Received: 6 August 2024 | Revised: 10 February 2025 | Accepted: 19 February 2025 | Published online: 4 March 2025

RESEARCH ARTICLE

Medinformatics
2025, Vol. 2(2) 120–131
DOI: 10.47852/bonviewMEDIN52024043

BON VIEW PUBLISHING

Classification of Heartbeats Using Convolutional Neural Network with Range Normalization

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Abstract: Electrocardiogram (ECGs) signals are the primary means by which physicians diagnose cardiovascular-related illnesses such as abnormal heart rhythms, heart attack, and rheumatic heart. Automatically analyzing electrocardiogram (ECG) signals is a complex machine learning problem. This is because ECG waveforms can exhibit significant variability in their morphological (shape) and temporal (time-based) characteristics across different individuals. Doctors can reliably analyze electrocardiogram (ECG) signals using visual inspection of the signal waveform. However, doctors often find it challenging to analyze lengthy ECG records within a short time frame. Furthermore, the human eye has limitations in detecting subtle morphological variations within ECG signals. Although ECG signals can reveal a diverse range of heart conditions, the task of observing and categorizing long-term ECG beats can be challenging even for experts. Furthermore, because of the large volume of data, there is a significant risk of missing important information. As a result, effective computational techniques are essential to tackle this challenge. This paper introduces a deep learning approach for improving the classification of electrocardiogram (ECG) signals. The novelty in our approach is applying range normalization, which scales input data to a range of 0 to 1 before feeding it into neural network layers. The method classifies ECG signals into five categories, evaluated using the Massachusetts Institute of Technology and Boston Hospital and PTB datasets and adhering to AAMI standards. A comparison of normalization techniques with a convolutional neural network (CNN) classifier shows that the proposed method achieves average $F1$-scores of 99%, 85%, 95%, 81%, and 99% for the N, S, V, F, and Q classes, respectively. The overall accuracy of 98.73% demonstrates that the proposed technique outperforms existing methods.

Keywords: normalization, classification, ECG signal, cardiovascular diseases

1. Introduction

Heart-related diseases are the leading causes of illness and death worldwide [1–3], with their growing prevalence imposing a substantial economic strain on healthcare systems [4]. Developing and middle-income countries account majority of cardiovascular disease (CVD) fatalities globally [5]. Risk factors associated with CVDs include tobacco use, obesity, a sedentary lifestyle, excessive alcohol consumption, and an unhealthy diet [6]. Avoiding risk factors [7] and early detection of CVD using physiological and biochemical factors [8] can help reduce cardiovascular fatalities. Early detection provides clinicians with information to intervene before they progress to severe stages. Continuous monitoring and analysis of electrocardiogram (ECG) signals play a crucial role in improving the diagnosis, management, and prevention of various cardiovascular ailments. Heart rate monitors are becoming increasingly common in daily life, with the electrocardiogram (ECG) established as a standard diagnostic tool for CVDs [9]. Widely used in healthcare, ECG is employed in various settings, including intensive care units, routine medical care, and remote monitoring through devices like Holter monitors [10]. A Holter monitor, a portable ECG device, continuously records the heart's electrical activity remotely [11]. Its sensors are attached to the skin to detect the heart's electrical signals during each beat. Electrocardiogram remains a key diagnostic method for the early detection of heart conditions.

An electrocardiogram (ECG or EKG) is a non-invasive method used to assess heart activity by converting the electrical impulses produced during the polarization and depolarization of cardiac tissue into a waveform signal. This signal is essential for measuring heart rate, identifying regular and irregular heart rhythms, and evaluating the strength and timing of electrical signals as they travel through different regions of the heart. Consequently, ECGs are indispensable in both diagnostic and research settings, aiding in the detection and analysis of cardiac abnormalities as well as the study of other conditions that may impact heart function.

Owing to its ease of use and non-intrusive approach, the ECG is extensively utilized to evaluate cardiac health, offering crucial information about the heart's wellbeing. Despite being one of the oldest and most fundamental cardiac assessments, the electrocardiogram (ECG) offers a wealth of information for diagnosing cardiac issues. Based on relatively straightforward electro-physiological principles, ECG signals can be quickly and easily obtained with modern equipment. It has been proven a

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reliable tool for monitoring the cardiovascular system [12], delivering comprehensive information about heart and cardiovascular health [13]. It captures the heart's rhythm and electrical activity, commonly used to detect arrhythmia, a major cardiovascular condition [14]. Patients with arrhythmia (irregular heartbeats) may experience both cardiovascular and non-cardiovascular comorbidities. The ECG is a well-established diagnostic tool that enjoys universal acceptance. It displays changes in the heart's electrical activity over time and provides crucial physiological data commonly used to assess heart function [15]. For example, doctors use it to determine whether a patient's heartbeat is normal or irregular, offering cardiologists valuable insights into diagnosing heart-related diseases. Analyzing and processing ECG signals is essential for diagnosing cardiovascular conditions, with a growing research focus on classification increasingly supported by machine learning (ML) algorithms [16]. According to the literature, most classification methods employ convolutional neural networks (CNNs), which have shown success in numerous classification tasks [17]. Currently, the prevalence of CVDs is rising, posing a significant global health challenge [18]. ECG data provide extensive information for diagnosing cardiac issues, and with the increasing volume of ECG signals generated daily, many heart conditions can be identified from these signals [19]. Various classifiers are employed to classify heartbeats, making heartbeat classification a vital step in assessing cardiac function. An ECG offers a graphical representation of heart signals, measuring the heart's electrical activity and commonly identifying abnormalities. The electrocardiogram (ECG) displays waves generated during heart activity, providing valuable information such as heart rate, rhythm, and morphology [20]. Each heartbeat corresponds to an ECG signal characterized by a recurring sequence of P, QRS, and T waves. Recently, there has been considerable interest in accurately classifying ECG signals using deep learning models. Many researchers have investigated various deep learning techniques in this domain [21]. This research actively contributes to the early detection and management of cardiac disorders in clinical settings [22]. The detection and classification of heart arrhythmias using ECG signals have also been a prominent focus of study [23]. This research aims to introduce a deep learning approach that improves the accuracy and performance of ECG data classification. The following contributions are proposed:

