Enhanced Heart Disease Classification and Heart Disease Prediction using Deep Learning

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***Abstract*—Heart disease prediction has become an important domain in the current scenario, with numerous research efforts aimed at developing systems capable of detecting heart disease before its severe consequences occur. Machine Learning technology plays a crucial role in collecting heart disease-related data to develop predictive models for disease prediction, but it also raises concerns about data privacy and security. To address such privacy issues, the proposed work introduces Federated Deep Learning model training, where Deep Learning models are trained using a privacy-preserving approach known as Federated Learning. The proposed work explores the effectiveness of hybrid deep learning models combining long short-term memory networks and convolutional neural networks for classifying electrocardiogram signals and predicting heart diseases. The study utilizes a comprehensive dataset of ECG recordings and employs rigorous training and evaluation processes to assess the model's performance. The result demonstrates the model's proficiency in accurately classifying diverse ECG signal patterns and its potential for robust heart disease prediction. This research contributes to advancing cardiovascular health diagnostics by proposing a federated deep learning approach that combines spatial and temporal information to enhance the accuracy of heart disease prediction.**

Keywords: Federated Deep Learning, Heart Disease Classification, Long Short-Term Memory, Convolutional Neural Network

I. Introduction

Cardiovascular diseases (CVDs) harm the heart and blood vessels, hindering the body's ability to circulate oxygen and blood effectively. Some common types of CVDs include cerebrovascular disease, coronary heart disease, peripheral artery disease, congenital heart disease, rheumatic heart disease, pulmonary embolism, and deep vein thrombosis. Developing advanced techniques for early detection and diagnosis is crucial to reduce the morbidity and mortality associated with CVDs.

Machine learning (ML) plays a pivotal role in healthcare by leveraging large datasets to predict, diagnose, and manage heart disease. By analyzing medical images and patient data, ML assists in diagnosing heart disease at earlier stages and devising tailored treatment plans. As ML continues to evolve, its integration into clinical decision support systems and precision medicine approaches promises to enhance further the efficiency and effectiveness of heart disease prediction and management, ultimately improving patient outcomes.

Electrocardiogram (ECG) data is a valuable source of information for diagnosing and predicting CVDs. However, ECG data is often noisy, variable, imbalanced, and scarce, making it difficult to analyze with traditional ML models. ML models, such as random forests [3], boosting techniques like XGBoost [5], K-nearest neighbors [20], and support vector machines, have shown limited capability as compared to regular medical practitioners in terms of accurate and precise predictions. The emergence of Deep Learning (DL) has presented a paradigm shift in medical data analysis, offering new possibilities for accurate classification and prediction of CVDs.

There are various DL models like bi-directional LSTM network [15], convolutional neural network [17], evolutionary neural system (based on SVM) [16], recurrent neural network [27] [2], and transformer-based deep neural network [11], which have been used for the detection of heart diseases. However, the ML and DL domain is expanding very rapidly and comprises the capabilities to track hidden patterns and reveal concrete insights, but it has been observed that due to the lack of available ECG data, these models are not showing effectiveness in dealing with heart disease detection. The unavailability of large datasets and low sampling rates lead to missing some vital cardiac conditions, the high complexity of existing models, and the long training time for models. Most of the popular existing arrhythmia datasets like UCI-ML dataset [21] has only 452 instances while MIT-BIH database [7] has only 48 half-hour excerpts.

Multiple factors could contribute to the unavailability of such data, posing obstacles to healthcare research. One significant factor is the concern for data privacy. Electrocardiogram data, being highly sensitive as it contains crucial information about the human body, may deter individuals from sharing such information with any external entity. ML raises significant privacy concerns due to the potential for sensitive personal data to be exposed or misused during model training and inference processes. Traditional ML approaches often involve centralizing data from multiple sources, which can pose risks such as data breaches, unauthorized access, and privacy violations. Federated Learning (FL) offers a promising solution to these privacy issues by allowing model training across decentralized data sources without sharing raw data. By keeping data on individual devices or servers and only transmitting updates in the model to a centralized server, FL minimizes the risk of data exposure or leakage.

