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A Novel Improved Method for Prediction of Heart Disease using ECG Hybrid 0F PTB-ECG and MIT-BIH Signal Dataset

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Abstract

Heart disease is the leading cause of death worldwide, making early detection critical. Various diagnostic methods, including clinical tests, CT, MRI, ECG, and impedance cardiography, are commonly used to detect heart disease. However, traditional coronary artery disease (CAD) detection methods using ECG data face challenges due to the time-series nature of ECG signals, which complicates handling multiple classes. To address this, the study proposes a deep learning-based approach that enhances CAD detection accuracy by integrating two models Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) with a hybrid dataset combining PTB-ECG and MIT-BIH data. This hybrid dataset consists of two target classes: normal (0) and abnormal (1), created by merging all MIT-BIH classes with the PTB-ECG normal class as “0” and abnormal samples from PTB-ECG as “1”. Pre-processing was performed using Gaussian distribution for normalization, standardization, and outlier removal. The study applied four classification approaches: CNN, CNN+LSTM, CNN with SMOTE-balanced data, and CNN+LSTM with SMOTE-balanced data. Results indicate

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that CNN with SMOTE-balanced data achieved the best performance, with training metrics of 0.9998 accuracy, 1.00 precision, 1.00 recall, and 1.00 F1-score for both classes. Testing results using CNN+SMOTE reached 0.9991 accuracy, 1.00 precision, 1.00 recall, and 1.00 F1-score. The model surpasses state-of-the-art studies, which achieved 0.992 accuracy and F1-score of 0.986 on PTB-ECG and MIT-BIH datasets, respectively. This study demonstrates that combining CNN with SMOTE on a hybrid dataset can significantly improve CAD detection accuracy.

Keywords: Deep learning, Machine learning, Heart disease, Coronary Artery Disease, PTB-ECG, MIT-BIH, Long Short-Term Memory, Convolution Neural Network.

1. Introduction

Over the past few years, cardiovascular disease has emerged as the primary cause of death worldwide. This is mostly because it has risk factors, such as hypertension, arrhythmias in the Pulse Rate (PR), diabetes, High Cholesterol (HC), and Glucose Levels (GL). Mental stress, physical inactivity, smoking, drunkenness, obesity, genetics, inadequate nutrition, and physical inactivity are all risk factors for cardiovascular disease. The electrocardiogram (ECG) signal is typically used to identify coronary artery disease, which is a kind of cardiovascular disease. This is because the ECG signal can detect abnormalities in the heart. However, because the amplitude of the ECG signal is typically relatively low, physicians frequently miss the opportunity to recognize its abnormalities. As a result, creating dependable deep learning-based models for the early detection and robust classification of Coronary Artery Disease (CAD) is a challenge that presents a significant obstacle. The fundamental challenge is correctly classifying coronary artery disease based on the ECG signal. Because of using ECG, the conventional models developed for correctly classifying coronary artery disease frequently require significant time to extract features and evaluate feature quality. Deep learning (DL) [1-7] was suggested as a solution to these issues by several researchers due to its ability to automatically and successfully extract abstract data. Inaccurate diagnosis may result from misclassification if these methods fail to adjust for long-range dependencies among data instances and vanishing or bursting gradients resulting from complex recursive structures. The gradient may become low, and parameter updates may become inconsequential for long sequences with several hundred-time steps, such as when processing ECG data with classic recurrent neural networks (RNN), making learning difficult with erroneous results. Additionally, other deep learning-based have emerged as a powerful approach for processing time series data, such as (PTB-ECG and MIT-BIH). In addition, the recent work given in Table 1 can be expanded to reduce the cost of implementing the previously created approach and raise the speed of operation by merging these two datasets so that the diagnosis can be determined based on the hybrid dataset. In this proposed study, we use two distinct DL models Convolution Neural Network (CNN) [8-9] and a Long Short-Term Memory (LSTM), with two sets of target data, normal and abnormal, to solve the problem of detecting CAD from a hybrid ECG signal dataset.