1) We present an overview of cutting-edge deep learning approaches, with particular emphasis on deep learning methods.
2) We present a deep learning-based methodology for classifying normal and arrhythmic heartbeats from ECG data.
3) Using an actual ECG dataset, we evaluate the methodology and compare its results to those of contemporary methods.

The rest of this paper is organized as follows: Section 2 reviews related work on ECG signal classification using machine learning techniques. Section 3 presents the methodology in detail, while Section 4 discusses the experimental evaluation of the proposed approach. Finally, Section 5 concludes with key insights and directions for future research.

1.1. Background

The human body's tissues and organs produce electrical signals known as biopotentials that indicate the state of each organ or tissue's function. These voltages, or electrical impulses, are produced by bodily physiological processes. The heart (electrocardiogram), brain (electroencephalogram), and muscle (electromyogram) are a few examples of organs that produce biopotentials. It is possible to identify both normal organ function and abnormal organ function by measuring these biopotentials from the human body [24].

An ECG captures the heart's electrical activity as it occurs on the skin's surface. This electrical activity consists of a series of waves that cause the heart to constrict and relax. The ECG detects these waves as changes on the skin's surface. Each successive cycle on the ECG corresponds to the depolarization and repolarization of the atria and ventricles. The signals measured on the skin can be correlated with heart activity, making the ECG a key tool for diagnosing heart-related issues.

The electrical activity of the human heart is represented by electrocardiogram (ECG) signals, which consist of various waveforms: P, QRS, and T. Heart disorders are diagnosed by analyzing the duration and shape of each waveform, as well as the distances between distinct peaks [25]. ECGs are utilized in various healthcare settings to monitor and record the heart's electrical activity. They capture the heart's depolarization and repolarization, providing valuable insights into the condition of the heart [26]. ECGs are crucial for diagnosing heart diseases, including abnormal heart rhythms, heart attacks, and heart failure. An electrocardiogram (ECG) records the electrical activity of the heart over time. The device used to capture this activity is called an electrocardiograph, a diagnostic medical instrument invented by Willem Einthoven [27]. Electrodes attached to a patient's chest record the heart's electrical activity, which is then displayed as a graph over time [28, 29]. The electrical currents generated by the heart's depolarization and repolarization propagate not only within the heart but also throughout the body. An array of electrodes placed on the body surface can measure this electrical activity. The recorded tracing is referred to as an electrocardiogram (ECG), and the different waves that comprise it represent the sequence of depolarization and repolarization of the atria and ventricles. As illustrated in Figure 1(A), a typical ECG signal includes three types of waves: the P wave, QRS complex, and T wave [30]. Figure 1(B) illustrates the three segments of a typical ECG signal.

Physicians make decisions based on the interval and morphological information of an ECG signal, utilizing the shapes of the waves and the rhythm of the heartbeat [31]. Classifying ECG heartbeats is essential for diagnosing cardiac conditions, such as arrhythmias. However, the manual review of ECGs is time-consuming for cardiologists, highlighting the need for automated ECG analysis [32]. The primary challenge with manual analysis lies in the difficulty of recognizing and categorizing various waveforms and morphologies in ECG signals, as well as in other time-series data [32]. Cardiac anomalies are often indicated by subtle fluctuations in the amplitude and duration of the ECG signal, which are challenging to detect with the naked eye [33]. Therefore, a computer-aided diagnosis system can assist physicians in monitoring cardiac health effectively. Recording the heart's electrical activity (ECG) is commonly employed to diagnose and monitor heart conditions. A trained cardiologist is typically needed to analyze these signals; however, this expertise is not always readily accessible. This study presents a classification system for ECG data that categorizes the signals into five heartbeat classes.

The ECG signal is valuable for diagnosing cardiac arrhythmia as it offers insights into the heart's function. Heart arrhythmia is a common indicator of CVD. In modern medical practice, cardiologists must carefully examine the ECG signal to diagnose heart-related conditions. It plays a crucial role in cardiology, particularly for identifying arrhythmic beats.

