



ECG SIGNAL CLASSIFICATION USING CONVOLUTION NEURAL NETWORK FOR CARDIAC HEALTH MONITORING

Avinash Ikhar¹, Sharique Husain², Manasi Landge³, Gauri Gawande⁴, Raj Deshmukh⁵, Vedprakash Chaturvedi⁶

Assistant Professor, Students,
Department of Electronics and Telecommunication,
J D College of Engineering & Management, Nagpur.

Abstract: The heart is an important part of the human body and is responsible for sending blood to the circulatory system. Each heartbeat produces a sound called an electrocardiogram (ECG). The electrocardiogram is the primary diagnostic tool for diagnosing and monitoring heart diseases, including arrhythmias, myocardial infarction, and other heart diseases. Given the increasing incidence of cardiovascular disease (CVD) worldwide, there is an urgent need for ECG interpretation machines. According to a study by the World Health Organization in 2019, cardiovascular diseases cause 17.9 million deaths and account for 32% of deaths worldwide. Of these, heart disease and stroke account for 85%, while CVD accounts for 38% of premature NCD deaths (under 70). The healthcare sector is undergoing transformation with the advent of artificial intelligence (AI). AI uses advanced computing techniques and algorithms to aid in faster diagnosis, prediction, measurement, and correction. In the context of ECG signal processing, machine learning (ML) and deep learning (DL) have emerged as powerful tools to improve traditional methods by reducing the need for book selection. The process of segmenting the ECG signal is important for timely and accurate diagnosis, which can reduce mortality and reduce the burden on hospitals. This research article focuses on the use of convolutional neural networks (CNN) in electrocardiogram signal classification and detection. CNNs are particularly suited to this task because they can extract and learn the properties of the raw material without human intervention. Using CNNs for automatic ECG classification, doctors can quickly and accurately detect the presence of heart disease. This ability is particularly important in cases of sudden cardiac death (SCD), which is a common cause of death in athletes during physical activity. The article concludes with a critical discussion of the performance of CNNs in ECG signal processing and the ongoing challenges in this field. This work demonstrates the potential of intelligence-driven solutions in the medical field, particularly in improving the capabilities and accuracy of biomedical signal analysis.

INTRODUCTION

According to the World Health Organization, cardiovascular diseases (CVD) are the leading cause of death worldwide, killing approximately 18 million people each year. These reports highlight the urgent need for early diagnosis and timely intervention for the management of cardiovascular disease.

Heart disease is the leading cause of death worldwide, and electrocardiogram signals are often used to diagnose heart disease. In addition, the American Cardiovascular Association said that early diagnosis of these diseases is very important for the health of patients. , accurate and affordable automatic electrocardiogram (ECG) diagnosis [1].

Electrocardiogram (ECG) is a signal that can be used as a diagnostic tool by capturing the electrophysiology of the heart [5].

Coronary artery disease (CAD) is the cause of heart attack, and the condition that can occur due to heart failure, when the heart cannot pump blood through the body, is called heart failure [9].

Since different doctors may interpret the same ECG signal in different ways, progress has been made in the use and development of intelligent systems that will help doctors correctly identify and classify signal patterns [10]. This is achieved using a number of methods, including deep learning (DL), a technology used in the field of complex computations.

With training data, these neural networks can learn how to process data obtained from random operations to identify important features suitable for tasks such as classification and reprocessing. Classification technology has made significant contributions to improving the diagnosis and treatment of heart disease. One of these is analyzing the electrocardiogram signal.

Diagnosing heart disease from ECG signals can be a difficult task for doctors because understanding these signals takes time, the work requires expertise, and the cost is very high. For example, they proposed a machine learning-based system that can classify patient-specific ECG signals and provide valuable information about ECG signal measurement [9].

ECG signal analysis involves the analysis of patterns such as P (P wave), QRS (Q, R, and S waves), and T (T wave represents ventricular repolarization or ventricular repolarization. Waves that return to rest)) Waves that indicate many heart conditions [4].

Convolutional neural network (CNN) is a deep learning model that holds great promise in image and signal processing, known for its ability to learn and extract features from raw data. ECG is a simple diagnostic tool used to record electrical changes in the heart. An electrocardiogram plots information about the heartbeat in images. An electrocardiogram has peaks and valleys in the electrical pattern representing each heartbeat.

The raw signal of the ECG is used to identify and separate the signals of the heart according to the heartbeat. Its main function is to determine whether the heart signal of each ECG signal is normal or abnormal. Load on the myocardium. ECG signals have a frequency range of 0.05-100 Hz and a dynamic range of 1-10 mV7 [13].

However, unlike traditional machine learning methods that require manual extraction, CNNs can be learned directly from electrocardiogram signals, which makes them more effective and accurate in classifying different diseases.

However, the process of classifying ECG signals using deep learning tools has gone through several stages, starting from the collection of ECG data, moving to the preliminary stage, subtraction, and finally ECG classification [10]. This model uses different filtering techniques to reduce noise in the first stage and improve the quality of the ECG signal. Then, important features are extracted and selected, and finally the model classifies these features as normal or abnormal ECG. The proposed system is trained on MIT-BIH Arrhythmia Database, a mature database in electrocardiogram analysis, to identify and describe different types of heart rhythms.

