Neural Network Architectures Comparison for Atrial Fibrillation Detection

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***Abstract*—Atrial fibrillation (AF) is the most common cardiac arrhythmia affecting about 50,000 new people each year in Latin America. AF is characterized by irregular and rapid heartbeats that can lead to serious complications, such as stroke, heart failure, and all-cause mortality. Traditional methods for AF detection are time consuming and can be prone to human error. Therefore, this work reports the results from two methods using machine learning techniques to assist the diagnosis of AF through 2 hybrid models of neural networks: The 1D- CNN with BILSTM model and the MobileNetV2 with BILSTM model which reached 81 and 75% accuracy respectively.**

Keywords— Atrial fibrillation detection, AF diagnosis, AF detection with ML

I. Introduction

Atrial fibrillation (Afib or AF) is a type of irregular heart rhythm (arrhythmia). Arrhythmias are due to alterations in the electrical signal of the heart, being the most common cardiac arrhythmia affecting about 50,000 new people each year in Latin America, a region where it is among the 4 most common cardiovascular diseases [1]. The occurrence of AF increases with age, with prevalence ranging from 0.5% of 50-year-olds to almost 10% of the octogenarian population [2]. Furthermore, AF is characterized by irregular and rapid heartbeats that can lead to serious complications, such as stroke, heart failure, and all-cause mortality. A high incidence of AF is also observed in patients who have undergone a pulmonary vein isolation procedure. Therefore, detection of atrial fibrillation is an important task in the healthcare setting, as it allows early diagnosis and treatment, which can prevent or reduce the risk of complications such as stroke and heart failure, and improve the quality of life of those affected [3].

Traditional methods for AF detection, such as manual analysis of electrocardiogram (ECG) signals, are time consuming and can be prone to human error. Currently, there are several challenges in the field of atrial fibrillation (AF) detection as the demand for efficient health monitoring is increasing [4]. One of the main challenges is the detection of asymptomatic AF, which is AF that does not produce any symptoms. Asymptomatic AF is common and is often discovered only when a patient is tested for another condition [5]. Thus, one of the greatest challenges in detecting AF is paroxysmal AF (pAF), which accounts for approximately 30% of all patients with AF. AFpF is known to evade standard ECG recording and using 24-48 hour Holter ECGs can identify AFpF in 2-5% [6]. Despite prolonged ECG recordings and continuous hourly monitoring, AFpF is more likely to go undetected [7]. This hinders early detection and increases the risk of complications [4,5,6,7].

Another challenge is the high rate of false positives and false negatives in AF detection where manual analysis of electrocardiogram (ECG) signals, can be prone to human error and may not be able to detect AF accurately [3]. This can lead to missed diagnoses and unnecessary treatments. Also, non-ECG devices may give false positives as is the case with the Microlife WatchBP Home A device. Microlife identified AF in 58/72 AF patients and produced a false positive result in 79 patients in the AF arrest study involving 5969 patients with hypertension, diabetes mellitus, and/or aged 65 years or older where the corresponding sensitivity and specificity for AF detection were 80.6% [8]. Another large study of atrial fibrillation detection involved 1013 patients with hypertension, diabetes mellitus, and/or aged 65 years or older. Smartphone-based photoplethysmography was performed with the Cardiio Rhythm smartphone app. The app identified atrial fibrillation in 26/28 patients with atrial fibrillation and produced 23 false-positive results as the device had a sensitivity of 93% and specificity of 98% [9]. Although there are already several methods for the detection of AF, the daily challenge for researchers is to reach accurate detections, avoiding false negatives and positives because it could cause a specialist to misdiagnose and affect the patient.

In recent years, the field has shifted towards the use of machine learning techniques, in particular neural networks. Neural networks are a type of machine-learning model inspired by the structure and function of the human brain [10]. Neural networks, being a powerful machine learning technique, have shown great potential in various medical applications, such as image analysis, natural language processing, and signal processing [11]. In the healthcare field, neural networks have been used to analyze medical images, such as X-rays, CT scans, and MRI scans, to detect diseases such as cancer, lung disease, and heart disease [12]. They have also been used to process and analyze large amounts of medical data, such as electronic health records and genomic data, to improve patient outcomes [10,11,12].

In the field of medical signal processing, neural networks have been used to process and analyze various signals, such as ECG, EEG, and EMG signals, to detect diseases such as atrial fibrillation, seizures, and muscle disorders [13]. The ability of neural networks to learn complex patterns in data and achieve high throughput makes them a promising approach for AF detection. Thus, for automatic AF arrest with convolutional neural networks, they have relied mainly on two main features of AF in the ECG: (1) the absence of P waves (replaced by a series of low-amplitude oscillations called fibrillations) and (2) irregular RR intervals. In the presence of noise, AF detection algorithms that rely solely on the absence of P waves perform poorly because P waves are contaminated by noise and deviations from the signal baseline [10]. In this way, neural networks can be trained with large amounts of data and can automatically learn the features that are relevant for AF detection. This makes them a powerful tool for detecting AF, especially compared to traditional methods, such as manual analysis of ECG signals, which can be time-consuming and prone to human error [10,12,13].

