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Comparative Evaluation of Machine Learning Models for Arrhythmia Detection on the MIT-BIH Arrhythmia Dataset

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***Abstract*— The heart is one of the important organs for humans. It pumps blood and supplies it with nutrients to the different parts of the body. Hence, preserving a healthy heart is our necessity. Arrhythmia is an issue where heart's pumping becomes abnormal which is analyzed using Electrocardiogram using ECG signals. The peaks present in the ECG graph are utilized to identify heart diseases and arrhythmia is analyzed using its R-peak. In this work, deep CNN has been implemented to detect arrhythmia.**

***Keywords*— Arrhythmia, Electrocardiogram, MIT-BIH ECG signal dataset, CNN, PQRST wave.**

I. LITERATURE REVIEW

For this literature review, a varied set of recent and relevant paper in the field are selected. These papers are discussed in more details below and listed in Table 1.

ECG signals have been used to evaluate the heartbeat using machine learning and neural network techniques which have been reviewed in this work (Ali et al., 2022). The main parts in CNN are feature extraction along with classification. The feature extraction obtains the important and useful characteristics from the images and classification precisely classifies the ECG signals utilising the generated characteristics from the feature extraction (Ali et al., 2022). The feature extraction method comprises of layers: convolution and downsampling that are explained in detail in the Chapter 3. Convolution layer improves the quality of the ECG signals by reducing the noise. Another review (Ali et al., 2022) explored the use of machine learning and neural networks for ECG-based cardiac event prediction. The used CNN architecture included two convolutional layers, two down sampling layers, a fully connected layer, and an output layer. Convolutional layers helped in reducing noise while extracting useful local features from ECG data. This review highlighted the use of the MIT-BIH arrhythmia dataset, consisting of 48-hour ECG recordings from 47 patients digitized at 360 samples per second per channel. CNN models achieved 97.4% accuracy, slightly outperforming SVM models, which achieved 96% (Ali et al., 2022).

Another work using the same MIT-BIH arrhythmia dataset is implemented in this where beats were classified into five heartbeat types (Kiranyaz et al., 2015). This work has proposed the ECG classification utilizing CNN which used feature extraction and classification together.

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The experiment showed that this model obtained a superior performance of classification for the identification of cardiac events. The performance of ECG classification is measured using four metrics: accuracy, sensitivity, specificity, and positive predictivity. The best obtained accuracy from this model was 98.9% with a high sensitivity of 95.9% (Kiranyaz et al., 2015).

TABLE I: SUMMARY OF LITERATURE REVIEW FOR DIFFERENT DATASETS

Papers	Dataset	ML Techniques used	Best Result
(Atal and Singh, 2020)	MIT-BIH arrhythmia	CNN	Accuracy, specificity and sensitivity of 93.2%, 95%, and 94%
(Cheikhrouhou et al., 2021)	MIT-BIH arrhythmia	1D CNN	Accuracy of 99.5%
(Ali et al., 2022)	MIT-BIH arrhythmia	CNN and SVM	accuracy of CNN: 97.4% accuracy of SVM: 96%
(Al-Huseiny et al., 2020)	MIT-BIH arrhythmia	CNN	accuracy of 96.7%
(Kiranyaz et al., 2015)	MIT-BIH arrhythmia	CNN	accuracy of 98.9% & sensitivity of 95.9%
(Burger et al., 2020)	MIT-BIH arrhythmia	CNN	Accuracy of 97%
(Avanzato and Beritelli, 2020)	MIT-BIH arrhythmia	CNN	Accuracy of 98.3%
(Maweu et al., 2021)	MIT-BIH arrhythmia	1D CNN	Accuracy of 97.1%
(Wu et al., 2021)	MIT-BIH arrhythmia	CNN	Accuracy of 97.4%
(Król-Józaga, 2022)	MIT-BIH arrhythmia	CNN	Accuracy of 95%
(Rawi et al., 2022)	MIT-BIH arrhythmia	CNN	Accuracy of 97%
(Baloglu et al., 2019)	MIT-BIH arrhythmia	1D CNN	Accuracy of 99.8%
(Abdullah and Al-Ani, 2020)	MIT-BIH arrhythmia	CNN	Accuracy of 99.5%
(Abdalla et al., 2020)	MIT-BIH arrhythmia	CNN	Accuracy of 99.8%
(Shiri et al., 2021)	MIT-BIH arrhythmia	CNN	Accuracy of 95.2%
(Zheng et al., 2020)	MIT-BIH arrhythmia	CNN	Accuracy of 99%
(Gopika et al., 2020)	MIT-BIH arrhythmia	CNN	Accuracy of 98%
(Ullah et al., 2021)	MIT-BIH arrhythmia	CNN	Accuracy of 97.4%
(Xu et al., 2024)	MIT-BIH arrhythmia	CNN	Accuracy of 98.8% and F1 score of 92%