2. Literature Review

Table 1. Summary of Literature

Ref	Methodology	Results	Limitations and Shortcomings	Ref	Methodology	Results	Limitations and Shortcomings
[3]	HRFLM (Hybrid Random Forest & Linear Model)	Accuracy: 88.7 %	Limited dataset (UCI dataset with 303 records); no ECG signals used	[12]	Multi-layer Perceptron	Accuracy: 95.43%	Computation-intensive; limited ECG signal data
[4]	Random Forest with UCI Cleveland dataset	Accuracy: 90.16%	Small feature subset; limited dataset	[13]	CNN + LSTM	Specificity: 98.10%; Sensitivity: 94.5%	Requires high-quality ECG signals
[5]	K-Nearest Neighbor (k=7), RF, Decision Tree, Naïve Bayes	KNN achieved highest accuracy: 83.16%	Dataset-sensitive performance	[14]	Stacked CNN + Bi-LSTM	Diagnostic accuracy: 99.85%	High model complexity; intensive computation required

[6]	SVM, Logistic Regression, Naïve Bayes	SVM accuracy: 64.4%	Limited feature quality and missing data	[15]	SVNN + Genetic Bat Algorithm	Classification accuracy: 96.96%	Algorithmic complexity
[7]	KNN, LR, RF with 13 medical features	Accuracy: 87.5%	Dataset-specific results; accuracy may vary on new datasets	[16]	Bayesian XGBoost	Accuracy: 91.8%	High sensitivity to hyper parameters
[8]	NN, KNN, SVM for Algerian heart data	NN achieved 93% accuracy	Small dataset; limited generalizability	[17]	SOM + AE ensemble	MIT-BIH accuracy: 0.984; PTB-ECG accuracy: 0.992	Needs extensive computing resources
[9]	KNN and LR on heart disease dataset	KNN achieved 88% accuracy	Limited testing on additional features	[18]	CNN classifier (edge)	Accuracy: 98.18%; VEB & SVEB sensitivity: 96.34%	Limited to edge applications
[10]	CT, ANN, KNN, SVM, NB, LR	LR specificity: 81%; sensitivity: 89%	Small sample size and feature set limitations	[19]	Transformer + Bi-LSTM	F1-score: 99.2%	High computational demand for real-time processing
[11]	Cluster-based Decision Tree	Accuracy: 89.3%	Model may overfit with increased features				

The primary contributions of the current study on the classification of cardiovascular diseases are:

- To select two well-known datasets (PTB-ECG and MIT-BIH) that contain ECG signals for Cardiovascular disease. The PTB-ECG dataset comprises many labels (N, S, V, F, Q), whereas the MIT-BIH dataset comprises (normal, and abnormal).
- To create a hybrid of these two datasets, combine the PTB-ECG all label data and the MIT-BIH dataset normal class into one class and label it (0) while labelling the MIT-BIH abnormal class as (1).
- To identify Cardiovascular disease using deep learning models such as CNN and LSTM with balanced and imbalanced hybrid ECG signal (PTB-ECG and MIT-BIH) datasets.
- To analyse and monitor the performance of implanted models using a hybrid dataset and compare the test performance of the proposed method with a recent study by selecting the models with the highest accuracy.

The remainder of the research is structured as follows: Section 3 discusses the proposed method with details regarding the PTB-ECG and MIT-BIH datasets and their preprocessing. Section 4 discussed the achieved result with the help of a confusion matrix to evaluate and compare the results with previous studies. Section 5 concludes the result and gives future direction.

3. Proposed Methodology

The primary goal of the proposed approach is to recognize people with coronary artery disease as early as possible. This study uses a Neural network (NN) to detect and diagnose early cardiovascular disease employing two distinct datasets and a hybrid deep learning system. Pre-processing, data balancing, and feature extraction are critical steps in deep learning, including heart disease research, since they ensure that the data is provided to the neural network in a normalized and error-free state, allowing the network to classify incoming data correctly. The proposed approach was evaluated on two datasets, as shown in Figure 1.