There are several different types of neural network architectures that have been used in atrial fibrillation (AF) detection as can be seen in Table 1 which lists the different types of models developed for automatic AF detection. One of the most popular architectures includes: Feedforward Neural Networks (FFNN), which are a type of neural network architecture that uses supervised training with the back-propagation error algorithm and layers of interconnected nodes to classify ECG signals as normal or abnormal [14]. The study by Kumar et al. [15] used single-lead ECG recordings and a feature selection process to classify the recordings into 4 groups: Normal (N), Atrial Fibrillation (AF), Other rhythms (O), and noisy (~). The final model achieved a high robustness with an F1 score of 76% on the training data and 77% on the test data, indicating that the model did not overfit.

As for Convolutional Neural Networks (CNN) they are a type of neural network that is designed to process data that has a grid-like structure, such as an image or a signal. They consist of convolutional layers that extract features from the input data and fully connected layers that are used for classification. CNNs have been used to classify ECG signals as normal or abnormal and also to extract features from the signals [16]. For example, Hsieh et al. [17] proposed a CNN-based algorithm for AF detection that increases detection accuracy and reduces network complexity. The algorithm achieved an average F1 score of 78.2%, which is better compared to existing deep learning-based methods.

Another widely used neural network is the Recurrent Neural Network (RNN) which is a type of neural network that is designed to process sequential data, such as time series data. They have a feedback loop that allows them to maintain an internal state and model temporal dependencies in the data. RNNs have been used to classify ECG signals as normal or abnormal and also to model temporal dependencies in the signals [18]. For example, Shashikumar et al. [7] presented an attention-based deep learning framework for detection of paroxysmal AF episodes from a sequence of windows, where a deep convolutional neural network was used for image-based feature extraction and a bidirectional recurrent neural network with an attention layer was used for AF detection. The algorithm achieved an ACC of 94% on the test set and 96% on the training data, which outperforms benchmark models.

A type of RNNs that have been specifically designed to handle the problem of long-term dependencies in sequential data. LSTMs have been used to classify ECG signals as normal or abnormal and also to model the temporal dependencies of signals [19]. Faust et al. [20] used an LSTM-based deep learning system to detect AF beats in heart rate signals with the aim of reducing physician workload and enabling long-term monitoring. The system obtained an accuracy of 98.51 % with 10-fold cross-validation and 99.77% blinded, indicating good robustness. In contrast, Closed Recurrent Unit Networks (GRU) is an improved version of Long-term Memory Network (LSTM) and has a simpler structure and requires less computation. According to Thampi et al. [21] GRU is used to detect atrial fibrillation (AF) in electrocardiogram traces.

TABLE I. BENCHMARK PAPER ABOUT ATRIAL FIBRILLATION DETECTION

Classifier	Characteristics	Training Accuracy	Validation Accuracy	Ref
FFNN	One hidden layer with 128 units and 200 epochs.	76%	77%	[15]
1D-CNN	10 convolutional blocks, 2 fully connected layers, Softmax layer as the output prediction.	Not mentioned	78.2%	[17]
Attention-based BRNN	5 layer CNNs, BRNN, attention model and softmax regression.	96%	94%	[7]
LTMS	Fully connected layers, global max pooling layer and bidirectional LTMS layers.	Not mentioned	98.51%	[20]
GRU	100 epochs, 64 memory blocks and hidden GRU layer and dense layer with sigmoid activation function.	Not mentioned	100%	[21]
CNN-LSTM	3 convolutional blocks with max-pooling layers, LSTM layer.	Not mentioned	97.87%	[22]
Mobilenet V2-BiLSTM	MobilenetV2 has 16 interconnected blocks with BiLSTM added layers.	Not mentioned	86.21%	[23]

The study uses deep learning methods to detect AF in real time. The results indicate that GRU offers accuracy of 100%, and no preprocessing, denoising, or filtering methods are required [21]. Furthermore, Neural network architectures can be combined and adjusted to improve model performance. For example, Petmezas et al. [22] proposed a hybrid DL model that combines CNN and LSTM to classify different types of cardiovascular arrhythmias. The model uses the CNN as a feature extractor to supply the LSTM with the most discriminative features of the input and achieve dimensionality reduction. It also uses the focal loss function for prediction error reduction and data imbalance handling. The model was trained on the MIT-BIH Atrial Fibrillation Database and achieved a sensitivity of 97.87% and specificity of 99.29% using a ten-fold cross-validation strategy.