Hence, to improve the effectiveness of existing models in detecting heart disease and mitigate the data privacy and availability of ECG data, the proposed work utilizes federated learning with deep learning models as federated deep learning. The FL is applied to explore the synergy of convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, two prominent architectures to analyze ECG signals. By incorporating CNNs for spatial feature extraction and LSTM networks for capturing temporal dependencies, this study aims to enhance the accuracy and reliability of ECG-based heart disease classification, providing a robust framework for early detection and prognostication by preserving data privacy.

Furthermore, the proposed research endeavors to train these models for dual objectives. Firstly, employing a binary classifier aims to determine whether an individual exhibits symptoms of heart disease. Secondly, a multi-class classifier forecasts the various classes linked with arrhythmia. Combining the binary classification model and the multi-class arrhythmia classification model can aid in risk stratification, allowing healthcare providers to prioritize patients based on the severity and complexity of their cardiac conditions. Patients with high risk features identified by both models may require more aggressive monitoring and interventions, whereas those with low-risk features may undergo less intensive management strategies.

Healthcare providers can develop tailored treatment plans customized to each patient's condition by accurately identifying the presence of heart disease and specific arrhythmias. For example, patients identified as having heart disease but no arrhythmias may require different management strategies compared to those with both heart disease and specific arrhythmias. Having precise diagnostic information from both models enables healthcare providers to implement targeted interventions to improve patient outcomes.

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II. Literature Review

Various studies that have been conducted in the field of heart disease prediction, employ both binary and multi-class classification approaches separately. For instance, the study conducted by authors in [1] explored the feasibility of using deep learning methodologies for automatically detecting coronary artery disease (CAD) from ECG signals. Their research focused on binary classification, aiming to distinguish patients with CAD from those without CAD to improve diagnostic accuracy and facilitate early intervention. Similarly, authors in [24] proposed a deep learning-based approach for automated anomaly detection in ECG signals, aiming to classify signals as either normal or abnormal. Their method leveraged deep learning techniques to automate the detection of ECG anomalies, potentially aiding clinicians in diagnosing cardiac abnormalities more efficiently. Additionally, authors in [4] conducted a comparative study evaluating various machine learning techniques for binary classification of ECG signals, investigating the performance of support vector machines, naive Bayes, and random forests in distinguishing between normal and abnormal ECG patterns, thus providing insights into the effectiveness of different classification algorithms.

Moreover, there are also studies focusing on multi-class classification using ECG datasets. For example, authors in [18], [26] delved into predicting arrhythmias using deep learning models with 12-lead ECG signals. Arrhythmias, irregular heart rhythms, can indicate various cardiac conditions and are crucial to detect for timely medical intervention. On the other hand, authors in [9] focused on the effectiveness of deep learning methodologies, particularly convolutional neural networks, for classifying ECG signals. They explored CNN architectures tailored to the characteristics of ECG data, aiming to automate ECG interpretation and enhance diagnostic capabilities. Similarly, authors in [13] proposed a 2-D convolutional neural network for multi-class classification of ECG arrhythmias. Their research aimed at accurately differentiating between different types of arrhythmias, leveraging deep learning techniques to automate arrhythmia classification and facilitate timely medical intervention. Additionally, the authors proposed an attention-based convolutional recurrent neural network (CRNN) for multi-class arrhythmia detection in [25]. Their research focused on accurately classifying various arrhythmias from ECG signals, demonstrating the effectiveness of attention mechanisms in capturing informative features for classification.

Overall, these studies underscore the importance of machine learning and deep learning techniques in advancing binary and multi-class classification tasks in ECG analysis. They collectively contribute to developing automated systems for cardiac anomaly detection and disease diagnosis, aiming to improve patient outcomes and clinical decision-making in cardiovascular healthcare. All these existing works focused on traditional ML approaches, avoiding the privacy issues of ECG data. Hence, it is essential to ensure data privacy by developing such models using privacy-preserving approaches.

