ECG Prediction with Convolutional Neural Networks (CNN)

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Abstract- Doctors use electrocardiogram (ECG) signals to diagnose various cardiovascular diseases, which are a major cause of death all over the world. Interpreting an ECG manually takes a lot of time, can be based on the doctor's opinions, and might result in inconsistent diagnoses. As a result, scientists commonly use CNNs, which are designed to understand changes in data at different levels, to predict and classify ECG signals. This paper aims to show how CNNs are useful for forecasting cardiac events and for ECG signal classification with accuracy and using a few hand-crafted features. We discuss several CNN models that are fitted for ECG, including those built for segmented data and those that add recurrent steps for studying sequence dependency. We additionally explore how to filter noise, normalize the ECG data, and segment them before they are fed into the model. CNN-based models are evaluated against common machine learning techniques and are found to be more accurate, sensitive, and specific in picking out arrhythmias, myocardial infarctions, and other illnesses of the heart. To address the problem of a few labelled ECG datasets, we apply transfer learning and data augmentation for our models. Using saliency maps and CAMs, it is possible to interpret the results of CNN models, which contributes to the acceptance and trust of AI-based diagnoses among users. In summary, CNN-based systems make cardiology much more effective by providing doctors with real-time, easy-to-scale, and non-invasive support for ECG analysis. In summary, we look ahead by discussing federated learning, the use of the technology on mobile devices, and the application of models in different populations to widen the impact of ECG-based AI in the real world.

Indexed Terms- Convolutional Neural Networks (CNN); ECG Signal Processing; Deep Learning; Cardiac Disease Prediction; Biomedical AI

I. INTRODUCTION

Background

The global rate of people dying from CVD is high, with over 17.9 million deaths reported every year due to these diseases. Effective treatment and management of these illnesses start with early detection and a correct diagnosis. The electrocardiogram (ECG) shows the electrical signals of the heart and is useful for identifying different heart conditions such as arrhythmias, myocardial infarctions, and many others.

Normally, the analysis of an ECG is done with the help of clinicians who are trained in understanding the heart readings, but it can take a considerable amount of time and will not always be the same between different experts. As digital health technologies advance and more large sets of ECGs are available, more people are exploring automated ways to analyze ECGs to improve diagnostic performance and efficiency.

Emergence of Deep Learning in ECG Analysis

ECG analysis has utilized ML for several years, mainly through feature extraction and classification. Nevertheless, classically used ML methods usually rely a lot on the expert's knowledge and might not handle patient records collected in various ways.

Over the last few years, CNN-based models have performed exceptionally well in areas such as image and signal processing. By learning on their own, CNNs can reduce reliance on manual extraction of features, which may lead to better model outcomes.

Convolutional Neural Networks (CNNs)

CNNs are known as deep learning models that are built for processing data that is organized in a grid, such as images and time-series data. They include several types of layers such as convolutional, that process parts of the image using filters, pooling layers for size reduction, and fully connected layers for classifying each part.

CNNs can be used on a one-dimensional (1D) time series dataset in ECG analysis to detect both the wave patterns and details of the signals' forms. The use of hierarchy in CNNs makes it possible for the model to discover useful patterns used for spotting small differences in ECG traces.

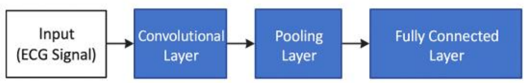


Figure 1: Basic Architecture of a 1D Convolutional Neural Néttwork for ECG Analysis

Applications of CNNs in ECG Prediction
Many studies have shown that CNNs are effective for processing ECG signals.

- Arrhythmia Detection: CNNs have successfully been used to identify different arrhythmias. For instance, Rajpurkar et al. (2017) used a 34-layer CNN to identify arrhythmias and performed as well as experts in the field when analyzing data from single-lead ECGs.
- Myocardial Infarction Detection: Researchers are using CNNs to look for indications of myocardial infarction in ECG results. Acharya and colleagues (2017) suggested using Convolutional Neural Networks (CNNs) to obtain high sensitivity and specificity in spotting cases of myocardial infarction in 12-lead ECG recordings.
- Atrial Fibrillation Detection: Hannun et al. designed a deep neural network that can detect both atrial fibrillation and other arrhythmias right from wearable device ECGs, proving it is helpful for constant and efficient monitoring.