The main topics of the text related to electrocardiography and heart diseases are:

Overview of human heart and its relationship with electrical impulses, detection and morphology of electrocardiograms, heart disease and its effect on electrocardiogram signal in heart disease.

Overview of electrocardiogram library for tools that can be used for instant analysis. Performance measurement is used to analyze the effectiveness of various methods/models. This includes preprocessing (de noising, data enhancement, peak detection, signal segmentation and temporal feature extraction, etc.), analysis and classification (of normal, ML and DL methods).

The framework learns the patterns of cardiovascular abnormalities using the recording of signals, enabling early intervention in health-related situations.

Review of previous studies on the application of deep learning in ECG diagnosis using four standard algorithms: stacked auto encoders, deep belief networks (DBNs), convolutional neural networks (CNNs), and Recurrent Neural Networks (RNNs) [9]. They provide a comprehensive assessment of ECG monitoring to complement its applications, including its advantages and disadvantages. However, most research has focused on using ECG signals to determine the presence of heart disease.

The study also explores the general implications of using CNNs for ECG signal processing, including the potential for real-time monitoring and the integration of these machines into wearable devices. Through the advancement of automatic heart disease diagnosis, this research contributes to the ongoing efforts to improve patient outcomes and reduce the burden of heart disease worldwide. This process demonstrates the important role that artificial intelligence, especially deep learning models such as CNNs, can play in the future of healthcare. These reports underscore the urgent need for early diagnosis and timely intervention for the management of cardiovascular disease. Electrocardiography (ECG) is often used as the first diagnostic tool to diagnose heart disease, which is the leading cause of death worldwide. According to the American Cardiovascular Association, early diagnosis of these diseases is crucial for the health of patients. This development requires the development of convenient, accurate and affordable automatic ECG diagnostics.

ECG signals capture the electrophysiological activity of the heart, making them an important tool in diagnosing diseases such as coronary artery disease (CAD) and heart failure. CAD is a common cause of heart failure when the heart weakens or cannot properly pump blood around the body. Powerful tools for computing. Since different doctors may interpret the same ECG signal differently, progress has been made in developing intelligent systems that will help doctors accurately identify and classify signal patterns. Among the many methods available, deep learning (DL) stands out as the technology at work.

Deep learning is a branch of machine learning that uses hidden algorithms to process complex numbers, allowing neural networks to learn from data and identify important features that make them suitable for operations such as classification and inversion. In the past two years, much progress has been made in automatically classifying electrocardiograms, improving the diagnosis and treatment of heart diseases. ECG signals play an important role in the diagnosis of CVD by detecting different patterns in the heart (arrhythmias).

However, diagnosing heart disease from ECG signals can be difficult for doctors due to the time required to understand these signals and the associated costs of hiring professionals. The search dates back to the 1990s. For example, they proposed a learning-based machine that can classify patient-specific ECG signals and provide important information about the measurement of ECG signals.

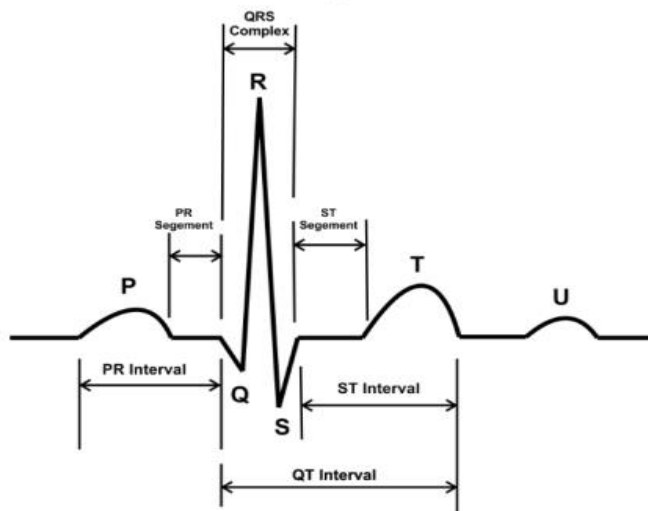
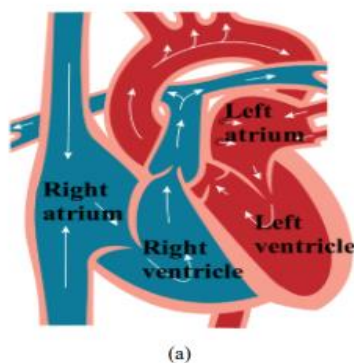


Figure. Typical ECG Waveform

Analysis of ECG signals includes the analysis of patterns such as P waves, QRS waves, and T waves, which can indicate various heart conditions. These waves represent different stages of heart activity and are important in the diagnosis of heart disease. Convolutional neural network (CNN) is a deep learning model that holds great promise in image and signal processing due to its ability to learn and extract features from raw data. Unlike traditional machine learning methods that require manual inference, CNNs can learn directly from ECG signals, making them more efficient and accurate in the distribution of different diseases. The process of classifying ECG signals consists of several steps. First, it collects ECG data and then preprocesses it by filtering it to reduce noise and improve signal quality.