On the other hand, automating the classification of various heart diseases can provide objective diagnostic results and save time for

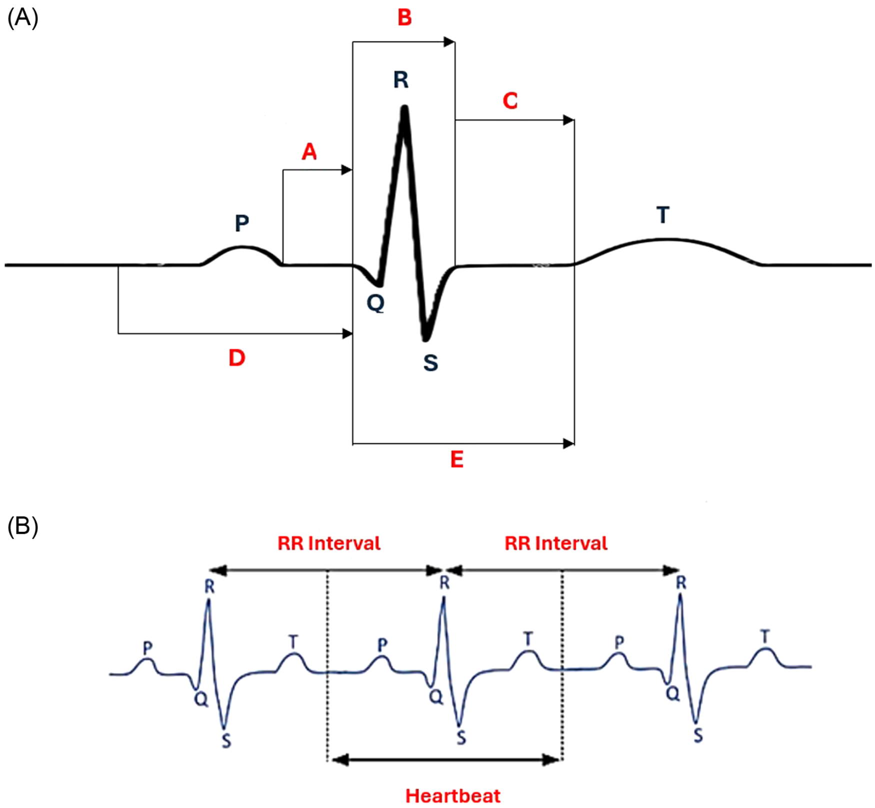

Figure 1. (A). ECG signal. A – PR segment, B – QRS complex, C – ST segment, D – PQ interval and E – ST interval. (B). A segmented heartbeat from ECG signals.

cardiologists. This has led to growing interest in computer-based classification tools that can assist physicians in making more informed decisions based on ECG signals. One application of pattern recognition techniques is in analyzing ECG signals. The aim of pattern recognition is to automatically categorize a structure into one of several predefined classes. The Figure 1(B) above illustrates a segmented ECG signal.

By analyzing ECG data, physicians can diagnose various types of arrhythmias. They evaluate the intervals and morphological features of the ECG signal, such as the shape of the three primary waves and the heartbeat rhythm [30]. Doctors use electrocardiograms to identify patterns in these heartbeats and rhythms, assisting in the diagnosis of different heart conditions. By examining the electrical signals of each heartbeat recorded in the ECG, they can detect any irregularities in heart function. An ECG primarily monitors the heart's activity, including its rate (heart rate) and the regularity of the beats (heart rhythm).

1.2. Classification of ECG signals

Cardiologists and physicians often use ECG alongside other tests for diagnosing and monitoring heart conditions. Due to complex patterns associated with different heartbeats in the ECG signals, analyzing manually ECG signals is a difficult and time-consuming process. ECG signals are characterized as time-series data, and the challenge lies in detecting and categorizing the various waveforms and morphologies within the signal, a common issue with time-series data. To address these challenges, many studies have explored the application of ML techniques for the precise classification of heartbeats in ECG signals [12]. However, these techniques have limitations, including the need for manual feature extraction and a steep learning curve for the models [34]. In this paper, we present a model that classifies each ECG heartbeat into four AAMI heartbeat categories, with an additional category for unknown heartbeats. This approach can help physicians quickly identify different types of heartbeats, potentially saving valuable time in healthcare delivery.

1.3. Covariate shift problem

In deep neural networks, covariate shift is a prevalent issue that impacts supervised ML techniques. Recent literature on ECG signal classification using deep learning methods has demonstrated superior performance compared to traditional shallow ML techniques [35]. Deep learning allows for automatic feature learning, eliminating the need for hand-crafted features [36]. However, training deep neural networks poses challenges [37], primarily due to a phenomenon known as internal covariate shift [38]. This issue involves continuously changing input distributions, which slows down the training process and prolongs convergence to a global minimum. Consequently, long training times represent a fundamental challenge in deep learning [39]. Deep feedforward neural networks are particularly susceptible to covariate shift [40], which diminishes their training efficiency [41]. The problem of internal covariate shift was first identified by Ioffe and Szegedy in 2015 [38]. Covariate shift refers to changes in the input distribution between the training and testing phases [42]. This shift occurs continuously during the training of feedforward neural networks, as modifications to a layer's parameters impact the input distribution for all subsequent layers. The presence of covariate shift is known to hinder the training efficiency of deep neural networks [43]. CNNs have become widely used for classifying ECG signals. A CNN consists of multiple convolutional layers that apply convolutional operations to inputs in order to detect various features. Moreover, advanced CNN techniques utilize batch normalization to address the issue of internal covariate shift and speed up neural network training [44]. Batch normalization [37] helps mitigate the impact of internal covariate shift, enabling faster training rates [45].

2. Related Work

In recent years, artificial intelligence has been applied to the analysis of ECG signals. ML, particularly deep learning techniques, has proven to be highly effective in identifying various ECG waveforms and events, significantly enhancing the detection accuracy of different heart conditions. Classifying ECG signals is a crucial yet challenging task. To address this challenge, several approaches have been proposed in the literature. A variety of signal processing and ML methods have been utilized for classifying ECG signals [46].