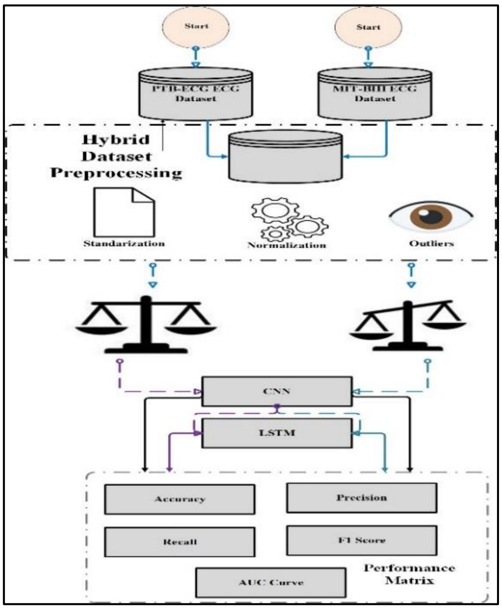

Figure 1. Proposed Method Framework Works with Balanced and Imbalanced Dataset

3.1 Description of the Dataset

Collecting more appropriate data for the situation and accurately and efficiently capturing the field of interest pattern is the first and most crucial stage in creating an intelligent computation mechanism. The availability of an organized collection of data relevant to the computation problem can significantly impact the algorithm's effectiveness. This dataset consists of two groups of heartbeat signals, one from the PTB Diagnostic ECG databases and the other from the MIT-BIH Arrhythmia Dataset, frequently used to classify cardiovascular diseases. Both datasets include enough samples to be suitable for deep neural network training.

3.2 Pre-processing and Classifications

The dataset does not have any missing values; however, it does have many outliers that need to be dealt with appropriately; also, the dataset is not balanced. First and foremost, we made a significant contribution by merging the hybrid of MIT-BIH Arrhythmia dataset and the PTB Diagnostic ECG dataset. The PTB-ECG dataset has five classes: class 0 (normal), class 1 (fusion of paced and normal), class 2 (premature ventricular contraction), class 3 (atrial premature), and class 4 (fusion of ventricular and normal), with 90588, 8039, 7236, 2779, and 803 entries in these categories, respectively. The MIT-BIH Arrhythmia dataset also has 4046 and 10506 records, with class 0 (normal) and class 1 (abnormal). As a result, the PTB-ECG dataset's classes 0 through 4 have been combined into class 0, and the dataset's abnormal categories have been moved to Class 1. Class 0 = 113,492 records, Class 1 = 10506 records, etc. When the dataset's statistics are examined, the normal distribution exhibits a distinct variance, indicating that it is significant when comparing the features critical for HD to those not significant for heart disease. These statistical results support the concept that the Gaussian distribution has a role in the genesis of heart disease. Four approaches are used, the first of which involves feeding the hybrid data directly into the CNN algorithms without any balancing method, the second of which involves extracting features using a CNN and then feeding those features to an LSTM system to classify the data. The outcomes of our third approach are optimistic because it involves using a balanced dataset to prevent overfitting prior to CNN classifier. Our fourth technique leverages a CNN to pick out features from a balanced dataset, which is then fed into an LSTM algorithm to be categorized.

4. Results and Discussion

In the Performance Evaluation Process (PEP) the proposed model used confusion matrix (CM) structures, accuracy scores, precision matrices, recall matrices, sensitivity matrices, F1-scores, and area under the receiver operating characteristic (AUC-ROC) curves. In the first of its four portions, "true positive" (Tp) values are recognized as true and in fact were true as well. Second, a false-positive (Fp) occurs when an incorrect value is predicted to be correct; third, a false-negative (Fn) occurs when a correct value is incorrectly predicted to be negative; and fourth, a true-negative (Tn) occurs when a correct value is correctly predicted to be negative. Since we only have two classes, which have already been addressed in our pre-processing section, the primary focus of this discussion will be on the binary confusion matrix shown in Figure 2.