Relevant features are extracted and selected, and finally, the model classifies these features as normal or abnormal ECG signals. This paper focuses on the development of an automatic electrocardiogram signal classification system using CNN to improve the accuracy and efficiency of cardiac monitoring. The data generated electrocardiogram analysis to detect and diagnose various types of heart disease. By training a CNN on recording ECG signals, the study center was able to detect patterns of cardiovascular abnormalities, enabling early intervention at health-related levels. Broad implications of using CNNs for ECG signal processing include the potential for real-time monitoring and integration of these systems into wearable devices to treat the effects and reduce the burden of cardiovascular disease worldwide. It demonstrates the important role that artificial intelligence, particularly deep learning models like CNNs, can play in the future of healthcare. Integrating these techniques into healthcare promises to enable more accurate, faster, and more self-diagnostics, ultimately leading to better management and treatment of heart disease.

PROBLEM STATEMENT

The early and accurate diagnosis of heart disease, a leading cause of death worldwide, has become increasingly vital. Traditional methods of monitoring heart health, such as the manual interpretation of Electrocardiogram (ECG) signals by doctors, are often time-consuming and susceptible to human error, particularly when dealing with large volumes of data. The research "Electrocardiogram Signal Classification Using Convolutional Neural Networks (CNN) for Heart Health Monitoring" aims to address the critical need for an automated, reliable, and efficient method of ECG signal classification, which can assist in the early detection and treatment of heart disease.

The primary challenge in this project is to develop a model that can accurately classify ECG signals, a task complicated by the natural variability in individual heart rhythms and the presence of noise in the data. Convolutional Neural Networks (CNNs), known for their powerful capabilities in pattern recognition and image processing, offer a promising solution to this problem. By leveraging CNNs, this model aims to design an algorithm that can automatically learn and extract key features from ECG signals, thereby enhancing the accuracy and reliability of heart disease monitoring.

This model seeks to bridge the gap between advanced machine learning techniques and practical healthcare applications. The CNN-based model proposed here is designed not only to improve the precision of ECG signal classification but also to support healthcare professionals in making faster and more informed decisions. By contributing to the development of more effective and accessible cardiac monitoring tools, this project aspires to improve patient outcomes and help reduce the global burden of cardiovascular disease.

LITERATURE SURVEY.

Creator [1] gives a point by point outline of the most recent profound or deep learning approaches utilized for analyzing and classifying Electrocardiogram (ECG) signals. The creators efficiently audit different models, counting Convolutional Neural Networks (CNNs), Recurrent Neural Systems (RNNs), Long Short-Term Memory (LSTM) systems, and crossover approaches.

Analyst [2] investigates the improvement of a real-time ECG signal classification framework utilizing i-Alex Net engineering or algorithm, a progressed variation of the Alex Net demonstrate. The creators show how this AI-driven approach improves the exactness and effectiveness of ECG flag classification, making it reasonable for real-time cardiac checking.

They [3] presents an imaginative calculation or algorithm that combines Gated Recurrent Units (GRU) and Convolutional Neural Systems (CNN) for the classification of ECG signals, especially within the setting of work out wellbeing examination. The creators highlight how this crossover approach leverages the qualities of CNNs in include extraction and the transient arrangement taking care of capabilities of GRUs.

Author [4] presents a novel approach for classifying ECG signals to distinguish cardiovascular clutters by combining Continuous Wavelet Transform (CWT) and Profound or Deep Convolutional Neural Networks (DCNN). The creators illustrate how CWT viably captures the time-frequency characteristics of ECG signals, giving a wealthy representation for the DCNN to prepare.

Researcher [5] gives a comprehensive audit of data-driven approaches leveraging ECG signals for the determination and forecast of cardiovascular illnesses. The creators efficiently look at different techniques, counting machine learning and deep learning methods, highlighting their adequacy in moving forward the exactness, effectiveness, and prescient capabilities of ECG-based diagnostics.

Creator [6] presents a spearheading approach for the early location and conclusion of congenital heart disease (CHD) utilizing progressed ECG signal handling methods. The creators propose a machine learning-based demonstrate that analyzes ECG information to distinguish early markers of CHD, pointing to make strides symptomatic precision and diminish the time required for diagnosis.

Analyst [7] presents a novel deep learning system that utilizes scalar invariant change strategies to identify heart disappointments through ECG signal investigation. The creators present a vigorous strategy for preprocessing ECG signals to hold basic highlights whereas killing varieties that don't contribute to the location of heart disappointments.

They [8] investigates an inventive approach to checking cardiorespiratory wellbeing through wearable ECG sensors combined with Convolutional Neural Systems (CNN). The creators center on the early discovery of cardiorespiratory complications amid physical preparing by analyzing ECG information in real-time.