The use of neural networks for atrial fibrillation (AF) detection has shown promising results, but it is important to evaluate different architectures to determine the most effective approach. Different architectures such as feedforward neural networks, convolutional neural networks, and recurrent neural networks, may have different strengths and weaknesses with regard to AF detection. In this context, the present study aims to compare the performance of different neural network architectures for AF detection and identify the best approach for this task. This pursuit is crucial to establish whether these novel models outperform or are at least comparable to cutting-edge techniques. Specifically, this study will evaluate the performance of two hybrid neural networks of CNN-BiLSTM and MobileNetV2 in terms of accuracy and sensitivity, generalization capabilities, and computational cost. Additionally, the selection of the CNN-BiLSTM architecture is grounded in the well-established notion that both BiLSTM and CNN networks exhibit exceptional precision. This hybrid approach is expected to facilitate an intricate exploration of local and global features within AF data, thereby potentially elevating accuracy and sensitivity in AF detection.

This study originates from the concern to evaluate the performance of neural networks in two distinct contexts: one in which signal data is presented in its numerical format for 1D-CNN model and another in which the model (MobileNetV2) operates using this data in image format. The primary objective is to determine whether this variation in input formats, and consequently, in the models employed, has any significant impact on the diagnosis of atrial fibrillation (AF). Furthermore, it is noteworthy to emphasize that in the current era, the widespread availability of smart mobile devices may enable them to serve as accessible means for obtaining images of ECG signals. Consequently, it is imperative to assess these differences, given the increasing proliferation of these devices as potential tools in the field of medical diagnosis. By providing a comprehensive comparison of these neural network architectures, this study will contribute to the advancement of research in AF detection using machine learning techniques.

II. MATERIALS AND METHODOLOGY

The proposed algorithm aims to solve a problem of binary classification, where the input is an ECG recording of a patient and the output will announce if the patient has atrial fibrillation or if it is apparently healthy.

A. *Dataset*

We trained the 1D-CNN algorithm using the "MIT-BIH Physionet ECG Dataset (2017 competition version)" which contains 8528 ECG recordings ranging from 9 to 60 seconds. The dataset was provided by the AliveCor device for the 2017 PhysioNet/CinC Challenge. It is important to mention that the data is band-pass filtered by the same device. We also used the "Autonomic Aging" database to obtain ECG signals from healthy patients. All dataset contains both a .mat file and a .hea file. The .mat file includes the ECG data while the .hea file contains information about the waveform [24]. More details on the training set can be found in Table 2.

TABLE II. DATA PROFILE FOR THE TRAINING SET

Type	**# Recording**	**Time length (s)**				
		Mean	SD	Max	Median	Min
Normal	5154	31.9	10.0	61.0	30	9.0
AF	771	31.6	12.5	60	30	10.0
Other rhythm	2557	34.1	11.8	60.9	30	9.1
Noisy	46	27.1	9.0	60	30	10.2
Total	8528	32.5	10.9	61.0	30	9.0

B. *Signal Preprocessing*

Signal preprocessing is essential before applying Machine Learning techniques since the raw data contains alterations that need to be "cleaned" or corrected to facilitate further processing (Fig 1). Therefore, with this methodology the training of the data is accelerated, as well as the percentage of accuracy in the results is increased [25]. In the present work, 3 signal preprocessing techniques are applied: ECG Normalization, ECG Length Segmentation and Denoise Filtering.

In addition, to train the hybrid MobileNetv2 and BiLSTM model, images of each segmented signal were manually generated to create a new database of 260 training images, 94 validation images, and 62 test images.

a) ECG Normalization

Both databases vary in their total amplitude, therefore the amplitude (y axis) will be normalized to the same standard value to facilitate the subsequent treatment of the data in the neural networks. Normalizing the amplitude is also a good technique to avoid the offset effect [26].

b) ECG Length Segmentation

Due to the high variation of the length of both databases, we are developing an ECG Length Segmentation algorithm to cut all the data in the same length (x axis). We established a data length of 30 seconds. Furthermore, thanks to this algorithm, more signal segments can be generated to improve network training, as Hsieh and colleagues did in their work [27].

c) Denoise Filtering

It is always recommended to process the signals with filters to eliminate the alterations that can be generated by baseline wander, myoelectric noises, breathing sounds, motion artifact and powerline interferences [28,29,30]. Removing the noise before training the neural networks is a crucial step as it allows to improve the signal-to-noise ratio [31], as well as obtain efficient models with reliable results.