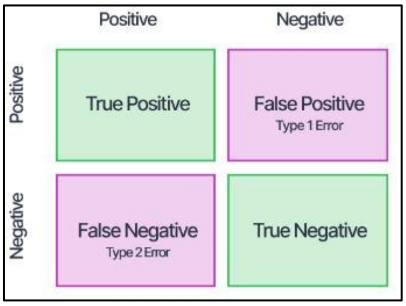

Figure 2. Shows a Sample of the Confusion matrix with Negative and Positive Value

4.1 Experimental Result using 1st Approach

Using CNN in the first approach, Table 2 shows that when the target class 0, 1, is divided 80/20 for training and testing purposes, the target class is not balanced. The results shown in Table 2 show that throughout the training phase, accuracy(A) for Class 0 was obtained at (1.00), as was precision(P), recall(R), and F1-score(F). The accuracy achieved for class 1 using CNN with performance matrix is (A-1.00, P-1.00, R-1.00, F-1.00), a decent and acceptable result for the training phase. Similar to training accuracy, precision, recall, and F1 score, for testing, CNN achieved (A-0.9984, P-1.00, R-1.00, F-1.00) for class 0 and (A-0.9985, P-0.99, R-1.00, F-0.9900) for class 1.

Table 2: Shows the Achieved Result of the CNN Algorithm using an Imbalanced Dataset with Two Target Features

	Class No	**Sample No.**	**Accuracy(A)**	**Precision(P)**	**Recall(R)**	**F1-Score(F)**
Training	0	72636	1.00	1.00	1.00	1.00
	1	6724	1.00	1.00	1.00	1.00
Testing	0	18159	0.9985	1.00	1.00	1.00
	1	1681	0.9985	0.99	1.00	0.99

Figure 3 illustrates a confusion matrix for evaluating the Unbalanced dataset, which includes all correctly classified (true-positive and true-negative) and incorrectly classified observations (false-positive and false-negative). According to the confusion matrix in Figure 3(a), the CNN classifier predicts (72634) accurately for class 0 (normal) during training but predicts (0) incorrectly as abnormal. It properly predicts (6722) out of (6724) abnormal cases for the class 1 training phase, and it predicts (2) cases incorrectly. Figure 3(b) shows the testing phase where the CNN classifier incorrectly classifies class (6) as class 1 and class (18153) as class 0 (normal). In a test for class 1, CNN correctly predicted (1657) out of (1681), however, it incorrectly predicted (24) as normal.

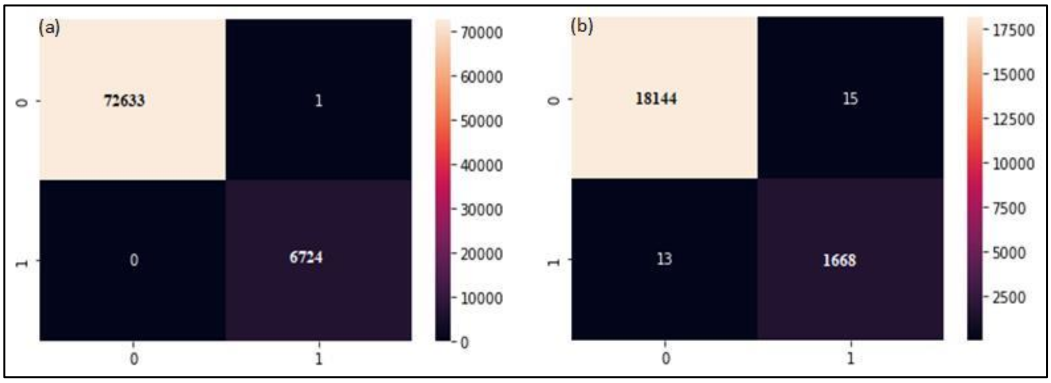

Figure 3: Shows a Confusion Matrix of Unbalanced Dataset using CNN Method where (a) Represents Training Matrix while (b) Testing Matrix

4.2 Experimental Result using 2nd Approach

while we divide 80/20 for training and testing purposes while using CNN+LSTM+ SMOTE in the second approach, there is no equal distribution of the target class 0, 1. The results shown in Table 3 show that the training phase produced the same results for class (0, 1) as the CNN in the experimental first approach (A-1.00, P-1.00, R-1.00, F-1.00). The obtained evaluation matrix for validation CNN+LSTM are (A-0.9985, P-1.00, R-1.00, F-1.00) for class 0, and (A-0.9985, P-0.99, R-0.99, F-0.99) for class 1. Furthermore, the first approach and second approach results are nearly identical, with the main variation being that when we use CNN+LSTM, our precision is 0.99, and when we use CNN, our precision is 1.00.