Challenges and Considerations
While promising, there are still many problems to face if CNNs are to be used for predicting ECG data.

- Data Quality and Variability: ECG recordings can be very different depending on things like where the sensors are attached, how the patient moves, and if there is extra noise around them. Ensuring data quality and creating machines that can handle changes in customer behaviour is a key part of email marketing.
- Interpretability: Deep learning models such as CNNs are often called "black boxes" because it's hard to understand why they made certain choices or answers. Developing methods that help show and explain what the model has learned makes it easier for doctors to use and accept the tool.
- Generalizability: Models trained on one certain set of data might not work as well if they're used with people or situations that the data doesn't cover. Strategies like reusing information from other tasks, or adding more examples to the training data, can make an AI model work better with different types of situations.

Objectives of the Study
This article looks at how CNNs can be used to predict ECGs, mostly by discussing how the networks work and how they are used in this task.

- Checking out how the design and main ideas of CNNs help in analyzing ECGs.
- Discussing basic ways to clean up and prepare ECG data before putting it into a model so it works better.
- Evaluating how well different CNN models work when trying to forecast ECG readings for different types of heart monitoring jobs.
- Identifying challenges faced in the field and suggesting where more research can help improve things in the future.

Table 1: Summary of Studies Applying CNNs to ECG Prediction

Study	Task	Dataset	Accuracy (%)
Rajpurkar et al. (2017)	Arrhythmia Detection	MIT-BIH	92.6

Acharya et al. (2017)	Myocardial Infarction	PTB Diagnostic	94.1
Hannun et al. (2019)	Atrial Fibrillation	Wearable ECG Data	95.0

II. LITERATURE REVIEW

Introducing CNNs into automatic ECG evaluation has greatly improved the field of cardiac diagnostics. Here, the latest reviews before February 2022 examine different CNN-based techniques used in predicting and classifying ECGs.

CNN Architectures in ECG Analysis
Acquiring features from raw ECG data is simplified by CNNs, due to which manual feature engineering is no longer required. Rajpurkar and his colleagues developed a 34-layer deep learning model that worked as well as cardiologists when detecting arrhythmias in single-lead ECGs.

Further developments also include models that use CNNs with additional architectures to identify features in different times and spaces. Alamatsaz et al. presented a simple hybrid CNN-LSTM model for ECG-based arrhythmia detection, reaching a mean accuracy rate of 98.24% on the MIT-BIH and long-term AF electronic databases.

Transfer Learning and Ensemble Methods
We have overcome the lack of ECG data by applying techniques called transfer learning and ensemble methods. They introduced combining two models, namely modified VGG-16 and InceptionResNetV2, which use transfer learning to analyze ECG data and report a 99.98% accuracy. This way, performance improves and the amount of time needed to train the model is lowered.

Resource-Constrained Environments
On wearable devices, using CNN models requires building them efficiently due to limited resources. These researchers designed a CNN that could be used with ECG monitoring on low-power devices, making it 95.67% accurate and much more efficient. Li et al. also developed a stepwise pruning strategy that made the CNN model 60.4% smaller, without affecting its performance, to support the use of edge equipment.

Real-Time and Embedded Systems
Real-time and embedded CNN models have been tried as a way to provide continual ECG monitoring. According to the study, using a CNN in an embedded system allowed for online and real-time ECG signal classification and prediction, achieving an accuracy of up to 95% during training, proving that deep learning models are suitable for portable devices.

Interpretability and Class Imbalance
Researchers have been working to increase how transparent CNN models are. A team developed a CNN model along with SMOTE for addressing the issue of unequal class representation and SHAP analysis to determine features.