This work (Al-Huseiny et al., 2020) presented a technique to diagnose cardiac disorders by recognizing 17 different types of arrhythmias. Arrhythmia is the irregular heartbeat and the prime index of serious heart issues (NIH, 2022). This work (Al-Huseiny et al., 2020) included training and validating a 2D-CNN with ECG from MIT-BIH database. The diagnosis of cardiac disorders is susceptible to human error due to the high variations in individuals at different phases of disease which can even lead to loss of life in some cases. To obtain accuracy and consistency of detection, many works have been implemented in the field of machine learning to automatically detect and predict arrhythmias. This work (Al-Huseiny et al., 2020) developed a machine learning technique which helped diagnosis of cardiac arrhythmias rapidly with high accuracy. This work has achieved an accuracy of 96.7% with reduced processing time. It has proposed as future work that the further step for the research in this field can be the fusion of other data with ECG images to model more robust and thorough health diagnostic system that can help in deciding and scheduling the following stages of health plans for the patients (Al-Huseiny et al., 2020).

1D-CNN approach has been implemented in this work (Cheikhrouhou et al., 2021) on MIT-BIH arrhythmia database to investigate ECG signals captured from IoT wearable devices and to predict CVD with an accuracy of 99.5%. This 1D- CNN has data extraction and classification part where convolution, batch normalization, activation, and max pooling layers are included in extraction and Softmax layers, flatten, and fully connected are included in classification part. This model has given an accuracy of 99.5% in 44 epochs. The study proposed extending this approach by testing with other deep learning models in the future (Cheikhrouhou et al., 2021).

A recent study utilizing the MIT-BIH arrhythmia dataset is presented in (Xu et al., 2024). The authors proposed a novel multimodality data augmentation network to classify arrhythmias, which they claim is the first multimodal analysis of ECG. The dataset was processed using the WFDB tool, and both ECG signal data and ECG image data were concatenated for the multimodal analysis. An augmentation technique was employed to balance the dataset. The model achieved an accuracy of 98.8% and an F1 score of 92% (Xu et al., 2024).

This section outlines the approach developed for the research, as illustrated in Fig. 3.1, which includes the dataset, various balancing techniques, and the machine learning algorithms are employed. This work has been implemented using Python. CNN are inherently complex because of their depth, vast number of trainable parameters, and the need for large datasets, which necessitate the use of GPUs to accelerate training. For instance, when attempting to implement CNN for the MIT-BIH arrhythmia dataset on a Windows 10 laptop with a CPU and 16GB of RAM, the process was unworkable without a GPU. Consequently, we utilised the high-performance computing (HPC) cluster at Liverpool John Moores University (LJMU) to expedite the training process. The “Big-IP Edge Client” VPN was installed on the laptop, providing access to the LJMU GPU server, “sad.cms.livjm.ac.uk”, which reduced the CNN code execution time to approximately 2 to 3 hours.

II. MIT-BIH ARRHYTHMIA DATASET

To assess the CNN model’s performance on more complex biomedical signals, the CNN was applied to ECG image data. For this purpose, the MIT-BIH Arrhythmia dataset was selected due to its widespread use as a benchmark in ECG-based research. This dataset is the outcome of a collaborative effort between the Massachusetts Institute of Technology (MIT) and Beth Israel Hospital (BIH) and is publicly accessible via PhysioNet (George Moody, 2005; Rexy et al., 2021; Abdallah Wagih Ibrahim, 2024). It has become a standard resource for arrhythmia detection studies (Rexy et al., 2021).

The MIT-BIH Arrhythmia dataset comprises 48 ECG recordings collected from 47 patients between 1975 and 1979. Each recording includes data from two ECG leads (leads II & V5) and spans a duration of 30 minutes, recorded at a sampling rate of 360 Hz. This implies that each second of ECG data contains 360 data points. The recordings are stored in comma-separated values (CSV) and plain text (TXT) formats, with the annotations provided in corresponding files (George Moody, 2005). These annotations label each heartbeat and were interpreted by two or more cardiologists based on the R-peak positions, yielding approximately 110,000 annotated heartbeats distributed across 17 categories (Rexy et al., 2021).