Table 3: Shows the Achieved Result of CNN+LSTM Algorithm using Imbalanced Dataset with Two Target Features

	Class	**Sample**	**Accuracy (A)**	**Precision (P)**	**Recall(R)**	**F1-Score (F)**
Training	0	72636	100%	100%	100%	100%
	1	6724	100%	100%	100%	100%
Testing	0	18159	99.85%	100%	100%	100%
	1	1681	99.85%	99%	99%	99%

Figure 4 is a confusion matrix used to evaluate the ECG signal dataset, which includes all correctly classified (true-positive and true-negative) and incorrectly classified (false-positive and false-negative) signals. Figure 4(a) shows that during training, the CNN+LSTM classifier correctly predicted that (72633) were in class 0 (normal), but it incorrectly predicted that (1) was in class 1. For class 1, in the training phase, it predicts (6724) abnormal cases accurately and (0) cases incorrectly. Figure 4(b) shows that during the testing phase, the CNN+LSTM classifier thought that (18147) were in class 0 (normal) and (12) was in class 1 (abnormal). When CNN+LSTM+SMOTE was tested on class 1, it got (1664) out of (1681) right, but it got (17) incorrectly as class (normal).

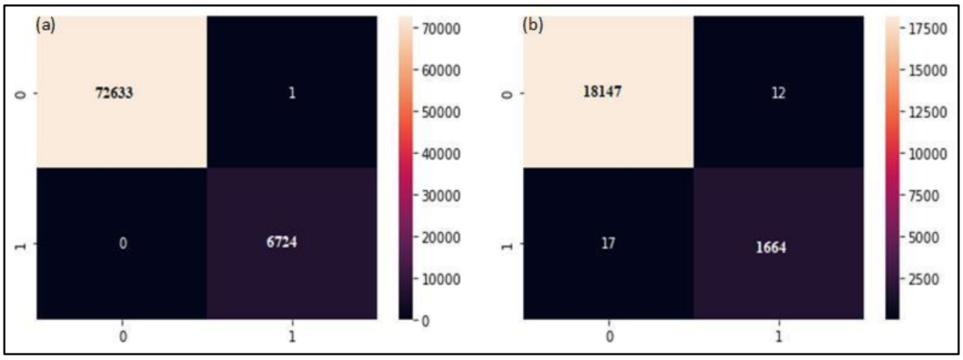

Figure 4: Shows a Confusion Matrix of Unbalanced Dataset using CNN+LSTM Method where (a) Represents Training Matrix while (b) Testing Matrix

4.3 Experimental Result using 3rd Approach with Balanced Dataset

Table 4 shows that when we divide the target class into 80/20 for training and testing purposes, there is now an equal distribution of the target classes 0,1 when using CNN and SMOTE in the third approach. The results in Table 4 demonstrate that during the training phase, accuracy for Class 0 was obtained at 0.9998, precision at 1.00, recall at 1.00, and F1 score at 1.00. The accuracy for class 1 obtained by CNN with performance matrix accuracy, precision, recall, and F1 score is (0.9998, 1.00, 1.00, 1.00), which is a respectable and acceptable result for the training phase. Similar to training, the testing evaluation matrix using CNN+SMOTE was reached (A-0.9991, P-1.00, R-1.00, F-1.00) for class 0 and (A-0.991, P-1.00, R-1.00, F-1.00) for class 1.