III. Background

Various key concepts set a foundation for the proposed work. These concepts are elaborated as follows:

A. *Electrocardiogram Data*

Electrocardiogram (ECG) data is the graphical representation of the heart's electrical activity over time. This data is typically recorded using electrodes placed on the skin, which detect the tiny electrical changes generated by the heart muscle during each heartbeat. These electrical impulses are then amplified and recorded by an ECG machine, producing waveforms representing various aspects of cardiac function. The ECG waveform consists of several distinct components, as represented in Figure [6], each reflecting different phases of the cardiac cycle:

- P Wave: The P wave signifies the electrical stimulation responsible for atrial depolarization, initiating the contraction of the atria (upper chambers), and facilitating blood flow into the ventricles.
- QRS Complex: The QRS complex indicates ventricular depolarization, prompting the ventricles (lower chambers) contraction to pump blood out to the body. It comprises three distinct waves: Q, R, and S.
- T Wave: The T wave signifies ventricular re-polarization, marking the recovery phase of the ventricles as they reset for the subsequent heartbeat.

In addition to these main components, the ECG waveform may also include other features, such as the PR interval (from the beginning of the P wave to the beginning of the QRS complex), the QT interval (from the beginning of the QRS complex to the end of the T wave), and the ST segment (from the end of the S wave to the beginning of the T wave). Changes in these intervals and segments can provide important diagnostic information about the heart's electrical activity and function.

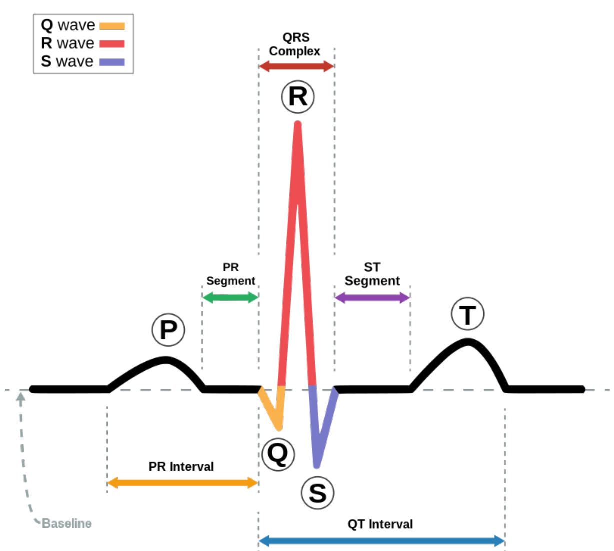

Fig. 1: ECG wavelet

Analyzing ECG data requires the examination of waveform shapes, duration, and intervals to evaluate heart rate, rhythm, and conduction. Deviations from normal waveforms can signal diverse cardiac issues such as arrhythmias, myocardial infarction, electrolyte imbalances, and structural heart diseases. Consequently, ECG data is pivotal for diagnosing, monitoring, and treating cardiac disorders.

The proposed work utilizes a 12-lead ECG dataset [6], which provides 12 different heart views using 10 electrodes attached to the body. This allows for a more comprehensive and accurate arrhythmia diagnosis by covering more than 10,000 patients, created under the auspices of Chapman University and Shaoxing People's Hospital [12]. This database has a sampling rate of 500 Hertz, which enables us to identify some vital cardiac conditions that could not have been detected with previous data. The dataset's size also helps us improve our models' accuracy, generalization, and robustness. It also reduces the risk of over-fitting or under-fitting in the proposed model.

Four steps were involved in gathering the data. Initially, a 12-lead resting electrocardiogram (ECG) was performed on each individual for ten seconds. The GE MUSE ECG system contained the data.Secondly, the rhythm and other cardiac problems were labeled by a professional physician. After that, XML files representing the GE MUSE ECG systems were exported and converted to CSV format. To denoise the ECG data, a Butterworth low pass filter and LOESS smoother were employed in order.