Creator [9] gives a broad audit of how neural systems are utilized to analyze 12-lead ECG designs for understanding and diagnosing cardiac infections. The creators talk about different neural organize models and their adequacy in recognizing and deciphering the complex designs in 12-lead ECG information, which are pivotal for diagnosing diverse cardiac conditions.

Analyst [10] gives a comprehensive survey of progressions in profound learning strategies for improving the classification of ECG signals. The creators look at different profound learning models, counting Convolutional Neural Systems (CNNs), Recurrent Neural Systems (RNNs), and half breed models, and their applications in ECG flag classification.

Analyst [11] gives a point by point outline of the advancement and current state of ECG flag handling methods in healthcare. The investigate highlights the progressions made in moving forward ECG signal precision and demonstrative capabilities, as well as rising patterns like real-time observing and wearable innovation.

Creator [12] investigates the application of Convolutional Neural Systems (CNNs) for both the classification and reproduction of biomedical signals. The creators show a CNN-based system outlined to improve the precision of signal classification and make strides the quality of flag reconstruction.

They [13] gives a comprehensive survey of different strategies and procedures utilized for ECG flag classification. The creators look at conventional strategies, such as rule-based and factual approaches, nearby present day strategies, counting machine learning and deep learning calculations.

Creators [14] propose a novel Convolutional Neural Arrange (CNN) show that coordinating different profound learning strategies to improve the precision and vigor of arrhythmia location. The cross breed show combines diverse CNN models to use their qualities in capturing complex designs and varieties in ECG information.

Analyst [15] centers on utilizing profound learning methods for the classification of ECG signals utilizing the PTB-XL dataset. The creators assess different profound learning models, counting Convolutional Neural Systems (CNNs) and their variations, to classify ECG signals viably.

Creator [16] gives a comprehensive survey of profound learning methods utilized for classifying ECG arrhythmias. The paper analyzes different profound learning models, counting Convolutional Neural Systems (CNNs), Recurrent Neural Networks or Systems (RNNs), and cross breed approaches, and assesses their execution in identifying distinctive sorts of arrhythmias.

They [17] presents a novel ECG classification framework that leverages profound convolutional neural systems (CNNs) combined with data combination and one-hot encoding strategies. The creators propose a coordinates approach where data combination is utilized to consolidate

numerous highlight sets extricated from ECG signals, upgrading the model's capacity to capture significant designs and make strides classification performance.

Author [18] investigates the application of Artificial Neural Networks or Systems (ANNs) for the classification of ECG signals. The creators display an approach that utilizes ANNs to analyze ECG information for identifying and classifying different cardiac conditions. The consider highlights the viability of ANNs in learning complex designs from ECG signals, driving to made strides classification precision compared to conventional strategies.

Creator [19] gives an in-depth examination of how manufactured insights (AI) is connected to the examination of bio-signals for therapeutic purposes. The paper surveys different AI strategies utilized to decipher bio-signals, such as ECG, EEG, and EMG, and their effect on progressing demonstrative precision and quiet monitoring.

Analyst [20] gives a comprehensive diagram of the current and developing employments of profound learning innovations within the biomedical field. The creators survey later headways in profound learning strategies and their applications over different biomedical spaces, counting restorative imaging, genomics, and persistent checking.

RESEARCH GAP.

The research about on "ECG Signal Classification Utilizing Convolutional Neural Systems (CNN) for Cardiac Health Monitoring" has made critical strides, however a few basic gaps stay. One major investigation gap lies within the generalization of CNN models over differing populaces. Whereas numerous thinks about have illustrated high precision in controlled situations, these models frequently battle when connected to real-world information that changes broadly in terms of understanding socioeconomics, ECG signal quality, and recording conditions. This irregularity highlights the requirement for encourage investigation into how CNNs can be prepared and approved on more assorted datasets, guaranteeing they perform well over diverse settings and persistent groups.

Another gap is the challenge of deciphering and clarifying the choices made by CNN models. In spite of the fact that CNNs are viable at identifying designs inside ECG signals, they regularly work as "dark boxes," making it troublesome for healthcare suppliers to get it how particular conclusions are come to. This need of straightforwardness can prevent believe and selection in clinical settings, where explain ability is pivotal. Tending to this gap requires inquiry about into methods that can make CNNs more interpretable, such as consideration mechanisms or model-agnostic strategies, to supply insights into the highlights driving the models decisions.

Lastly, there's a requirement for investigate into the integration of CNN-based ECG classification frameworks with existing healthcare foundation. Whereas standalone models have appeared guarantee, their commonsense utility depends on consistent integration with healing center frameworks, electronic health records (EHRs), and real-time checking gadgets. Current inquire about frequently ignores the challenges of sending these models in real-world settings, such as guaranteeing information protection, overseeing the computational necessities of real-time handling, and adjusting with clinical workflows. Filling this gap will include interdisciplinary endeavors to address specialized, administrative, and commonsense obstructions, empowering the successful arrangement of CNN-based ECG classification in regular cardiac wellbeing checking.