Table 4: Shows the Achieved Result of the CNN Algorithm using Balanced Dataset with Two Target Features

	Class	Sample	Accuracy (A)	Precision (P)	Recall (R)	F1 Score (F)
Training	0	77174	0.9998	1.00	1.00	1.00
	1	77174	0.9998	1.00	1.00	1.00
Testing	0	13619	0.9991	1.00	1.00	1.00
	1	13619	0.9991	1.00	1.00	1.00

A confusion matrix is shown in Figure 5 to analyse the balanced ECG signal dataset, which contains all correctly classified (true-positive and true-negative) and incorrectly classified (false-positive and false-negative) signals. The confusion matrix in Figure 5 (a) demonstrates that in training, the CNN+SMOTE classifier correctly predicts (77168) for class 0 (normal) while incorrectly predicts (6) for class 0 as (abnormal). In the training phase, class 1 correctly predicts (77174) cases as (abnormal) and incorrectly predicts (0) cases as (normal). Figure 5 (b) depicts the testing phase, in which the CNN+SMOTE classifier correctly predicts (13596) as class 0 (normal) and incorrectly predicts (23) as class 1 (abnormal). In tests for class 1, CNN successfully predicted (13617) (abnormal) out of (13619), but incorrectly predicted (2) as class 0 (normal). Here, it is obvious that by balancing our dataset with CNN and SMOTE algorithms, we enhanced our attained accuracy from 0.9985 to 0.9991.

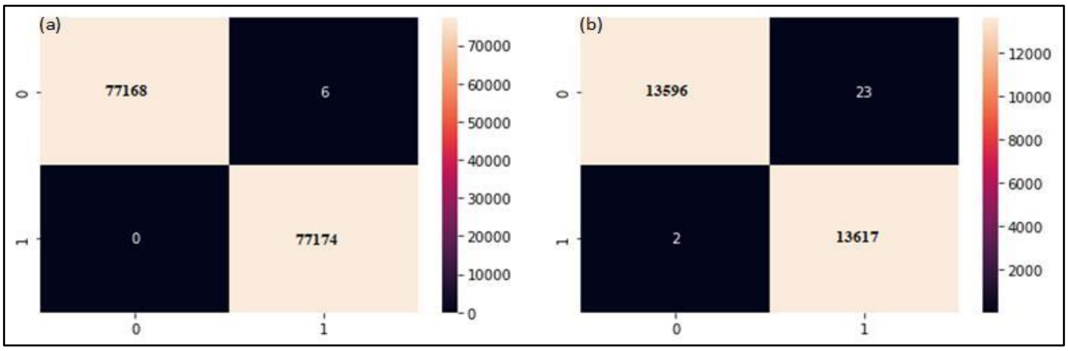

Figure 5: Shows a Confusion Matrix of Balanced Dataset using CNN+SMOTE Method where (a) Represents Training Matrix while (b) Testing Matrix

4.4 Experimental Result using 4th Approach with Balanced Dataset

Using CNN+LSTM and SMOTE in the fourth approach, as shown in Table 5, there is now an equal distribution of the target class 0, 1 when we divide 80/20 for training and testing. Table 5 shows that the achieved evaluation matrix for class 0 is (A-0.9999, P-1.00, R-1.00, F-1.00) and for 1 is (A-0.9999, P-1.00, R-1.00, F-1.00), during the training phase. For validation, the achieved results using the same evaluation matrix are (A-0.9985, P-1.00, R-1.00, F-1.00) for class 0 and (A-0.9985, P-1.00, R-1.00, F-1.00) for class 1.

