Heart Rate Monitoring System Using Feature Extraction in Electrocardiogram Signal by Convolutional Neural Network

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***Abstract*—A new deep learning architecture, which is heart rate monitoring system using feature extraction in electrocardiogram signal by Convolutional Neural Network (CNN). Electrocardiogram based healthcare applications is presented in a federated context. The proposed system correctly diagnoses arrhythmias using an auto encoder and a classifier, both based on CNN. The module is provided to explain the classification findings in which the proposed classifier via employing an auto encoder and a classifier could check whether the rhythms of heart are normal, paced up or the heartbeat rate is irregular depending on the patient's situations. The module could offer the explanations of the classification findings in order to allow medical practitioners to quickly make the trustworthy judgments in preliminary diagnoses. Finally, the result shows that the proposed classifier could explain the classification for finding the two arrhythmias conditions which allow healthcare practitioners to rapidly make the correct conclusions.**

Keywords—Deep Learning, Electrocardiogram (ECG) Based Healthcare Applications, Convolutional Neural Network, Federated Scenarios and Configurations, Arrhythmias, Tachycardia, Bradycardia.

I. INTRODUCTION

Millions of data have been created as the number of internet of things (IoT) devices utilized in the twenty-first century has been increased [1]. Owing to their capacity to self-learn, next generation machine learning models, particularly those based on deep learning, can tackle difficulties connected to multi-dimensional data [2]. For example, in assisting in the detection of life-threatening illnesses[3] . Some individual sources may be unwilling to provide their data with a central data collector since medical data is very sensitive and confidential [4]. One of the most significant disadvantages of this technique is privacy concerns [5]. Because medical data is very sensitive and personal, some individual sources often refuse to provide their information [6]. Now-a-days a clinical practitioner needs know the explanation for a deep learning model's prediction, this uncertainty limits deep learning in healthcare[7]. Selvaraju, for example, suggested Grad-CAM [9] as a way for visualizing input areas that are essential for predictions[9]. Finally, we use the GradCAM model [9] to explain the categorization findings in the framework. In addition, the new deep learning architecture, which is heart rate monitoring system using feature extraction in electrocardiogram signal by Convolutional Neural Network (CNN), where the monitoring system according to the previous studies [24-27] is so important for this applications. The following is a list of our work's contributions [11].

1. In a federated scenario, we construct a CNN-based autoencoder to denoise the raw time series of ECG signal gathered data from patients. We utilize the denoised version of input provided by the autoencoder to explain the predictions.
2. Using transfer learning, we create a CNN-based classifier along with encoder component of the proposed autoencoder to categorise supplied ECG data into five categories: non-ectopic beats (N), supraventricular ectopic beats (S), ventricular ectopic beats (V), fusion beats (F), and unknown beats (Q).
3. To train our proposed system, we employed the MIT-BIH Arrhythmia Database [12]. We first upsample it to produce additional data samples, and then add 10- 30% random noise. The suggested framework has a 94 percent overall accuracy with noisy data and a 98 percent overall accuracy with clean data in the original MIT-BIH database.
4. Furthermore, we assessed the proposed framework's performance using four standard metrics: classification accuracy, precision, recall, and F1-score. Because of the federated setup, the proposed framework offers users with a higher level of privacy protection.

The remainder of the paper is laid out as follows. The background and related works are presented in Section II. The proposed methodology is described in Section III. The IV. The results and discussions are presented in sections IV. Finally, Section V is the conclusions.

II. SURVEY OF RELATED WORKS

Signals from some cognitive disorders control some bodily functions [13]. A stroke, for example, may cause a change in gait. Several studies proposed utilizing wearable sensors to track users' actions, with the assistance of which diverse human body actions may be identified [14]. When it comes to ECG analysis in healthcare, ML and DL are critical. Many techniques for categorizing ECGs into arrhythmia categories have been proposed. Rubin *et al.* [15] used deep learning to automate cardiac auscultation, which is the process of detecting anomalies in heart sounds. A modified loss function is used to train their CNN architecture, which directly optimizes the trade-off between sensitivity and specificity. Gjoreski *et al.* [16] described a technique for detecting chronic heart failure (CHF) using heart sounds. The signal's Huang *et al.* [17] have proposed an intelligent ECG classifier employing rapid compression residual convolutional neural networks to allow high-accuracy intelligent categorization of arrhythmias (FCResNet). Due to privacy issues, typical centralized healthcare apps have limited applicability [18]. Due to is privacy preserving and efficient communication constraints, FL finds several applications in healthcare. Xu *et al.* [19] summarized the general solutions to the statistical challenges, system challenges, and privacy, and point out the implications and potentials of FL's application in healthcare.