B. Federated Learning

Federated Learning is a machine learning approach that enables model training across various decentralized data sources while keeping the data localized. It was introduced by Google in 2017, this was specially introduced to address privacy concerns associated with centralized model training, particularly in settings where data cannot be easily shared due to privacy regulations or sensitive nature. The concept of federated learning involves training a global model collaboratively across multiple edge devices, such as smartphones, Internet of Things devices, or servers, without transmitting raw data to a central server. Instead, only model updates, typically in the form of gradients or parameters, are sent to the coordinator or client-server, where they are aggregated to update the global model.

Federated Learning has gained significant attention across various industries, including healthcare, finance, and telecommunications, due to its ability to preserve data privacy while enabling collaborative model training and learning from distributed data sources. Techniques such as differential privacy, encryption, and secure aggregation further enhance privacy by adding noise to model updates, encrypting transmissions, and aggregating updates without decrypting them. With federated learning, data remains local, preserving privacy while still allowing collaborative model training across distributed data sources, making it a promising solution for applications in healthcare, finance, and other domains where data privacy is paramount. Figure [8] represents the architecture of federated learning where multiple clients trained their local model and shared the weights of the trained model with a central global model for further aggregation process.

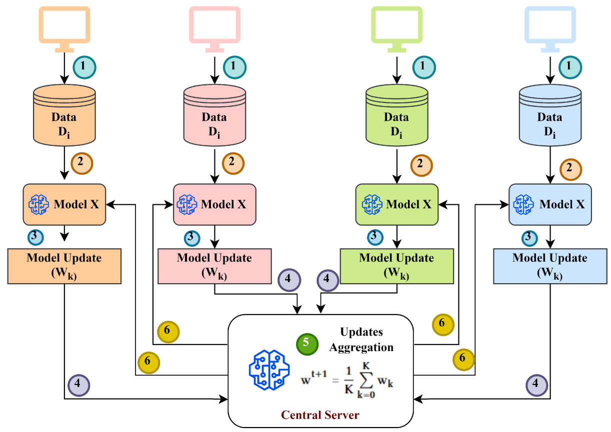

Fig. 2: Federated Learning Architecture [8]

C. Deep Learning Models

The proposed work takes advantage of two DL architectures, CNN(Convolutional Neural Networks) and Long Short-Term Memory [10]. The synergy between CNN and LSTM networks combines the strengths of both architectures, enabling powerful analysis of sequential data such as time series or sequential images. CNNs excel at capturing spatial features through their convolutional layers, extracting hierarchical representations from input data. On the other hand, LSTMs are adept at modeling temporal dependencies and capturing long-range dependencies in sequential data. When integrated, CNNs can extract spatial features from input sequences, while LSTMs can effectively analyze temporal dynamics, providing a comprehensive understanding of complex sequential data. This combined approach has found applications in diverse fields, such as natural language processing, video analysis, and medical diagnostics, where both spatial and temporal information are crucial for accurate prediction and classification tasks.

IV. Experimental Overview

The Proposed Methodology introduces a holistic approach to classifying cardiac rhythms, employing a federated deep learning model with a sequential architecture integrating Convolutional Neural Network and Long Short-Term Memory layers. The experiment involves training two deep learning models using a federated learning approach. These models, one for binary classification and the other for multi-class classification aim to predict the presence of heart disease and determine its specific type, respectively. The experiment uses 12 Lead ECG datasets in a distributed approach so that the entire work can be deployed in a federated learning manner.

In the binary classification task, the model architecture is configured as a sequential neural network comprising two initial CNN layers followed by two LSTM layers. Subsequently, two additional CNN layers are introduced, each followed by a MaxPooling layer to capture salient features. A flattening layer is then added to convert the learned features from the convolution and pooling layers into a vector format suitable for further processing. The network has two fully connected layers, enabling comprehensive feature extraction and representation. We employ the Adam optimizer for optimization, chosen for its ability to adapt learning rates for improved dynamic convergence. The loss function utilized is categorical cross-entropy, measuring the disparity between the predicted and true probabilities of the cardiac rhythm classes. Evaluation is based on accuracy, representing the percentage of correctly classified cardiac rhythms.