Traditionally, identifying segments of the P-QRS-T interval in electrocardiogram signals and classifying heartbeats were accomplished through signal processing techniques. These methods involved decomposing ECG signals into wavelet-like components using approaches such as Fourier and wavelet transformations. Key features, such as irregularities in rhythm or rhythm frequency, became more apparent due to these transformations. These approaches attained an accuracy of 93% on the Massachusetts Institute of Technology and Boston Hospital (MIT-BIH) Arrhythmia Dataset [47].

ML techniques have outperformed signal processing methods in both performance and generalization, making them widely used today. Numerous studies, including those by Cömert et al. [48], Su et al. [49], Dey et al. [50], Wasimuddin et al. [51], and Petmezas et al. [52], showcase the use of ML methods for ECG signal classification. These techniques can be broadly categorized into traditional methods and deep learning approaches. Traditional algorithms, such as support vector machines (SVM) [53] and K-Nearest Neighbors (KNN) [54], have been commonly applied to classify ECG signals. For example, Saini et al. [55] employed KNN to detect QRS waves in ECG signals, while Walsh [56] utilized SVM for classifying ECG signals. However, traditional ML techniques are constrained by manually crafted features, often leading to suboptimal performance. State-of-the-art approaches documented in the literature primarily employ deep learning models, which have shown enhanced accuracy in diagnosing cardiovascular conditions using ECG signals. CNNs and recurrent neural networks (RNNs) are the most widely used deep learning methods for ECG classification. In recent years, numerous deep learning techniques have been introduced for classifying ECG signals with neural networks. For example, Kachuee et al. [12] utilized a CNN to classify ECG signals from the MIT-BIH and PTB databases, focusing on five AAMI EC57 classes for the MIT-BIH data and two classes for the PTB data. Zhang et al. [57] classified ECG signals into eight micro-classes using deep learning techniques. Cheng et al. [58], Murugesan et al. [59], and Xie et al. [60] have combined CNNs and RNNs for ECG signal classification. Recent research highlights the effectiveness of CNNs in classification tasks, emphasizing that accurate heartbeat classification is essential for diagnosing CVDs.

3. Methodology

3.1. Problem formulation

In this work, we approach ECG heartbeat classification as a time-series classification task, where a classifier extracts key information from ECG data to accurately predict the corresponding heartbeat class. The model takes signal input and outputs a class indicating the heartbeat's category. Our aim is to reduce the cross-entropy between the predicted and true distributions. The purpose of supervised learning is to build a model that effectively links inputs to outputs accurately. To accomplish this, we require a technique that automatically labels each ECG heartbeat with a class such as "Normal", "Supraventricular ectopic", "Ventricular ectopic", "Fusion", or "Unclassifiable". This classification task necessitates a training dataset $H = (h_i\ , h_2, \ldots, h_n)$. ECG heartbeats have been pre-labeled with their corresponding classes. We then construct a classification model capable of assigning the correct class C_i to a new heartbeat h_i. This represents a multi-class classification problem.

3.2. Research objectives

In this research, we introduced a one-dimensional CNN with layer normalization techniques to categorize ECG data into five distinct heartbeat classes. We conducted a comparative analysis of two distinct CNN architectures: one leveraging conventional batch normalization and the other employing the novel range normalization approach. The following were the study's objectives:

1) To first investigate the problem of heartbeat classification,
2) To classify heartbeats into five distinct categories: Normal (N), Supraventricular (S) ectopic, Ventricular (V) ectopic, Fusion (F), and Unknown (Q) – in alignment with the guidelines established by the Association for the Advancement of Medical Instrumentation [61], employing the ECG Heartbeat Classification Dataset.
3) To improve classification methodology over previous approaches.

3.3. Theoretical background

Supervised ML methods, such as neural networks, assume that training and testing samples are drawn from the same distribution. However, this assumption often does not hold in many classification tasks. Common violations of this assumption include class imbalance [62], concept drift [63], and covariate shift [64]. The covariate shift problem occurs when the distribution of variables in the training data differs from those in the testing data. To mitigate this issue, it is essential to align the distribution of the training data with that of the test data. Let's consider the inputs X to a model and its outputs Y. In a classification problem, the training data represents samples from the joint distribution P(X, Y), while ML generally models P(Y|X). The joint distribution P(X, Y) can be decomposed in two ways:

$$P(X,\ Y) \ =\ P(Y|X)P(X) \tag{1}$$

$$P(X,\ Y) \ =\ P(X|Y)P(Y) \tag{2}$$

where P(Y|X) represents the conditional probability of the output given the input. P(X) represents the probability density function of the input. P(Y) represents the probability density function of the output. Covariate shift occurs when P(X) changes, while P(Y|X) remains invariant.

One approach to address this issue is batch normalization, a method for normalizing activations in the intermediate layers of deep neural networks. Due to its effectiveness in enhancing accuracy and accelerating training, it has become a widely adopted technique in deep learning [65]. The process involves standardizing the output of each layer to have zero mean and unit variance. Consider a single neuron, and let x_i ,... ..., x_n be the original outputs in a mini-batch, we add a normalization layer that modifies the above outputs using the Equation (3) below:

$$BN(x_i) = \frac{x_i - \mu}{\sigma} \tag{3}$$

where μ represents the mean and σ denotes the variance, as defined by Equations (4) and (5), respectively.