III. PROPOSED METHODOLOGY

Humans can comprehend and express how an AI system reached a choice using CNN [20, 22]. It aids in the evaluation of model correctness, fairness, transparency, and results in AI-assisted decision-making. Understanding how an AI-enabled system arrived at a certain result offers several advantages and could assist developers in ensuring that the system is operating as intended, it may be required to fulfil regulatory requirements, or it may be critical in allowing individuals affected by a decision to question or modify the conclusion. According to research, it will be critical in healthcare, manufacturing, insurance, and cars.

The number of hidden neurons N is specified to be equal to the dimension K of the signal character representation, i.e., N K is equal to 156. A training set and a validation set are created from the loaded data. With a total length of *lc* is 4,844,569 characters long, the training set corresponds to 98 percent of the data. The number of characters predicted on which the loss is predicated during one training sequence iteration corresponds to the length of the training sequence *T* being 25. When testing and displaying the network, the generation sequence length *Tg* 200 is the number of anticipated characters. He initialization, that is, samples of a zero mean normal distribution with a variant, is used to randomly initialize the weights**.** Through federated transfer learning the proposed system seeks to deliver accurate and efficient personal healthcare without compromising privacy. The proposed approach is depicted in Figure 1. The autoencoder, classifier, and AI module are the three primary components of the proposed approach.

The Fourier Transform, as indicated, is used to remove low-frequency noisy signals by transforming the signal into frequency domain from time domain and then back to time domain for subsequent repetitions [23]. The identification of Rpeak from an ECG signal is critical since it plays a key role in the proposed method. Rpeak is identified using a threshold detection method and has a distinct feature in an ECG signal in that it has a much larger amplitude than the remainder of the signal. As a result, finding the position of a Rpeak using a threshold value and calculating Rpeak to Rpeak time is simple. The Rpeak is detected using a 0.25mV threshold (this value may vary from signal to signal). Rpeak's amplitude fluctuates from 0.25mV to greater levels, as it does in general. The width of the sliding window was expected to equal one R-R interval in Phase 1. It indicates that the packet stream is handled every two R-R interval blocks in a row. One R-R interval string is shifted per clock cycle, and a new byte for the packet stream of two consecutive R-R intervals is taken to construct the packet stream, i.e., boundaries (in bytes) which is R-peak.

