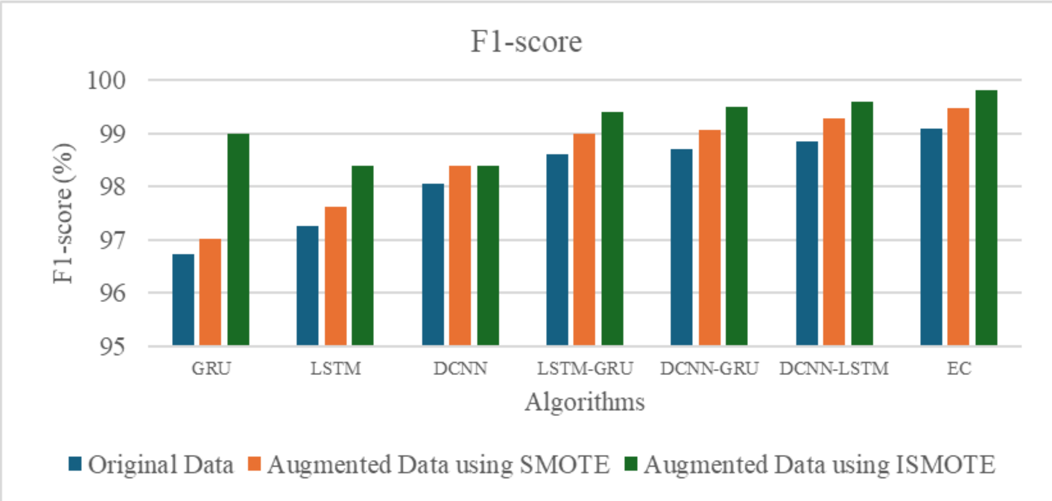


Fig. 8 F1-score comparison of various methods for CHD prediction

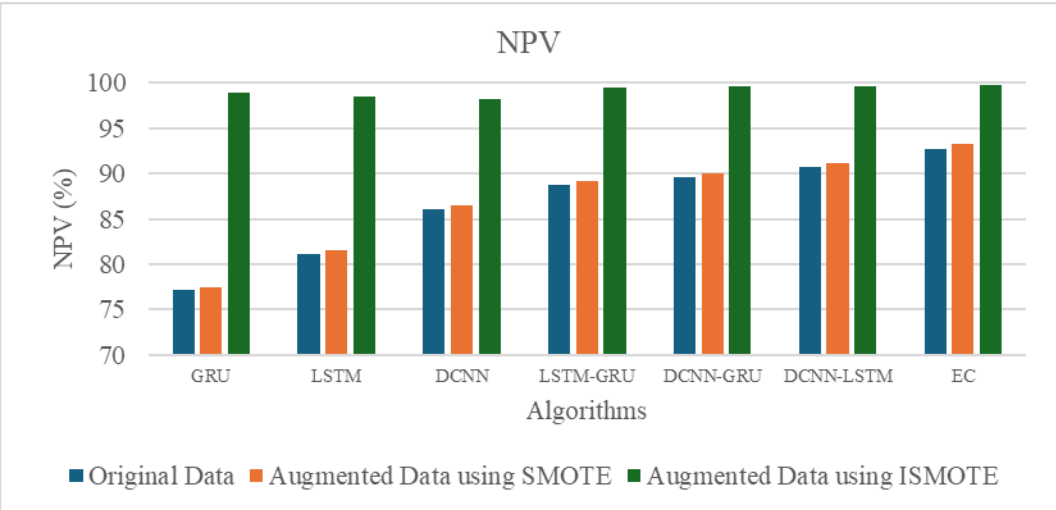


Fig. 9 NPV comparison of various methods for CHD prediction

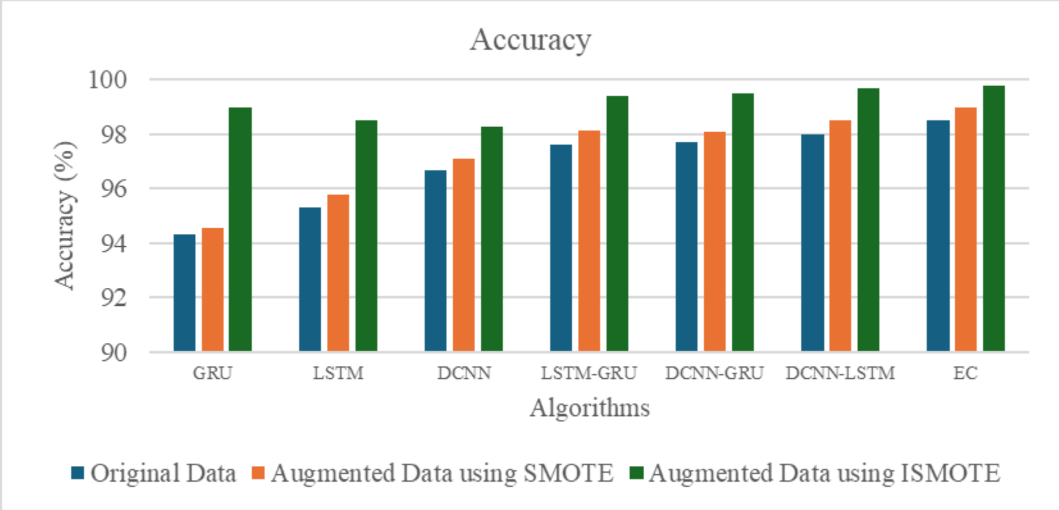


Fig. 10 Accuracy comparison of various methods for CHD prediction

3.4 Comparative Results of EC with previous state of the arts

The comparative analysis of various CHD prediction models using the Framingham dataset shows a clear progression in classification performance as given in Table 3. Earlier approaches like SVM by Hagan et al. [26] and the ensemble model by Mienye et al. [25] achieved accuracies of 92% and 91%, respectively. Ahamed et al. reported a lower accuracy of 87.03% using RF. In contrast, Krishnan et al. [24] demonstrated a substantial improvement by combining GRU-RNN with SMOTE, reaching an accuracy of 98.78%. Building upon this, the proposed method employs EC, which achieved an accuracy of 98.5%. Incorporating SMOTE with EC further improved the performance to 99.0%, effectively addressing the class imbalance. The highest accuracy of 99.8% was achieved using EC with ISMOTE, indicating that enhanced oversampling strategies significantly improve prediction reliability. These results validate the effectiveness of combining EC with advanced sampling techniques for accurate CHD risk prediction.