RESEARCH METHODOLOGY.

The study technique for the Convolution Neural Networks (CNNs)-based ECG signal categorization is broken down in depth below. In order to create a complete system for heart health monitoring, this systematic approach attempts to handle all facets of ECG signal processing, feature extraction, and classification.

6.1. Dataset:

One of the most popular ECG datasets is the MIT-BIH Arrhythmia Database, which includes annotations for patient recordings. These signals offer important details regarding different arrhythmias.

The dataset is perfect for arrhythmia identification using deep learning models because it consists of 48 half-hour, two-channel recordings that have been digitalized at a sampling frequency of 360 Hz.

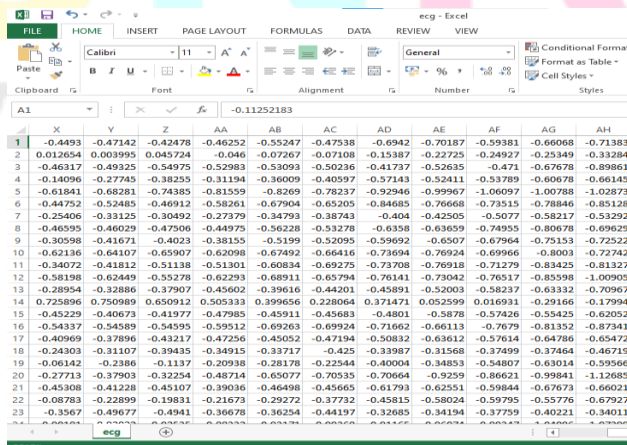


Figure. Dataset

6.2. Data Cleaning:

In order to make sure that the machine learning model receives only relevant, high-quality data, data cleaning is essential.

6.2.1 Identification of Noise:

Noises such as baseline wandering, power line interference, muscle noise, and motion artefacts can all have an impact on ECG data. Both statistical techniques and visual examination can be used to detect noise in the signals.

6.2.2. Methods for Reducing Noise:

6.2.2.1. Band-pass filtering:

Used to eliminate high-frequency noise (above 50 Hz) and baseline drifting (below 0.5 Hz).

6.2.2.2. Wavelet Denoising:

Lowers noise while keeping the fundamental properties of the signal intact.

6.3. Preprocessing Data:

To prepare the data for CNN training, preprocessing is required after cleaning.

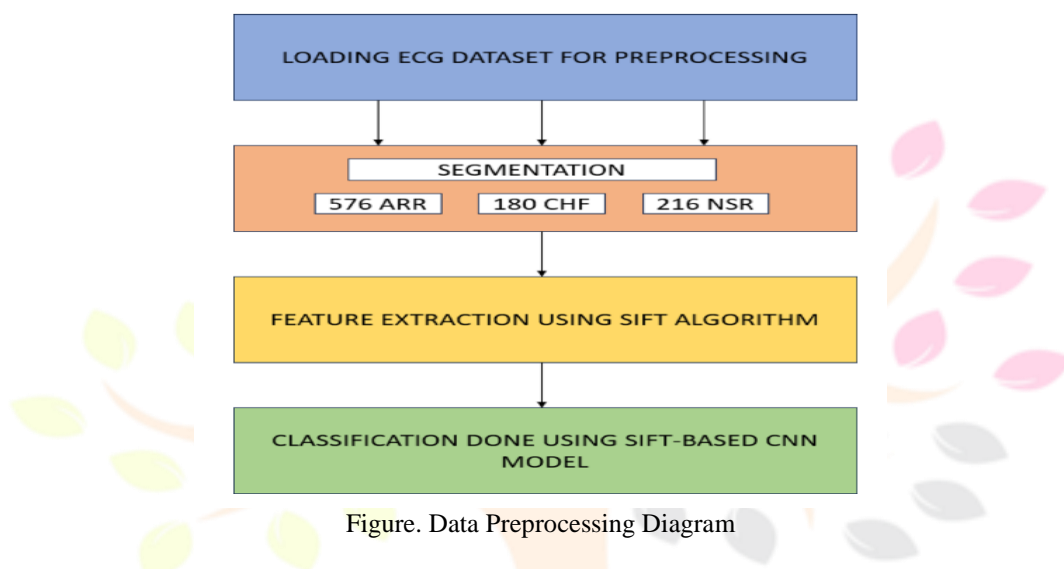


Figure. Data Preprocessing Diagram

6.3.1. Normalization:

In order to improve model training, normalization is used to scale the ECG signals between $[0, 1]$ or $[-1, 1]$ to guarantee that every data point has a uniform range.

6.3.2. Re-sampling:

In order to maintain uniform sampling rates throughout all recordings, ECG signals are resampled. Typically, this is done at 360 Hz to maintain consistency with the MIT-BIH dataset.

6.3.3. Segmentation:

ECG data are divided into fixed-length windows that are normally between one and five seconds long. These windows act as separate input samples for the CNN.