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{4}$$

$$\sigma^2 = \frac{1}{n}\sum_{i=2}^{n} (x_i - \mu)^2 \tag{5}$$

This normalization technique is commonly employed to stabilize training, accelerate convergence, and enhance the generalization of deep neural networks.

3.4. CNN

This feedforward neural network consists of multiple layers of neurons that extract key features from input data, typically represented as arrays or tensors. A typical CNN includes convolutional and pooling layers, followed by fully connected layers. Nonlinear functions like Rectified Linear Units (ReLU) enable CNNs to learn complex patterns in the data [66]. In this paper, we present a CNN-based model for supervised automatic arrhythmia classification. The ground truth labels, denoting the arrhythmia types, were assigned by expert cardiologists and utilized for supervised training. These class labels were mapped to the spectrogram representations of each heartbeat segment.

3.5. Overview of our approach

This study presents a novel layer normalization technique for classifying ECG signals. We developed a one-dimensional (1D) CNN to classify ECG data into five categories and incorporated layer normalization to enhance automatic classification of the five distinct heartbeat types. We implemented a 1D-CNN due to its suitability for time-series data, such as ECG signals, where samples are consistently collected at regular intervals [67]. Our CNN architecture consists of three convolutional blocks (nine layers), followed by three fully connected layers and an output softmax classification layer. In this work, we introduced 'range normalization,' a standard min-max procedure that scales all variable values to a specified range, such as [0,1]. This technique is used to normalize the inputs to our neural network layers by scaling them to a range of 0 to 1. In our proposed normalization approach, we incorporate a normalization layer that continuously takes the output from the proceeding layer, normalizes it, and then forwards it to the next layer.

The input layer feeds the ECG beats into the model. Each beat sequentially passes through a series of convolution and max-pooling layers, converting them into feature maps of varying widths. These feature maps are then analyzed to generate an automated class prediction for the dense layer. Both input and output values are normalized to the range [0,1] using the range normalization technique. Equation (1) is applied to normalize the data value xxx from the interval [a, b] to the interval [0,1]:

$$X_{new} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

This layer is applied to the output of the convolution layer using Equation (1), which performs a linear transformation to map the data to the desired range of [0,1]. Suppose there are nnn values xix_ixi (i = 1,2, . . . ,ni = 1,2, . . . ,ni = 1,2, . . . ,n) that need to be mapped to the range [0,1]. The corresponding results yiy_iyi (i = 1,2, . . . ,ni = 1,2, . . . ,ni = 1,2, . . . ,n) can be obtained using the following Equation (2):

$$y_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{2}$$

where x_{min} and x_{max} represent the minimum and maximum values of x_i. Since this is a linear function, the minimum value of $\mathrm{y_i}$ occurs when $\mathrm{x_i}$ equals x_{min}, which also corresponds to the maximum value of y_i. Substituting x_{min} into x_i gives us y_{min}=0. Similarly, we also find that y_{max}=1. Consequently, the new values y_i will be distributed within the range [0,1] as desired. Note that a special case may arise when $x_{min} = x_{max}$, indicating that all values of x_i are identical ($x_i = x_{max}$).

In this scenario, the denominator of Equation (2) is 0, leading to a "division by zero" error. To resolve this, we can set $\mathrm{y_i}$'s to 0.5.

Internal covariate shift is a significant challenge in training deep neural networks, as it affects both the learning process and the convergence time of the models [68]. This often happens during neural network training due to the changing distribution of inputs, which can slow down the model's training process. Because the output of each layer is passed to the next, changes in a layer's parameters also influence the input distribution for the following layers.

To mitigate this issue, it is essential to maintain consistent data distribution. Batch normalization is a technique utilized in deep learning models, including CNNs and RNNs. It represents a significant advancement in deep learning and is widely used in modern neural network architectures. This method has also inspired several other normalization techniques [69]. This approach has proven effective in reducing distribution variance, thereby accelerating the training process and improving model performance [70]. To assess the effectiveness of range normalization, we propose a CNN model that incorporates batch normalization.

The pooling layer utilizes the feature space from previous layers to create a new feature space by extracting the maximum values from specific regions. Its primary purpose is to reduce the dimensionality of the feature maps by half, thereby decreasing the computational load and mitigating the risk of overfitting. The CNN also includes a flattened layer, which converts the input features from the preceding layer into the required output size before passing them to the dense layer. The final layer employs Softmax to normalize the results from previous layers, generating a probability distribution across the different classes [71]. We selected CNNs for our ECG classification approach due to their ability to automatically and adaptively learn relevant features, recognizing temporal patterns from time-series ECG data. Moreover, CNNs provide a notable advantage in noise resistance over other methods.

3.6. Description of the dataset

The dataset employed in this study is sourced from the renowned MIT-BIH Arrhythmia Dataset, a benchmark widely used for heartbeat classification [72, 73]. First released in 1987 by the MIT and BIH, it includes ECG recordings from 47 subjects, with a sampling rate of 360 Hz. The dataset spans 47 patients, comprising 25 males aged 32 to 89 and 22 females aged 23 to 89, of which 60% are inpatients. Each ECG record is meticulously annotated by cardiologists, resulting in nearly 110,000 computer-readable reference labels for individual heartbeats [51]. The MIT-BIH database categorizes 15 distinct heartbeat types, aligning them with the five primary classes defined by the AAMI standard [50].