This constitutes a multi-class classification problem, with only approximately 10 percent of the heartbeats classified as abnormal, thus introducing a significant class imbalance (George Moody, 2005; Abdallah Wagih Ibrahim, 2024). To address this imbalance, appropriate sampling techniques are employed. According to the standards set by the Association for the Advancement of Medical Instrumentation (AAMI), 17 heartbeat types in the dataset are consolidated into several broader classes. For the purposes of this study, five principal classes are selected: Normal (N), Left Bundle Branch Block (L), Right Bundle Branch Block (R), Atrial Premature Beat (A), and Ventricular Premature Beat (V). The distribution of samples across these classes is presented in Table 2.

TABLE II: DIFFERENT TYPES OF ECG FOR MIT-BIH ARRHYTHMIA DATASET (GEORGE MOODY, 2005).

Output	Number of records
Normal	75011
Left Bundle	8071
Right bundle	7255
Atrial premature	7129
Ventricular premature	2546

Fig. 2 presents a doughnut chart illustrating the distribution of record counts across the various classes within the MIT-BIH Arrhythmia dataset.

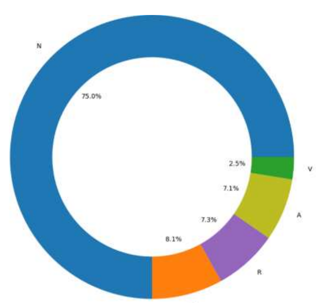

Fig. 1. Donut chart showing the classes of MIT-BIH arrhythmia dataset.

The MIT-BIH dataset was chosen for two primary reasons: firstly, its widespread use in the literature facilitates direct comparison with previous studies; secondly, its 1D time-series structure provides an opportunity to test the flexibility of CNN beyond 2D images.

III. RESULTS FOR MIT-BIH ARRHYTHMIA DATASET

Preprocessing steps such as CLAHE was critical to mitigate noise and bias. The extraction segment consists of convolution, activation and average pooling layers whereas classification segment includes of flatten, fully connected and Softmax layers.

The MIT-BIH arrhythmia dataset is organized in a 2D format where the horizontal direction represents the time axis, and the vertical direction corresponds to the features related to each timestamp. As this is a 1D problem so 1D CNN is implemented for it. The extraction part of the 1D CNN consists of four blocks of convolution, activation and average pooling layer. The classification part includes one flatten layer, two dense layers, and Softmax layers. A dropout function is applied to prevent the overfitting during the training stage. The output layer of this CNN model represents 5 different heartbeat groups: normal (N), left bundle branch block (L), right bundle branch block (R), atrial premature beat (A) and ventricular premature beat (V). Since the dataset is imbalanced, it has been balanced as shown in Fig. 3 before implementation of the CNN.

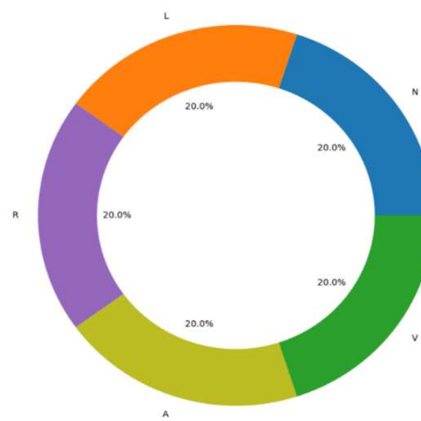

Fig.3. Balanced classes for MIT-BIH arrhythmia dataset.

IV. Results Obtained from MIT-BIH Arrhythmia Dataset

Figs. 4 and 5 illustrate the changes in loss and accuracy for training and test datasets, respectively, for the best case.