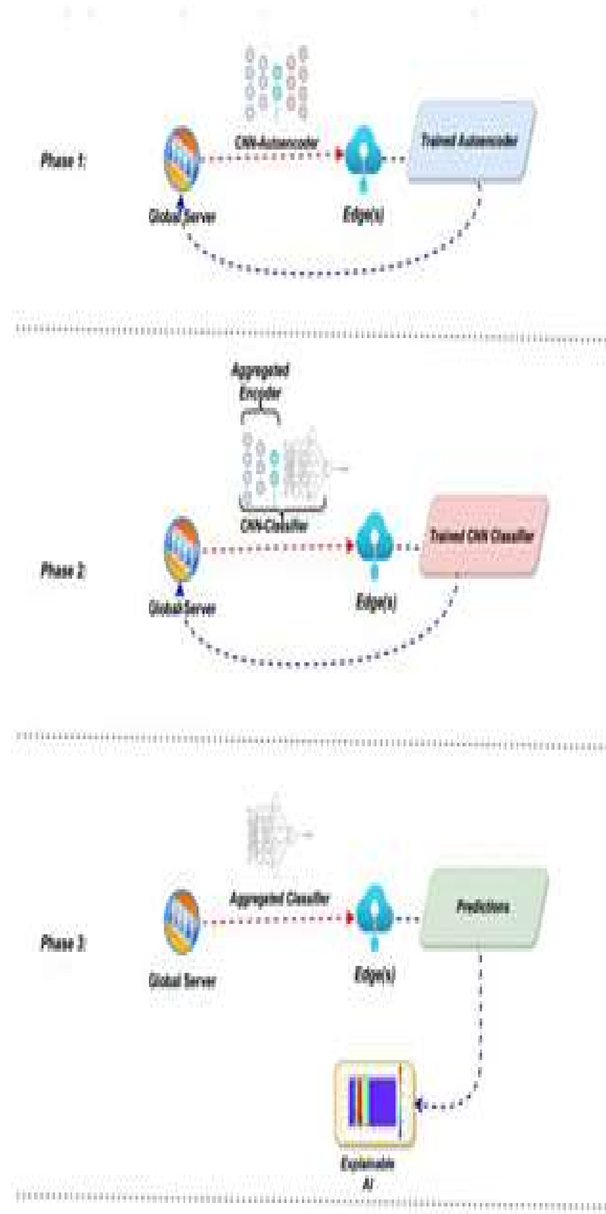


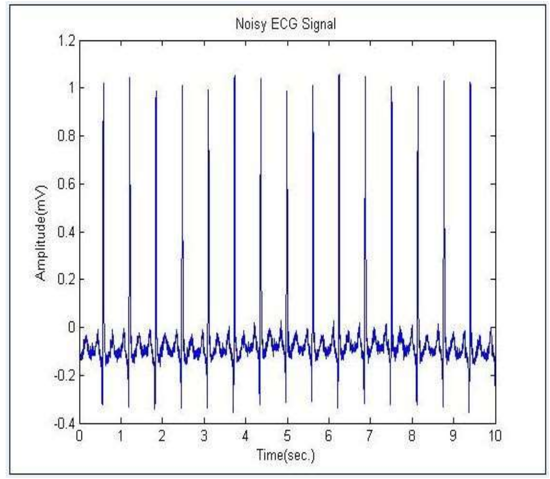
Figure 1 Overview of Proposed work

The comparison is based on differences in network architecture and feature vectors utilized in network training. The number of neurons in the input layer was chosen to be thirteen, equivalent to FL, and the number of neurons in the output layer was chosen to be three, corresponding to three separate classes. The number of concealed nodes was tested between 5 and 25 to determine the design that provided the best performance and accuracy. To verify a predictive model with high generalization performance, the dataset is randomly divided into 70% for training the network, 15% for validation, and 15% for evaluating the model's predictive performance. Around 20 networks were trained for each sequence in the training and testing sets, and the best five networks were averaged to derive the performance parameters. The "Analog to Digital VI" converts the ECG signal into a digital signal, which is then transformed into a binary array by the "Digital to Binary VI" to identify the Rpeak [18]. The "Extract Portion VI" offers information on the Q to R and R to S portions in relation to this Rpeak. QRS complex features such as QRS duration in terms of sample number have been computed using this information. The suggested approach has detected the Rpeak time and Rpeak sample index. In terms of sample index and quantization level, the suggested digital-based system has all the features. The characteristics acquired by this method are beneficial for ECG signal categorization**.** The maximum and minimum of A waveform's minimum values and associated time values are defined by "Waveform Min Max VI," as the name suggests. Extracts data from input signals and returns it in chunks. data that has been extracted It is possible to extract a single point or a range of data, data by time or index. Time and index of the first occurrence of a value are also included. The QRS waveform which means QRS wave in ECG has been arbitrarily labeled in alphabetical order the Q wave is a Short Downwards Deflection [20]. The R wave is a Conspicuous Upward Stroke, and the S wave is a return to below the level of base line. This QRS waveform varies due to the signal's time-varying shape when subjected to physiological circumstances (duration and amplitude). This value served as an index into the array i. For the array I, the resulting value serves as a memory address 'n'. As a result, when the hit location is incremented, the array locations serve as a counter as well. The hash result of the ECG features (''H-QR", ''H-RS", ''Slope-R", ''Slope-RS", and ''Ratio-RR",) which also indicate memory location is the counter index in the respective memory elements.

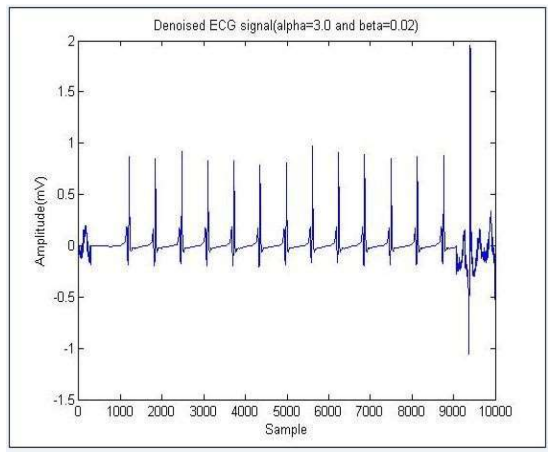
IV. RESULTS AND DISCUSSIONS

Fig.4 shows the denoising procedure with high and low values of the parameters [20]. The noisy ECG signal is seen in Fig. b. Fig. c shows a denoised ECG signal with a value of "3" and a value of "0.02". ECG signal with "0.2" and "0.02" is shown in Fig. b. A denoised ECG signal with "1.3" and ":0.2" is shown in Fig. 4(d). The signal appears to have been sufficiently denoised with these levels, but its morphology has been lost. A denoised ECG signal with "1.3" and "0" is shown in Fig. 4(e). The amplitude and breadth of the p-wave, QRS complex, and T-wave are all essential characteristics of an ECG graph, in general. In ECG analysis, these areas are critical [23]. The suggested framework's AI module demonstrates that the suggested classifier considers these key input sample characteristics.