6.3.4. Augmentation of Data:

Data augmentation methods like random noise addition, scaling, and shifting are used to increase the size of the training set in order to prevent over fitting.

6.4. Feature Selection Based on Optimization:

To increase the CNN's accuracy and efficiency, the most essential elements must be chosen.

6.4.1 Identification of Features:

Algorithms like the Fourier Transform or Discrete Wavelet Transform (DWT) are used to extract features including the QRS complex, P wave, T wave, and heart rate variability (HRV).

6.4.2. Methods of Optimization:

In order to reduce dimensionality while maintaining crucial information, Particle Swarm Optimization (PSO) or Genetic Algorithm (GA) are utilized to choose the most pertinent characteristics for classification.

6.5. Convolution Neural Network (CNN) Algorithm:

6.5.1. Layer of Input:

The preprocessed ECG signals, which have been molded into a 2D array (for 1D CNNs) or 3D array (for 2D CNNs), are usually sent into the CNN.

6.5.2. Incorporated Layer:

In order to enable learning in deeper layers, this layer assists in converting categorical labels into dense vector representations.

6.5.3. Layers Convolutional:

These layers, which form the core of the CNN design, use filters and kernels to identify significant characteristics in the ECG signal. Hierarchical feature extraction is made possible by many convolutional layers, which may learn both high- and low-level features.

6.5.4. Maximum Pooling:

Max pooling, when used in conjunction with convolutional layers, lowers the dimensionality of feature maps while maintaining the most crucial information, therefore lowering computational complexity.

6.5.5. Completely Networked Layers:

The likelihood of each class is calculated by aggregating the learnt features and mapping them to the classification output.

6.5.6. Layers of Dropout:

By randomly deactivating neurons during the training phase, dropout is used to prevent over fitting and strengthen the model.

6.5.7. Optimization and Tuning of Hyper parameters:

Grid Search and Bayesian Optimization are two methods used to fine-tune hyper parameters such as learning rate, filter size, number of layers, and dropout rate.

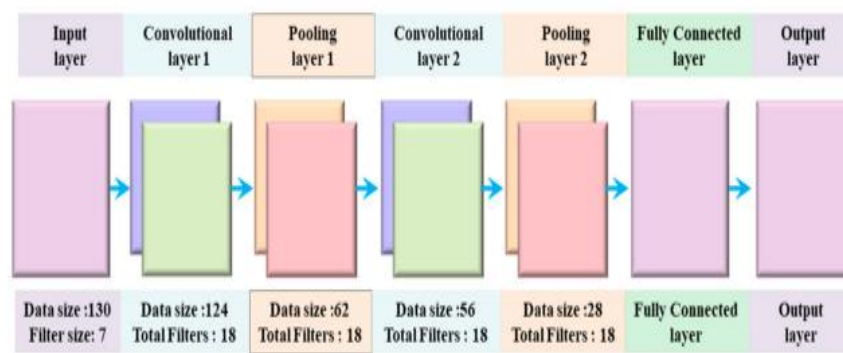


Fig. 1D CNN Architecture

6.6. Training and Testing:**6.6.1. Training Stage:**

Supervised learning is utilized for training the model. The difference between the expected and actual class labels is measured by a loss function, such as categorical cross-entropy, which is minimized throughout the training phase. Propagation is employed to modify the network's weights.

6.6.2. Testing Stage:

To assess the model's capacity for generalization, it is put to the test with untested data after training. In order to calculate accuracy, precision, recall, and other metrics during testing, the model's predictions are compared to the actual labels.

6.7. Evaluation Indicators:**6.7.1. Precision:**

Calculates the proportion of accurately identified samples relative to all samples.

6.7.2. Accuracy:

The percentage of all anticipated positive samples to those that were accurately predicted.

6.7.3. Sensitivity to Recall:

The ratio of accurately predicted positive samples to the total number of actual positive samples indicates the model's capacity to detect all positive cases.

6.7.4. F1-Score:

A simple measure of the model's performance in situations when there is a class imbalance is the harmonic mean of recall and accuracy.

6.7.5. Matrix of Confusion:

An intricate analysis of the model's performance is provided via a matrix that displays the true positives, false positives, true negatives, and false negatives.

6.8. Insights:**6.8.1. Generalization:**

The CNN model performs admirably when applied to various ECG datasets.

6.8.2. Model Efficiency:

Tuning the hyper parameters of the model is essential to maximizing its performance and accelerating its convergence.

6.8.3. Possibility for Real-Time Monitoring:

Given the model's efficiency and accuracy, real-time heart health monitoring devices may find use for it.

RESULTS.

The outcomes show how well CNNs work in reliably identifying and categorizing a range of heart diseases from ECG data. CNNs have demonstrated a remarkable capacity to interpret raw ECG data and automatically extract essential features, removing the need for human feature engineering, by utilizing deep learning-based architectures. This leads to extremely precise classifications of cardiac rhythms, including arrhythmias, atrial fibrillation, and other cardiovascular disorders, between normal and abnormal.