This dataset is extensively used for arrhythmia classification through deep learning methods. For this study, the dataset was sourced from the MIT-BIH database via the PhysioNet service (http://www.physionet.org) in plain text format. The MIT-BIH database is a publicly available resource that includes ECG signals linked to various arrhythmia. It contains two distinct types of heartbeat signals from the MIT-BIH Arrhythmia Dataset and the PTB Diagnostic ECG Database, both of which are well-regarded in the field of heartbeat classification. These collections provide a sufficient number of samples to effectively train a deep neural network. The ECG signals encompass both normal heartbeats and those affected by a range of arrhythmic conditions.

3.7. Preprocessing of the dataset

Prior to acquisition, the dataset underwent preprocessing steps including signal filtering and segmentation into fixed-length segments of 188 samples. Furthermore, the signals were cropped, down-sampled, and zero-padded to generate shorter beats, optimizing them for deep learning applications [12]. The resulting ECG dataset is partitioned into two subsets: training and test data. A summary of the heartbeat class distribution is presented in Table 1, while Figure 2 visualizes the percentage distribution of heartbeats across each class within the training and test datasets. Figure 3 illustrates example of each of the five heartbeat types found in the dataset.

4. Experimental Results and Discussion

In this section, we evaluate the effects of batch normalization and range normalization on our CNN model's performance. We detail the performance metrics used and discuss the resulting outcomes.

4.1. Performance metrics

The proposed deep CNN models were evaluated using the following standard metrics: $F1$ score, accuracy, precision, and recall. These metrics are derived from the concepts of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN).

Accuracy: the ratio of correct predictions to total predictions.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{3}$$

Precision (P): the ratio of total instances that are predicted to be positive

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{4}$$

Table 1. Heartbeat classes

Class	Heartbeat type	Number of ECG heartbeats (Training data)	Number of ECG heartbeats (Test data)
N	Normal	72,471	18,118
S	Supra ventricular ectopic	2,223	556
V	Ventricular ectopic	5,788	1,448
F	Fusion	641	162
Q	Unclassifiable	6,431	1,608

Recall (R): the ratio of the actual positive instances that were predicted correctly by the model

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{5}$$

F1 score: the weighted average of Precision and Recall

$$\text{F1 score} = 2 \text{ x } \frac{\text{P x R}}{\text{P} + \text{R}} \tag{6}$$

4.2. Results and discussion

The performance of the proposed techniques was assessed by partitioning the dataset into 70% for training and 30% for validation during the training phase, with accuracy and loss metrics computed. Following training, the models were tested on a separate, unseen dataset for ECG signal classification. The initial experiments focused on evaluating the model's performance through accuracy and validation loss.

The results of Classification accuracy and cross-entropy loss of batch normalization versus range normalization is shown in Figure 4.

The performance of the models on the test dataset, evaluated using Precision, Recall, and $F1$ score, is summarized in Table 2. The results indicate that both models performed exceptionally well. However, the CNN with range normalization demonstrated a 1% improvement in precision for classifying Supraventricular ectopic beats and unclassifiable beats, as well as a 4% improvement in the classification of Fusion beats.

In terms of Recall, the CNN with range normalization outperformed by 1% in classifying Ventricular ectopic beats, whereas the CNN with batch normalization achieved a 1% higher recall for Fusion beats. Regarding the $F1$ score, the CNN with batch normalization provided 2% better results in classifying Fusion beats. We conducted a comparative analysis between the proposed deep CNN model with range normalization and a CNN

Table 2. Findings from the performance evaluation based on *F*1 score, recall, and precision

	CNN batch normalization			CNN range normalization		
Class	Precision	Recall	*F*1 score	Precision	Recall	*F*1 score
N	0.99	1.00	0.99	0.99	1.00	0.99
S	0.91	0.79	0.85	0.92	0.79	0.85
V	0.95	0.95	0.95	0.95	0.96	0.95
F	0.83	0.76	0.79	0.87	0.75	0.81
Q	0.99	0.98	0.99	1.00	0.98	0.99