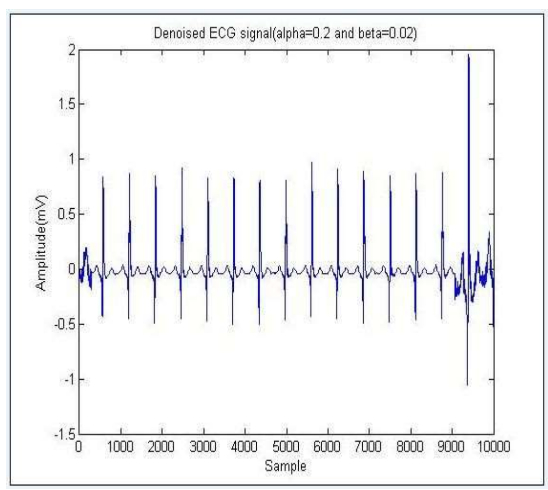
However, without first consulting a clinical practitioner, we highly urge that these results are not utilized for any medical advice. Heat Maps should be compared to doctors' existing expert knowledge. The four standard metrics reported in the literature [20] were used to assess classification performance: classification accuracy, precision, recall, and F1-score.



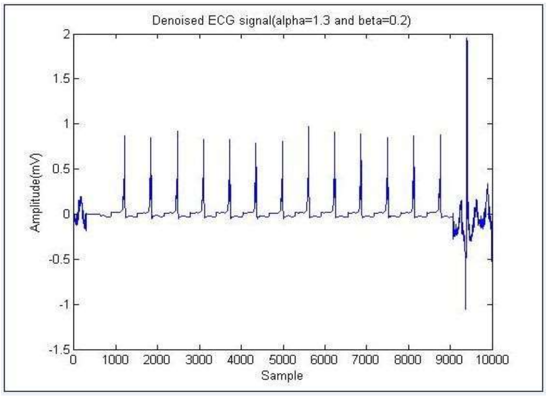
***a)* Noisy ECG signal**



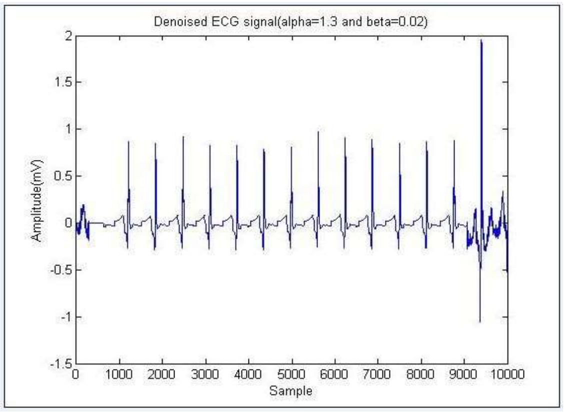
b) The value of alpha equals 3.0 and the value of beta equals 0.02



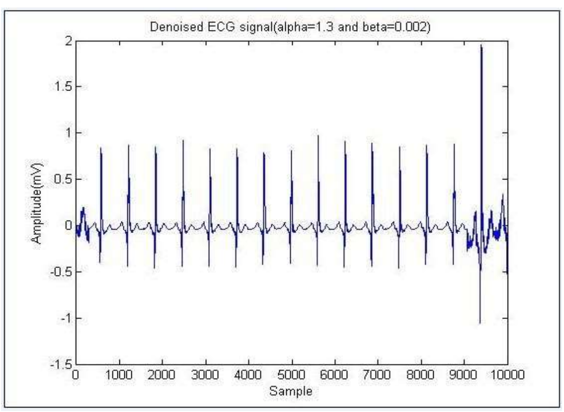
c) The value of alpha equals 0.2 and the value of beta equals 0.02



d) The value of alpha equals 1.3 and the value of beta equals 0.2



e) The value of alpha equals 1.3 and the value of beta equals 0.02



f) The value of alpha equals 1.3 and the value of beta equals 0.002

Figure 4 Noise removal process and their effect due to parameter α & β

V. CONCLUSION

In this manuscript, a deep learning architecture for heart rate monitoring system by using feature extraction in electrocardiogram signal via CNN algorithm, is presented in a federated context. This goal is to create an automated, reliable, and efficient prediction model that uses EEG data to diagnose the condition of an epileptic patient. The classification is based on quantitative characteristics extracted from neurophysiologic signals. The comparison is based on differences in network architecture and feature vectors utilized in network training. We developed an automated neural network model for categorizing seizure activity into 3 states: ictal, interracial, and normal, having accuracy of 99.3% with error rate of 0.33%.

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