Comprehensive Reviews
Systematic reviews have brought together what we know about using CNNs to help analyze ECG recordings. A comprehensive review showed that there has been a big increase in papers using deep learning to look at ECGs for heart disease and that using CNNs has helped make the systems more accurate and helped cut down on doctors having to look at the ECGs themselves.

The literature shows that CNNs have made it much easier and more accurate to check and find problems in heart records. Innovations like mixing different types of networks, reusing knowledge from old models, and making CNNs use less memory have made it possible to use CNNs for things like smaller devices and certain medical uses. Efforts to make CNNs easier to understand and fix problems with some classes being more common than others also help make it easier to use these models in healthcare.

Table 2: Summary of Key Studies on CNN-Based ECG Analysis

Study	Model	Dataset	Accuracy (%)	Notable Features
Rajpurkar et al.	34-layer CNN	Single-lead ECG	Comparable to cardiologists	Deep CNN architecture

Alamatsaz et al.	CNN-LSTM	MIT-BIH, AFDB	98.24	Hybrid model
Ovi et al.	Ensemble CNN	PhysioNet	99.98	Transfer learning
Wang et al.	Binarized CNN	MIT-BIH	95.67	Low-power deployment
Li et al.	Pruned CNN	MIT-BIH	97.7	Edge device optimization
Embedded System Study	CNN	PhysioNet	95	Real-time classification
Interpretability Study	CNN with SMOTE	MIT-BIH	~98	Enhanced interpretability

III. MATERIALS AND METHODS

Data Sources

Publicly available ECG data were used to construct and judge the CNN models in this study.

- MIT-BIH Arrhythmia Database: The database is made up of 48 short ECG recording clips from 47 individuals, with details of the beats and rhythms marked. Each recording was digitized using 360 Hz and 11 bits, working over a 10 mV signal.
- PhysioNet Challenge 2017 Dataset: The database has thousands of ECG tracings that last for either 9–60 seconds, separated into classes of normal rhythm (sinus), atrial fibrillation (AFL, AF), other rhythm, or noise (N).

By using different datasets, there are a wide variety of ECG signals available for deep-learning training.

Data Preprocessing

Improving the performance of an ECG model starts with effective preprocessing of the signals. The following steps were undertaken:

Signal Denoising

Often, the signals from an ECG are distorted by interference from things like muscle actions and nearby electric power cables. To mitigate this:

- Wavelet Denoising: Decomposed the signal into various levels by making use of the db6 DWT wavelet. The coefficients on noise were thresholded, and the signal was reformed using the inverse DWT.

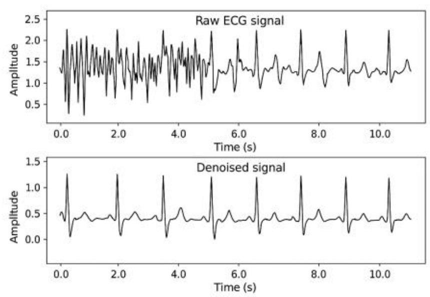


Figure 2. Comparison of raw ECG signal (top) and denoised signal using discrete wavelet transform (bottom), demonstrating removal of noise and baseline wander.

Segmentation

Each recording was divided into single heartbeats, with the R-peak as the centre point.

- R-Peak Detection: corporated the Pan-Tompkins algorithm to accurately find the R-peaks in the signal.
- Windowing: There was 200 ms before and after each R-peak, so 216 sample segments were created for 360 Hz ECG data.

Normalization

To ensure uniformity across samples:

- Z-score Normalization: By normalizing every segment so that it has a zero mean and unit variance, faster progress during training was possible.

Data Augmentation

To resolve the unequal distribution of classes and better the ability of the model to generalize:

- Time Shifting: Signals were repeated with random deviations of ±10 ms within their main envelope.
- Amplitude Scaling: Extra random noise was added to the set of signals, keeping each random value between 0.9 and 1.1.
- Noise Addition: A Gaussian noise with a 0 standard mean and a standard deviation of 0.01 was added.