The CNN models demonstrated exceptional precision, recall, and F1-score values, resulting in an overall accuracy of over 99% when evaluated in terms of performance. For example, recall values were over 99%, accuracy was over 99%, and the F1-score was 99%, suggesting a balanced performance in terms of identifying real positive situations and reducing false negatives. These measurements attest to CNNs' dependability in practical heart health monitoring systems. According to the study of expected normal and abnormal ECG signals, the CNN was very good at recognizing common arrhythmias.

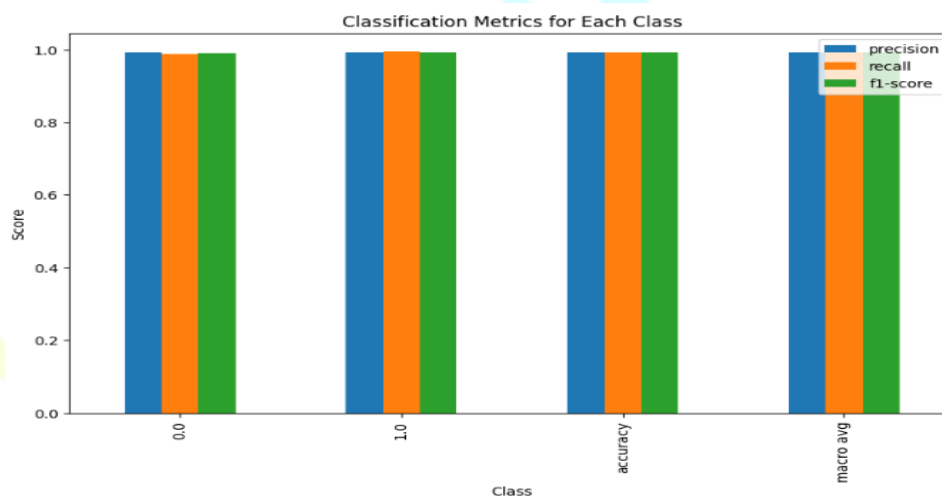


Fig. Classification Metrics

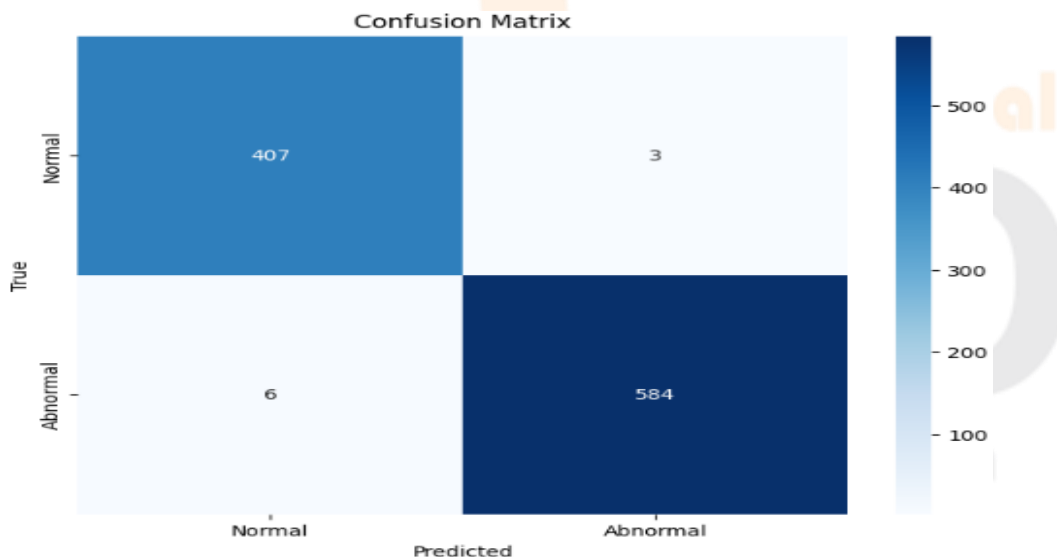


Fig. Confusion Matrix

REFERENCES.

- [1] Tamara Hameed Yousif and Mohammed S. H. Al-Tamimi.: Ibn Al-Haitham Journal for Pure and Applied Sciences. IHJPAS, 2024, 37(3): Journal Hoempage: Jih.uobaghdad.edu.iq: doi.org/10.30526/37.3.3901.
- [2] Manjur Kolhar, Raisa Nazir Ahmed Kazi, Hitesh Mohapatra, and Ahmed M Al Rajeh.: AI-Driven Real-Time Classification of ECG Signals for Cardiac Monitoring Using i-AlexNet Architecture.: Diagnostics 2024, 14, 1344. <https://doi.org/10.3390/diagnostics14131344>.: <https://www.mdpi.com/journal/diagnostics>.