In the multi-class classification task, a sequential neural network model is constructed, comprising two Convolutional Neural Network layers followed by two Long Short-Term Memory layers, with an additional pair of CNN layers. A MaxPooling layer is introduced after each additional CNN layer for feature reduction, culminating in two fully connected layers. The fully connected layers utilize the sigmoid activation function to facilitate the binary classification of the dataset. The model is compiled using the Adam optimizer, with binary cross-entropy employed as the loss function and accuracy as the evaluation metric.

The experiment applied weighted federated learning on the non-IID (Independent and Identically Distributed) dataset. Our approach involves generating client devices through data shards. The global model's weights are transferred to all local models during each communication round to serve as initial weights. Subsequently, the global model receives updated weights from all local models, which are then scaled to compute an average for updating the global weights. Each communication round concludes with testing the global model using the updated weights.

Additionally, the models are also trained in a traditional ML approach to compare the performance of the models using the federated approach and existing traditionally trained models.

V. Result and Analysis

In order to assess the effectiveness and suitability of different machine learning models for the detection of heart disease, we have conducted a comprehensive comparative analysis.

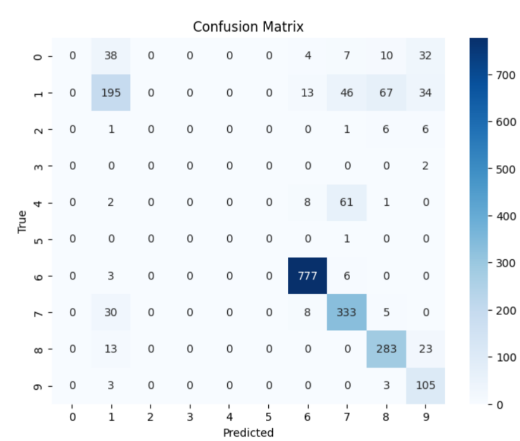

Fig. 3: Multiclass Classification Confusion Matrix

Various performance metrics were employed for evaluation, including accuracy, classification error, precision, F-measure, sensitivity, and specificity. The models considered for comparison encompassed Transformer model same as that of this paper. Confusion matrix are used to compare the actual vs predictive values obtained by our model. The confusion matrix obtained for binary classification shows 426 true positive, 1439 true negative, 114 false positive and 148 false negative cases. The confusion matrix obtained for multi class classification has 10 classes. The confusion matrix for multiclass classification is shown in the figure 3.

Although different and tailored for heart disease diagnosis, a meticulously curated dataset served as the basis for training and testing these models. The training of the both federated learning approach for binary and multi-class arrhythmia detection was performed by considering the presence of four different local data servers as clients. The training dataset was equally distributed among the four client servers.

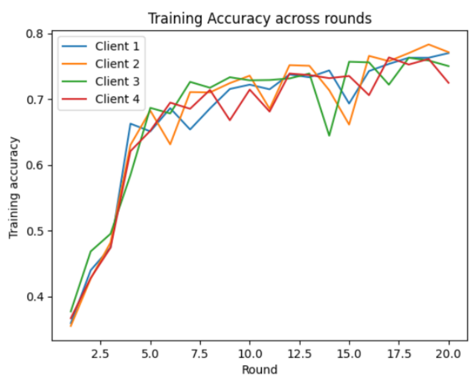

Fig. 4: Multiclass Classification Training Accuracy Graph

The training accuracy obtained on each client server for multiclass classification is shown in figure 4.