Table 5: Shows the Achieved Result of CNN+LSTM Algorithm using Balanced Dataset with Two Target Features

	Class	**Sample**	**Accuracy (A)**	**Precision (P)**	**Recall (R)**	**F1-Score (F)**
Training	0	17174	0.9999	1.00	1.00	1.00
	1	17174	0.9999	1.00	1.00	1.00
Testing	0	13619	0.9985	1.00	1.00	1.00
	1	13619	0.9985	1.00	1.00	1.00

A confusion matrix for the balanced ECG signal dataset, which contains both correctly and incorrectly classified signals (true-positive and true-negative), is shown in Figure 6. Figure 6(a) confusion matrix demonstrates that while the CNN+LSTM+SMOTE classifier correctly predicts (77168) for class 0 (normal) during training, it predicts (12) incorrectly as (abnormal). In the training phase, it correctly predicts (77174) (abnormal) cases for class 1, whereas it incorrectly predicts (0) (normal) cases. Figure 6(b) depicts the testing phase utilizing CNN+LSTM and SMOTE methods, which incorrectly classified (41) as a class 1 abnormality and correctly predict (13578) as a class 0 normality. It correctly predicted (13619) out of (13619) for class 1 using CNN+LSTM in testing, although it incorrectly predicted (0) as class 0 (normal).

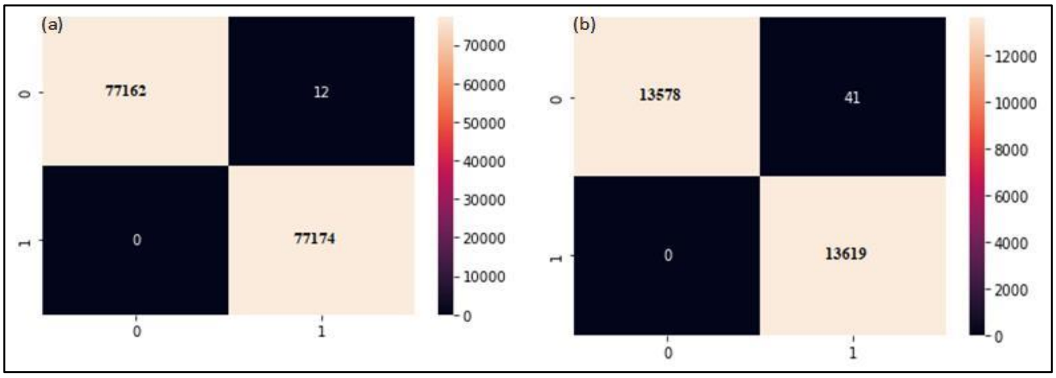

Figure 6. Shows a Confusion Matrix of Balanced Dataset using CNN+LSTM+SMOTE Method where (a) Represent Training Matrix while (b) Testing Matrix

4.5 AUC ROC Curve

For the hybrid PTB-ECG and MIT-BIH datasets, the AUC graphs of these two deep learning techniques have also been empirically discovered and compared in Figure 7. Figure 7 (a) displays the AUC curve for the CNN model using the Imbalanced dataset, which is 1.00, and Figure 7 (b) displays the AUC curve for the CNN+LSTM, which is 1.00 and same for the first and second proposed approaches. The proposed third and fourth approach employing the SMOTE method for balancing the hybrid dataset has an AUC curve of 1.00 shown in Figure 7(c)(d).

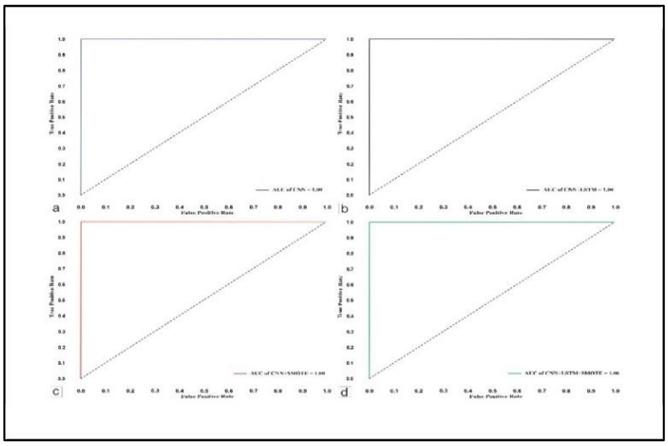

Figure 7. Shows the AUC Curve of Proposed Method using Two Target ECG Hybrid Dataset

4.6 Comparative Analysis

We also compared our results to Adyasha et al. [17], who achieved 0.992 accuracy, f1score 0.986, and AUC 0.995 for the PTB-ECG dataset using the SOM-AE ensemble model. The attained accuracy, F1 score, and AUC for the MIT-BIH dataset are 0.984, 0.971, and 0.997, respectively. In comparison to our model, which was created by combining PTB-ECG and MIT-BIH with two target classes (normal and abnormal), our CNN model with balanced dataset and SMOTE approaches achieved accuracy, precision, recall, F1 score, and AUC curve of (0.9991, 1.00, 1.00, 1.00, 1.00) as shown in Table 6.