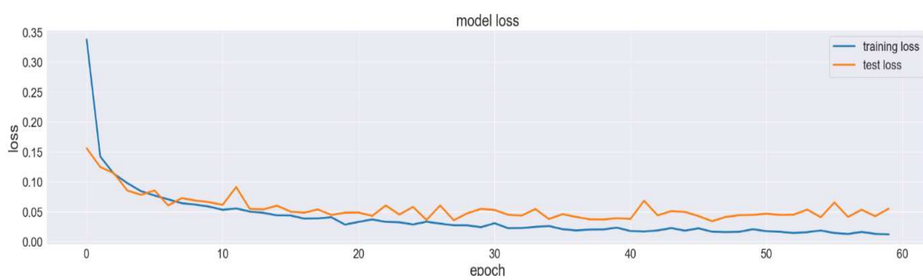

Fig. 4. Loss for MIT-BIH arrhythmia dataset

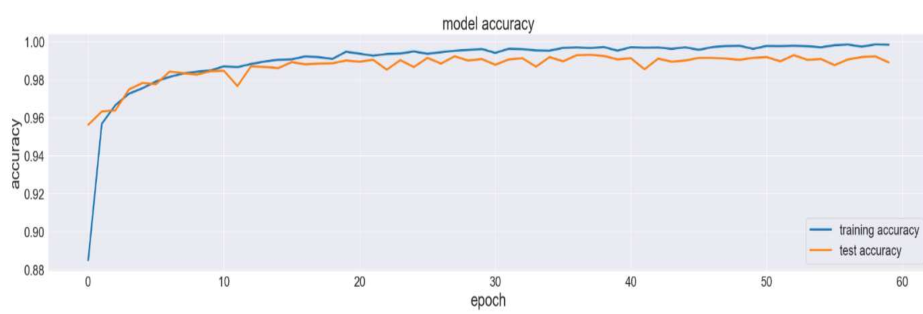

Fig. 5. Accuracy for MIT-BIH arrhythmia dataset.

The best model has achieved an accuracy of 98.9% with recall of 98.9% (Fig. 6), precision of 98.8% (Fig.7), F1 score of 98.8%, AUC of 99.8% (Fig.8) and MCC value of 0.98.

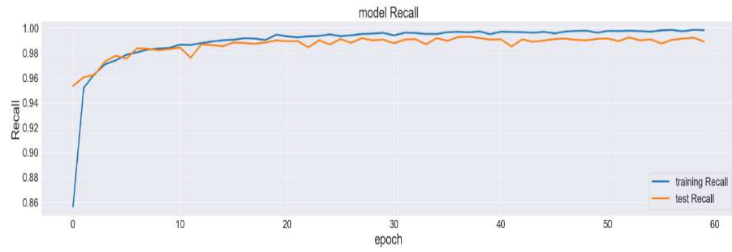

Fig. 6. Recall for MIT-BIH arrhythmia dataset

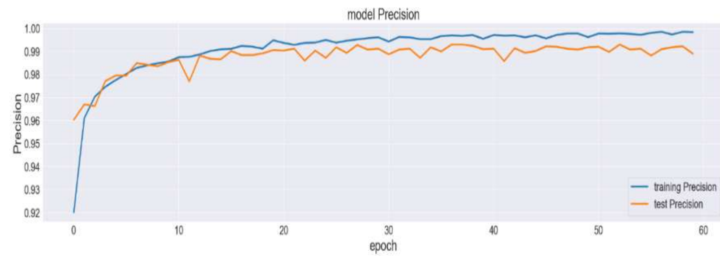

Fig.7. Precision for MIT-BIH arrhythmia dataset

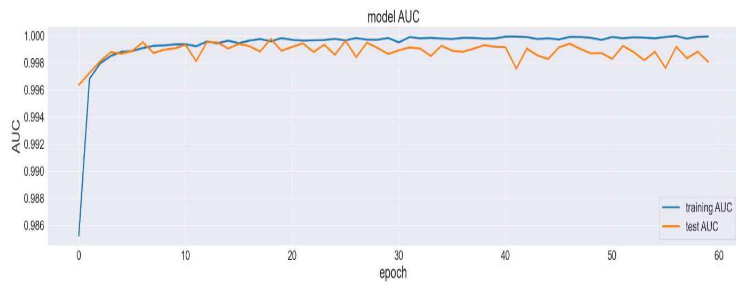

Fig.8. AUC for MIT-BIH arrhythmia dataset.

Figs. 9 and 10 present the confusion matrices and classification report for all five classes from the best-performing CNN model applied to the MIT-BIH arrhythmia dataset. The confusion matrix in Fig. 9 shows that for the L class, there are 4 false positives (FP) and 4 false negatives (FN). A total of 4,992 images (3,984 incorrect + 1,008 correct) were accurately predicted, yielding an accuracy of 99.8% for the L class.

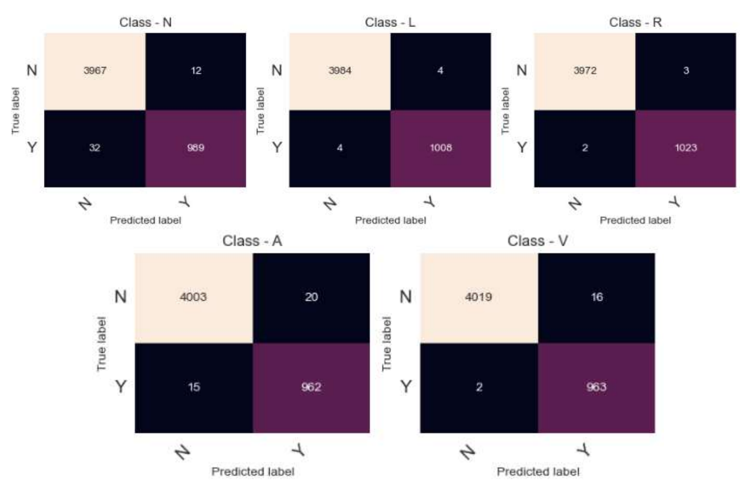

Fig.9. Confusion matrices for all five classes of MIT-BIH arrhythmia dataset.