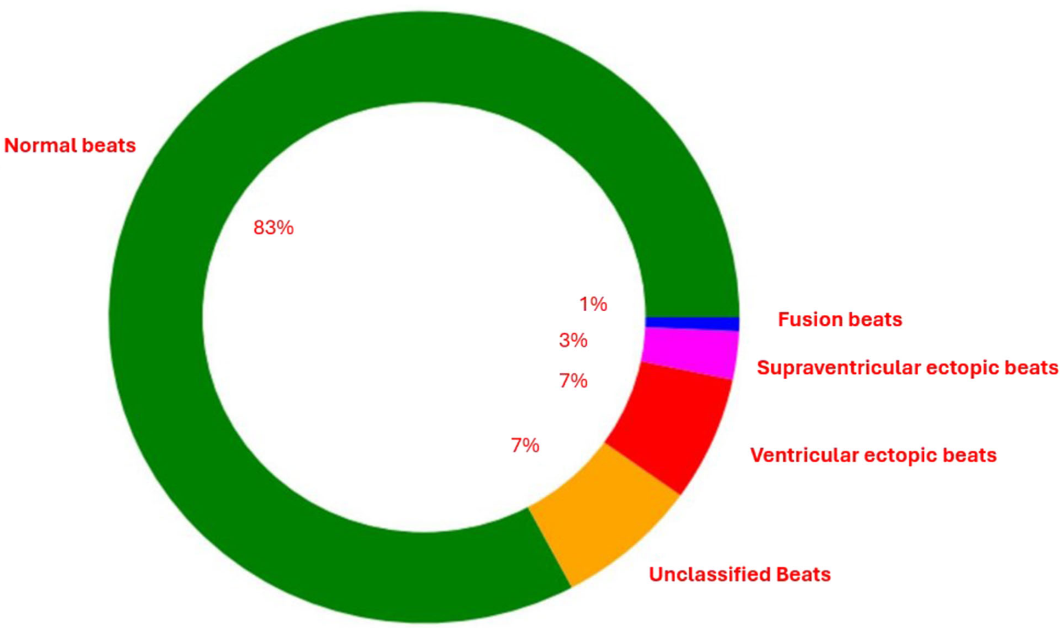

Figure 2. Distribution of the different heartbeat types in the dataset

model employing batch normalization to evaluate the efficacy of the range normalization strategy in enhancing classification performance.

To evaluate the effectiveness of the proposed approach, the results were compared with state-of-the-art methods, as summarized in Table 3. Numerous techniques have been developed for classifying ECG heartbeats in the MIT-BIH dataset, often leveraging deep learning architectures combined with various classification algorithms. Both the proposed models and the state-of-the-art methods were trained and tested using the MIT-BIH ECG dataset. Compared to previously reported classification outcomes, our technique achieved superior accuracy in arrhythmia classification. Additionally, the proposed method offers a relatively lightweight CNN architecture that is well-suited for handling one-dimensional ECG data efficiently.

Table 3. Comparison of our proposed approach to other existing methods

Reference	Approach	Database	Average accuracy (%)	Precision (%)	Recall (%)
[12]	Deep residual CNN	MIT-BIH	93.40	95.20	95.10
[74]	Augmentation + CNN	MIT-BIH	93.50	92.80	93.70
[75]	DWT + SVM	MIT-BIH	93.80	–	–
[76]	DWT + random forest	MIT-BIH	94. 60	–	–
[77]	CNN + genetic algorithm	MIT-BIH	98.45	98.00	98.00
[78]	CNN+LSTM	MIT-BIH	98.13	96.80	98.00
[78]	1-D CNN	MIT-BIH	97.55	96.00	97.51
[79]	CNN + Gaussian Mixture	MIT-BIH	98.25	97.58	96.79
Our approach	CNN + range normalization	MIT-BIH	98.73	98.46	98.48
Our approach	CNN + batch normalization	MIT-BIH	98.68	98.56	98.62