Table 6: Shows Achieved Result Comparison with State-of-the-art Techniques

Reference	**Author Name**	**Dataset**	**Accuracy**	**Precision**	**Recall**	**F1 score**	**AUC**
[17]	Adyasha et al.	PTB-ECG and MIT-BIH	0.992	--	--	0.986	0.971
Proposed work	--	Hybrid of PTB-ECG and MIT-BIH	0.9991	1.00	1.00	1.00	1.00

5. Conclusion

This research presents a hybrid deep learning-based method using PTB-ECG and MIT-BIH datasets for classification. The proposed approach combines both datasets with two target classes (normal (0), and abnormal (1)) to create a single dataset and named it as hybrid of PTB-ECG and MIT-BIH datasets. After making the final dataset, we perform some pre-processing operations to remove outliers, normalize, and standardize the dataset using Gaussian distribution. After pre-processing there were four different approaches, one of which skipped balancing in favor of feeding the data straight to convolution neural network (CNN) algorithms; the outcomes were good but not particularly encouraging because the best approach for classification required passing the balanced dataset. The second method involves extracting features with a Convolutional Neural Network (CNN) and then feeding those features to a Long Short-term Memory (LSTM) system to classify the data. The results of our third technique are promising because it employs a balanced dataset to prevent overfitting prior to the CNN classifier. Our fourth strategy employs a CNN to extract features from a balanced dataset, which are subsequently classified using an LSTM algorithm. The first approach indicates that Class 0 evaluation matrix accuracy(A), precision(p), recall(R), and f1-score(F) were all 1.00 during training, and for Class 1 are (A-1.00, P-1.00, R-1.00, F-1.00), which is suitable for training. Similar to training, the testing matrix for class 0 was (A-0.9984, P-1.00, R-1.00, F-1.00), while for class 1 was (A-0.9985, P-0.99, R-1.00, F-0.99). The second approach, CNN+LSTM matrix results, reveal that the training phase achieved the same results for class 0, 1 (A-1.00, P-1.00, R-1.00, F-1.00) as the CNN in the experimental first approach. For validation, the second approach received matrix for class 0 are (A-0.9985, P-1.00, R-1.00, F-1.00), and for class 1 (A-0.9985, P-0.99, R-0.99, F-0.99). The third approach shows that all over the training phase, Class 0 achieved matrix is (A-0.9998, P-1.00, R-1.00, F-1.00) and Class 1 (A-0.9998, P-1.00, R-1.00, F-1.00). Similar to training, the testing matrix using CNN+SMOTE, which reached (A-0.9991, P-1.00, R-1.00, F-1.00) for class 0 and (A-0.991%, P-1.00, R-1.00, F-1.00) for class 1. The fourth approach shows that the training matrix achieved for class 0 is (A-1.00, P-1.00, R-1.00, F-100) and class 1 is (A-0.9999, P-1.00, R-1.00, F-1.00), using CNN+LSTM+SMOTE performance matrix which is satisfactory for training. For validation, the achieved matrix for class 0 and class 1 are (A-0.9985, P-1.00, R-1.00, F-1.00). Lastly, it is demonstrated that in terms of accuracy(A), precision(P), recall(R), F1-score(F), and AUC, the CNN + SMOTE model outperformed all proposed approaches. It's also compared and outperformed state-of-the-art. The current work can be expanded to implement a time series classification with less complex models, to reduce the cost of implementation of the developed scheme, and increase the complexity time through parallel implementation, among other aspects.

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