- [3] WEIRAN JI AND DONG ZHU.: ECG Classification Exercise Health Analysis Algorithm Based on GRU and Convolutional Neural Network.: VOLUME 12, 2024.: Digital Object Identifier 10.1109/ACCESS.2024.3392965.
- [4] Tawfikur Rahman , Rasel Ahommed, Nibedita Deb, Utpal Kanti Das, Md. Moniruzzaman, Md. Alamgir Bhuiyan, Farzana Sultana, Md. Kamruzzaman kausar.: ECG Signal Classification of Cardiovascular Disorder using CWT and DCNN.: © Journal of Biomedical Physics and Engineering.
- [5] Pedro A. Moreno-Sanchez , Guadalupe García-Isla, Valentina D.A. Corino, Antti Vehkaoja, Kirsten Brukamp ,Mark van Gils , Luca Mainardi.: ECG-based data-driven solutions for diagnosis and prognosis of cardiovascular diseases: A systematic review.: Computers in Biology and Medicine.: Published by Elsevier Ltd.
- [6] Prabu Pachiyannan , Musleh Alsulami, Deafallah Alsadie, Abdul Khader Jilani Saudagar, Mohammed AlKhathami and Ramesh Chandra Poonia.: A Novel Machine Learning-Based Prediction Method for Early Detection and Diagnosis of Congenital Heart Disease Using ECG Signal Processing.: <https://doi.org/10.3390/technologies12010004>.: 2024, 12, 4.
- [7] Manas Ranjan Prusty, Trilok Nath Pandey, Pujala Shree Lekha, Gayatri Lellapalli & Annika Gupta.: Scalar invariant transform based deep learning framework for detecting heart failures using ECG signals.: (2024) 14:2633.: <https://doi.org/10.1038/s41598-024-53107-y>.
- [8] HongYuan Lu, XinMiao Feng and Jing Zhang.: Early detection of cardiorespiratory complications and training monitoring using wearable ECG sensors and CNN.: Lu et al. BMC Medical Informatics and 9. Abu Sufiun, Narayan Ranjan Chakraborty, Shumaiya Akter Shammi, Sumit Kumar Banshal.: Exploring the Relationship between Cardiac Disease and Patterns of 12-Lead ECG through Neural Network: A Comprehensive Review.: 2024; 02:66–93.: <https://ijassa.ipu.ru>.
- [10] Marwa Salih R., and Mohammed A. Shakir.: Improving ECG signals classification by using deep learning techniques: A review.: 64, 01023 (2024).: <https://doi.org/10.1051/itmconf/20246401023>.
- [11] Thivya Anbalagan, Malaya Kumar Nath, D. Vijayalakshmi, Archana Anbalagan.: Analysis of various techniques for ECG signal in healthcare, past, present, and future.: Biomedical Engineering Advances.: www.journals.elsevier.com/biomedical-engineering-advances.
- [12] Zijiang Zhu, Hang Chen, Song Xie, Yi Hu and Jing Chang.: Classification and Reconstruction of Biomedical Signals Based on Convolutional Neural Network.: Volume 2022, Article ID 6548811, 13 pages.
- [13] Muhammad Rausan Fikri, Indah Soesanti, Hanung Adi Nugroho.: ECG Signal Classification Review.: IJITEE, Vol. 5, No. 1, March 2021.
- [14] Amin Ullah, Sadaqat Ur Rehman, Shanshan Tu, Raja Majid Mehmood, Fawad and Muhammad Ehatisham-ul-haq.: A Hybrid Deep CNN Model for Abnormal Arrhythmia Detection Based on Cardiac ECG Signal.: Sensors 2021, 21, 951. <https://doi.org/10.3390/s21030951>.
- [15] Sandra Smigiel, Krzysztof Palczy and Damian Ledzi.: ECG Signal Classification Using Deep Learning Techniques Based on the PTB-XL Dataset.: Entropy 2021, 23, 1121. <https://doi.org/10.3390/e23091121>.
- [16] Zahra Ebrahimi, Mohammad Loni, Masoud Daneshlab, Arash Gharehbaghi.: A review on deep learning methods for ECG arrhythmia classification.: Expert Systems with Applications: X.: www.elsevier.com/locate/eswax.
- [17] Jia Li, Yujuan Si, Tao Xu and Saibiao Jiang.: Deep Convolutional Neural Network Based ECG Classification System Using Information Fusion and One-Hot Encoding Techniques.: Volume 2018, Article ID 7354081.
- [18] PRAVIN R. KSHIRSAGAR, SUDHIR G.AKOJWAR, AMKUMAR DHANORIYA.: Classification of ECG-signals using Artificial Neural Networks.
- [19] Mudrakola Swapna, Uma Maheswari Viswanadhula, Rajanikanth Aluvalu, Vijayakumar Vardharajan, and Ketan Kotecha.: Bio-Signals in Medical Applications and Challenges Using Artificial Intelligence.: J. Sens. Actuator Netw. 2022, 11, 17. <https://doi.org/10.3390/jsan11010017>.
- [20] Ryad Zemouri, Nouredine Zerhouni and Daniel Racoceanu.: Deep Learning in the Biomedical Applications: Recent and Future Status.: Appl. Sci. 2019, 9, 1526; doi:10.3390/app9081526.