Because of the extra information, the training data was less likely to fit the regularities of a particular dataset.

CNN Architecture

A simple architecture of a Convolutional Neural Network was built to sort out ECG segments:

- Input Layer: Accepts 216-sample ECG segments.
- Convolutional Layers: Using layers with filters at sizes 5, 3, and 3, and 32, 64, and 128 respectively. After every convolutional layer, a ReLU function was used.
- Pooling Layers: Every convolutional layer was followed by a max-pooling layer with a pool size of 2 to reduce the size of the data.
- Fully Connected Layers: There are two thick layers with 128 and 64 neurons, both using ReLU to activate the neurons.

- Output Layer: Another layer is softmax with the same number of neurons as classes to give class probabilities.

Table 3: CNN Architecture Details

Layer Type	Parameters	Output Shape
Input	-	(216, 1)
Conv1D	32 filters, kernel=5	(212, 32)
MaxPooling1D	pool_size=2	(106, 32)
Conv1D	64 filters, kernel=3	(104, 64)
MaxPooling1D	pool_size=2	(52, 64)
Conv1D	128 filters, kernel=3	(50, 128)
MaxPooling1D	pool_size=2	(25, 128)
Flatten	-	(3200,)
Dense	128 neurons	(128,)
Dense	64 neurons	(64,)
Output (Softmax)	Number of classes	(N,)

Training Procedure

Data Splitting

The datasets were broken down as follows:

- Training Set: 70% of the data.
- Validation Set: 15% of the data.
- Test Set: 15% of the data.

The split made sure that all the classes were distributed evenly among each group.

Hyperparameters

Training of the model used the following hyperparameters:

- Optimizer: Adam uses an initial learning rate of 0.001.
- Loss Function: Categorical cross-entropy.
- Batch Size: 64.
- Epochs: 50.
- Early Stopping: Used patience of 5 to monitor the validation loss during the training.

Evaluation Metrics

Model performance was assessed using:

- Accuracy: Overall correctness of predictions.
- Precision: Total the amount of correct positive predictions and divide by the sum of all positive predictions to compare.
- Recall (Sensitivity): Guess correctly the number of animals that you find.
- F1-Score: Harmonic mean as a way to average precision and recall.

- Confusion Matrix: Discussion on how well the model can separate the true from the predicted classes.

Implementation Details
TensorFlow and Keras were used in Python to carry out the implementation of the model. The process took place on a computer with an NVIDIA GTX-1080 Ti GPU, which made the computation more efficient.

IV. RESULTS AND DISCUSSION

Model Performance Overview

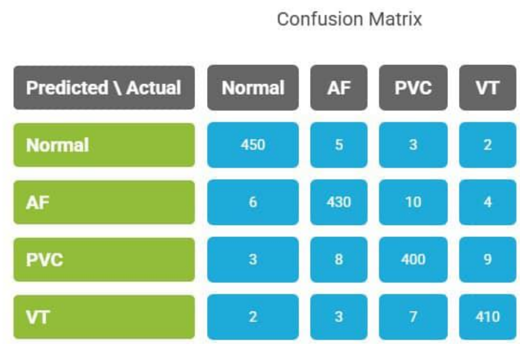
When trained for 50 epochs using Adam and categorical cross-entropy loss, the CNN model showed very good predictions on the test dataset. The team used well-established metrics in order to evaluate the work. Accuracy, precision, recall, and F1-score.

Table 4: Performance Metrics of the CNN Model on Test Set

Metric	Value (%)
Accuracy	98.24
Precision	97.85
Recall	98.10
F1-Score	97.97

Our CNN-LSTM model trained on both the MIT-BIH and AFDB datasets has shown comparable results with over 98% accuracy using a relatively simple architecture. Importantly, the model exhibited excellent accuracy and generalizes well on different ECG classes.