	precision	recall	f1-score	support
N	0.99	0.97	0.98	1021
L	1.00	1.00	1.00	1012
R	1.00	1.00	1.00	1025
A	0.98	0.98	0.98	977
V	0.98	1.00	0.99	965
micro avg	0.99	0.99	0.99	5000
macro avg	0.99	0.99	0.99	5000
weighted avg	0.99	0.99	0.99	5000
samples avg	0.99	0.99	0.99	5000

Fig.10. Classification report for all five classes of MIT-BIH arrhythmia dataset.

V. INTERPRETATION OF RESULTS

NORM: The model performs exceptionally well for the NORM class, with high accuracy, precision, recall, and F1 score, indicating its proficiency in identifying this class.
L: The model demonstrates excellent performance for the left bundle branch block (L) class, providing very high accuracy, precision, recall, and F1 score, which shows the model's ability to identify this class perfectly.
R: The model performs equally well for the right bundle branch block (R) class as it does for the L class, with very high accuracy, precision, recall, and F1 score, indicating its effectiveness in identifying the R class.
A: The model excels in identifying the atrial premature beat (A) class, with high accuracy, precision, recall, and F1 score, demonstrating its capability in recognising this class.
V: The model also performs very well for the ventricular premature beat (V) class, with high accuracy, precision, recall, and F1 score, indicating it is excellent at identifying this class as well.
Overall, the model is effective across all classes, demonstrating excellent performance. All classes have been classified with high accuracy, with the lowest recall being 97% for the normal class and 98% for the atrial premature class. The other three classes have a recall of 100%.
This dataset is used to calibrate the CNN model. Given its extensive documentation in other works, this dataset is utilised in this research to compare results with previous studies. The obtained results are compared with other published works in Table 3.

TABLE III: COMPARISON OF THE OBTAINED RESULT WITH OTHER REFERENCE WORKS FOR MIT-BIH ARRHYTHMIA DATASET

Reference Work	Accuracy	Precision	Recall	F1 score	AUC	MCC
(Atal and Singh, 2020)	93.2%	94%	95%	Not mentioned	Not mentioned	Not mentioned
(Cheikhrouhou et al., 2021)	99.5%	Not mentioned	Not mentioned	Not mentioned	Not mentioned	Not mentioned
(Ali et al., 2022)	97.4%	Not mentioned	Not mentioned	Not mentioned	Not mentioned	Not mentioned
(Al-Huseiny et al., 2020)	96.7%	Not mentioned	Not mentioned	Not mentioned	Not mentioned	Not mentioned
(Kiranyaz et al., 2015)	98.5%	Not mentioned	95.9%	Not mentioned	Not mentioned	Not mentioned
(Wasimuddin et al., 2019)	98.8%	Not mentioned	Not mentioned	92%	Not mentioned	Not mentioned
(Xu et al., 2024)	98.8%	Not mentioned	Not mentioned	92%	Not mentioned	Not mentioned
Our work	98.9%	98.8%	98.9%	98.8%	99.8%	0.98

It is evident from the table that our work includes several performance metrics which are not provided in other studies. The implemented model achieved an accuracy of 98.9%, with a recall of 98.9%, precision of 98.8%, F1 score of 98.8%, and AUC of 99.8%. An MCC score of 0.98 was obtained for this CNN model, indicating accurate predictions.

VI. CONCLUSION

The results achieved for MIT-BIH arrhythmia dataset for best hyper tuned CNN model are an accuracy of 98.9% with recall of 98.9%, precision of 98.8%, F1 score of 98.8%, and AUC of 99.8%. An MCC score of 0.98 is obtained for this CNN model which shows the model is accurately predicting. The model is effective for all classes and demonstrates great performance for all classes. All the classes have been classified very accurately where the lowest recall of 97% is obtained for normal class and the atrial premature class has the recall of 98%.

Other three classes have recall of 100%. One of the key advantages of this research is that many different performance metrics have been calculated for each dataset which is not provided in many works. This work has attained the better results compared to the other published works.

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