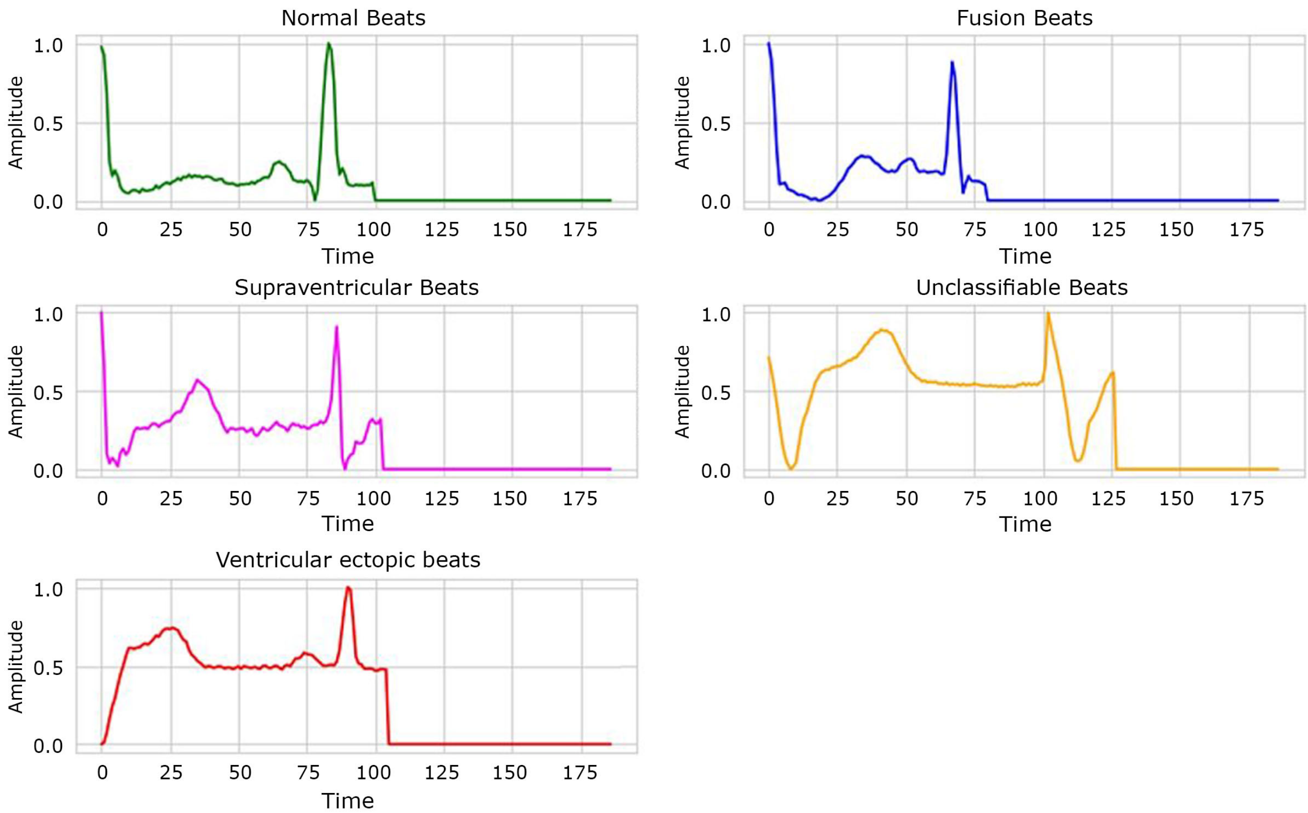

Figure 3. An example of each of the five heartbeat types found in the dataset is displayed visually

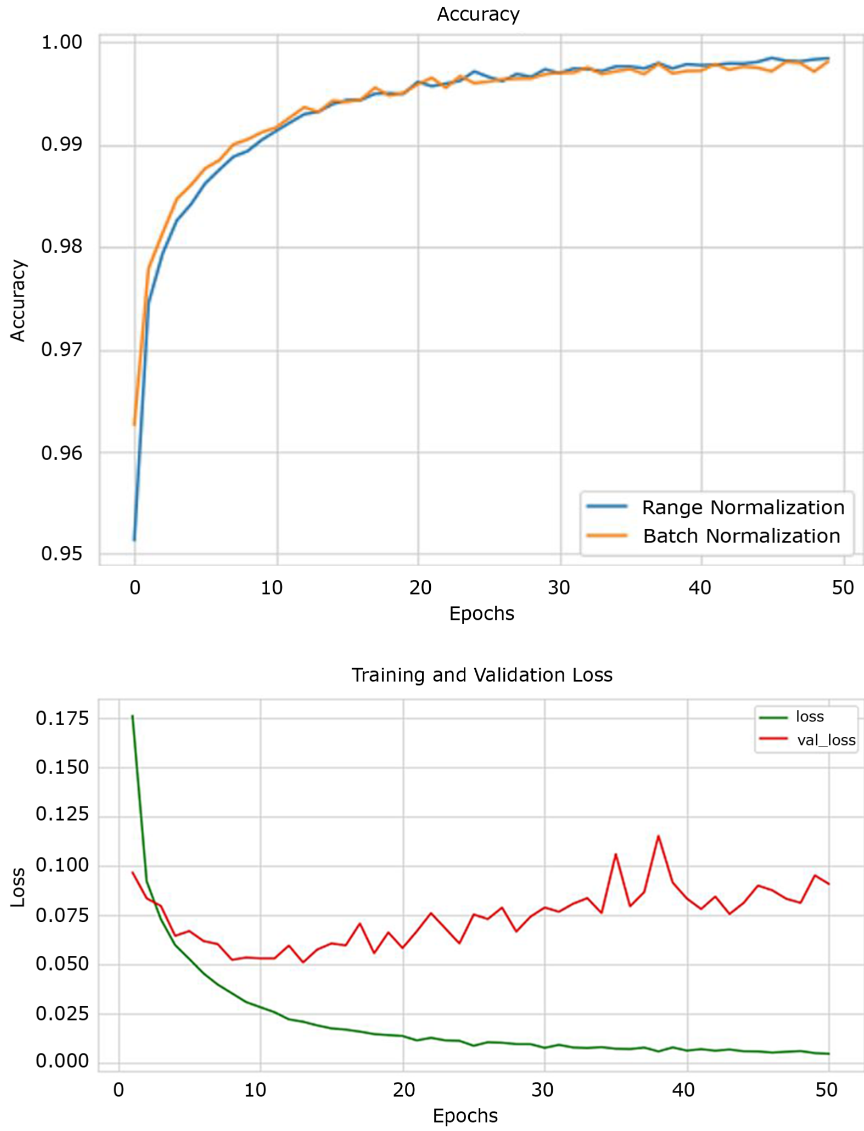

Figure 4. Classification accuracy and cross-entropy loss of batch normalization versus range normalization

5. Conclusion

In this study, we presented an advanced classification model for analyzing electrocardiogram (ECG) signals. To address the covariate shift problem frequently encountered in deep learning models, particularly those used for ECG classification, we introduced a novel normalization technique. By incorporating this layer normalization method into a CNN, we successfully classified heartbeats into the five standard categories defined by the AAMI standard.

The proposed normalization approach offers an innovative alternative to existing techniques by standardizing inputs within neural network layers. Its primary aim is to reduce the number of training epochs required to optimize the model while stabilizing the overall learning process. When applied to the MIT-BIH Arrhythmia Dataset, the proposed model achieved an accuracy of 98.73%, outperforming leading classification models. It also demonstrated a precision of 98.46% and a recall of 98.48%.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Jonah Kenei: Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing, Supervision, Project administration. **Juliet Moso:** Methodology, Software, Validation, Investigation, Resources, Data curation, Visualization.

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How to Cite: Kenei, J., & Moso, J. (2025). Classification of Heartbeats Using Convolutional Neural Network with Range Normalization. *Medinformatics*, *2*(2), 120–131. https://doi.org/10.47852/bonviewMEDIN52024043