Table 3: Comparative Results of EC with previous state of the arts

Author and Year	Method	Accuracy
Hagan et al. [26]	SVM	92%
Mienye et al. [25]	Ensemble Classifier	91%
Ahamed et al.	RF	87.03%
Krishnan et al. [24]	GRU-RNN-SMOTE	98.78 %
Proposed Method	EC	98.5%
	EC-SMOTE	99.0%
	EC-ISMOTE	99.8%

4 CONCLUSIONS

Thus, this work presents the CHD based on the EC, which combines the advantages of the DCNN, GRU, and LSTM for improving the feature depiction. It uses the ISMOTE for data augmentation, which increases the variability of the synthetic dataset. The proposed EC- ISMOTE offers improved accuracy of 99.8%, recall of 99.8%, precision of 98.8%, NPV of 99.8%, selectivity of 99.8%, and F1-score of 99.8%. The ensemble classifier resulted in improved accuracy of 99.8% compared with 99.7% of DCNN-LSTM, 99.5% of DCNN-GRU, 99.4% of LSTM-GRU, 98.3% of DCNN, 98.5% of LSTM, and 99% of GRU for the augmented dataset. In the future, the effectiveness of the system can be assessed for a larger real-time dataset, considering more behavioural and physical parameters. The system can be integrated with the ECG-based CHD to improve the CHD prediction accuracy.

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