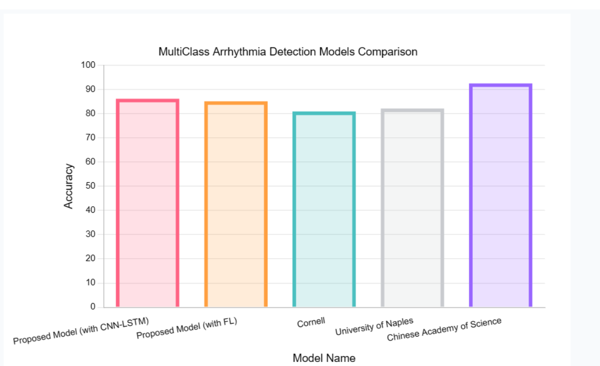

Fig. 5: Multiclass class Arrhythmia Detection Models Comparison

Our experimental results, showcasing the performance of each model, are presented in figures 5 and 6.The experiments yield promising results in which the multiclass classification model achieves an impressive global model accuracy of 85.14%, accompanied by a global loss of 1.755. The binary classification model also performs exceptionally well, achieving an accuracy of 95.7%, with a global loss of 0.425.

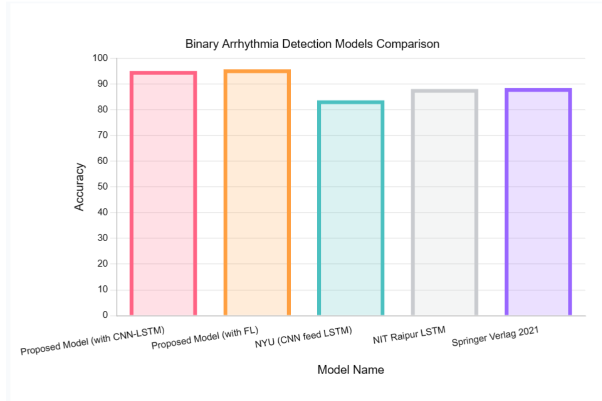

Fig. 6: Binary class Arrhythmia Detection Models Comparison

These outcomes demonstrate the effectiveness of the proposed weighted federated learning approach in handling non-IID data. The results are also compared with traditional ML approaches for the proposed deep learning models and existing DL models. The proposed multi-class detection model with hybrid CNN-LSTM architecture provided an accuracy of 86.4 percent, which was subpar with the existing model Deep Multi-Scale Fusion CNN [23]. However, the proposed model is better than the existing model with 34 Layered CNN [17] and Cascaded CNNs [14]. The binary detection model has an accuracy of 95.11 percent, which is better than the existing model CNN-LSTM [22], LSTM-RNN [19] and Cascaded CNN [14]. This comparative analysis provides valuable insights into the capabilities of each model for heart disease detection, empowering clinical decision-makers.

To conclude, the suggested federated deep learning strategy, combining both CNN and LSTM components, showed improved effectiveness in binary classification and significant advancements in multi-class classification compared to traditional machine learning methods. The FL approach used with the deep learning models showcased its effectiveness while dealing with data privacy and resolving the unavailability of heart disease-related datasets.

VI. Conclusion and Future Scope

In conclusion, our research has demonstrated significant advancements in cardiac arrhythmia detection through the implementation of a deep learning model utilizing Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) layers. Notably, the binary arrhythmia detection achieved a remarkable accuracy of 95.11%, outperforming the multiclass detection with an accuracy of 86.4%. This disparity in accuracy suggests that the binary classification, categorizing rhythms into 'Normal' (SA, SB, ST, SR) and 'Abnormal' (AFIB, AF, SI, SVT, AT, AVNRT, AVRT, SAAWR), yields superior results compared to the more complex multiclass detection.The success of our approach can be attributed to the discriminative power of CNNs and the sequence learning capabilities of LSTMs, which collectively enable the model to capture intricate patterns within electrocardiogram (ECG) signals. The decision to classify specific rhythms as 'Normal' in the binary detection approach contributes to the higher accuracy, as it simplifies the task by focusing on a more generalized categorization.These findings underscore the effectiveness of leveraging deep learning, particularly CNN and LSTM architectures, in enhancing the accuracy of cardiac arrhythmia detection. The research not only provides a valuable contribution to the field of automated diagnostic tools in cardiology but also emphasizes the importance of careful consideration in designing classification tasks, with binary detection yielding superior results in this context. The detailed insights gained from this study can inform future research and development efforts, steering the direction of improved cardiac health diagnostic systems.

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