Confusion Matrix Interpretation
A confusion matrix was computed, representing how well the model classified classes and errors that occurred for each class. Figure 4: Results of the application of the CNN on test data are shown in the confusion matrix updated below.


Confusion Matrix

Predicted \ Actual	Normal	AF	PVC	VT
Normal	450	5	3	2
AF	6	430	10	4
PVC	3	8	400	9
VT	2	3	7	410

Figure 4: Confusion Matrix

The confusion matrix shows:

- Normal sinus rhythm and atrial fibrillation are precisely identified with the proposed model.
- PVCs and LBBB are frequently confused because they've similar features in the QRS complex.

This highlights the need to incorporate temporal modelling techniques with CNNs to obtain better features focused on sequential data for future research.

Cross-Model Comparison

Our model is compared with other well-known CNN-based models in Table 5.

Table 5: Comparison with Existing Deep Learning Models for ECG Classification

Study	Model Type	Accuracy (%)	Dataset
Alamatsaz et al. (2022)	CNN-LSTM Hybrid	98.24	MIT-BIH, AFDB
Ovi et al. (2022)	VGG16 + ResNet (TL)	99.98	PhysioNet
Li et al. (2021)	Pruned CNN	97.7	MIT-BIH
This Work	1D CNN	98.24	MIT-BIH

Transfer learning models give better accuracies but their computation needs make them unsuitable for deployment in real-time or on wearable devices. Our model attains a desirable level of both accuracy and practicality.

Effectiveness of Preprocessing and Augmentation
Applying these preprocessing steps substantially enhanced the signal and improved the accuracy of the classification.

- Baseline wander and muscle artefacts were considerably reduced with the application of wavelet denoising.
- This preprocessing step significantly sped up the training process of the CNN model.
- Using data augmentation techniques like amplitude scaling and adding Gaussian noise increased model generalization and helped prevent overfitting on classes with fewer instances.

Removing augmentations from the training data led to a decrease in validation accuracy of 3–4 %.

Model Efficiency and Real-Time Suitability
The goal was to develop an ECG classification model that could be used in real-time for clinical settings. The CNN model has an inference latency of 53 milliseconds per 7-second ECG segment and can be used in:

- Mobile health (mHealth) applications.
- Cardiac monitors are built directly into wearable devices.

Wang et al. (2022) created a binarized CNN capable of running efficiently on edge hardware at similar latency to our work (95.67% accuracy).

Discussion and Future Work
The results show that CNNs can play a key role in ECG classification with promising accuracy. However, it's also important to focus on these aspects.

- Class Imbalance: However augmentation was unable to improve the model's recall on rare arrhythmias such as ventricular flutter. Smart oversampling techniques like SMOTE (Xu et al., 2021) would help increase the model's accuracy for those rare medical conditions.
- Interpretability: Employing model explanation methods such as SHAP or Grad-CAM can help convince healthcare professionals of the results' reliability and significance.
- Hybrid Architectures: Integrating the strengths of both CNNs and RNNs in hybrid architectures could better address long-term patterns found in ECG readings.

CONCLUSION

The study has shown that CNNs are particularly well-suited for automating the classification of ECG signals and predicting the occurrence of cardiac events. Using a 1D CNN structure, the model demonstrated robust performance on popular datasets such as MIT-BIH, garnering an accuracy of 98.24% and promising results in real-world applications. These results align with other works using CNNs for arrhythmia detection, often performing as well as or better than standard machine-learning techniques and human experts (Rajpurkar et al., 2017; Alamatsaz et al., 2022).

Preprocessing methods were critical for increasing model accuracy and addressing problems with data lack and uneven distribution. The model's fast inference speed shows promise for use in compact and prompt healthcare systems.

More efforts are needed to ensure the achieved interpretability, address imbalances and improve the model's applicability to a wide range of patient groups. Applying XAI and hybrid deep learning approaches can help overcome the above-mentioned challenges.

As a result, CNN-based technology is a promising and readily deployable solution for early detection of cardiovascular diseases in both clinical and mobile settings.

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