We applied a wavelet transform which can be thought of as a bandpass filter, since we will analyze non-stationary signals such as ECG recordings [32]. This filter helps to decompose the ECG signal to analyze it in different frequency bands through 2 low-pass filters and 2 high-pass filters [33-34]. Lyakhov et al. [35] mention that, by using this filter, noise can be efficiently removed and the most important features of the signal can be extracted.

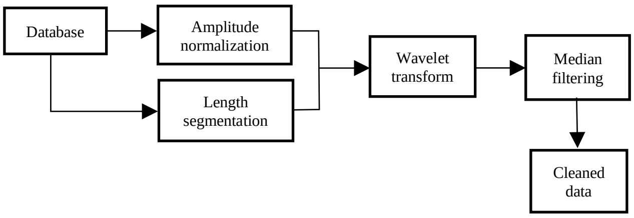

Fig. 1. ECG signal preprocessing.

C. Sensitivity and Specificity Test

The confusion matrix is a method in machine learning that helps measure recall, precision, accuracy, and AUC-ROC curve. It is used to allocate predictions to the original data classes and evaluate classification performance [36]. We calculated the sensitivity and specificity of each pacing class at different binary decision thresholds. The dataset consisted of 8258 records, with 70-80% of the data used for training the model and the remaining 15-30% used for validation at the end of each epoch. After training, we evaluated the algorithm on 1279 test records and constructed a confusion matrix to summarize the model's performance [37].

D. Deep Learning Algorithms

The machine learning algorithms selected to develop this problem of classification are 2 hybrid models. The first is a combination of 1d- CNN and BiLSTM algorithms and the second is a model with MobileNetV2 and BiLSTM assembled algorithms.

a) Hibrid Model: 1D-CNN and BILSTM

The 1D-CNN integrates in its algorithm 4 convolutional layers with other normalization, max pooling and dropout layers [38] that manage a relevant feature extraction from ECG signals (Fig 2).

On the other hand, the second neural network integrated in this model is a RNN. RNNs are a great work tool when the task is about processing time series [39]. Specifically, in this first model we incorporate the Bidirectional Long-Short Term Memory (BiLSTM) neural network which is used in cases when the data provided is highly variable over time [38,40], this particularity makes it ideal for working with ECG signals. It is characterized by having a forward transmission layer and a backward transmission layer that transports information from the future to the past and from the past to the future, which facilitates the classification task in the neural network [41] and also solves the problem of long-term dependency [42]. In addition, its algorithm incorporates a forget gate function with which it avoids losing information of our interest.

In summary, the 1D-CNN efficiently extracts features while maintaining their dimensionality, while the BiLSTM predicts classification without dimensionality issues. Together, they create a balanced model that complements each other's characteristics.

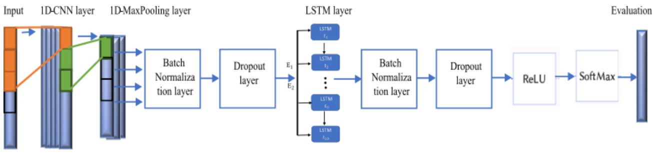

Fig. 2. CNN-BILSTM System Architecture.

b) Hybrid Model: MOBILENETV2 and BILSTM

The MobileNetV2 network is commonly integrated into mobile devices [43] since it is characterized by occupying fewer resources and generating higher performance than other heavier networks [23]. The architecture of this network is described in Fig 3.

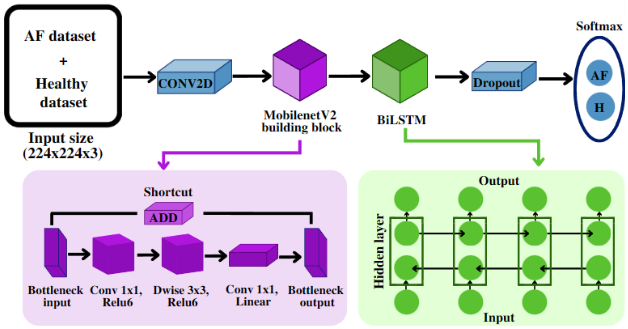

Fig. 3. MobilenetV2-BiLSTM system architecture.

MobilenetV2-BiLSTM is characterized by incorporating depthwise and pointwise convolution blocks for feature extraction that helps to reduce the number of parameters of the network, also it has a bottleneck algorithm in its architecture that reduces inefficient data loss [44] and it also has 1x1 convolutions that, being so small, occupy fewer resources.

Together with the aforementioned BiLSTM network, also described in Fig 3, will work to extract the most important characteristics of the signal and to give a reliable diagnosis.

III. Results

The training process yielded high accuracy for all cases. For the first CNN-BiLSTM-based model, after 50 epochs of training on the 3 classes, the validation set achieved an accuracy of 81% (Fig 4). The categorical cross-entropy function was used to calculate the loss, which was 0.385 for the validation set.

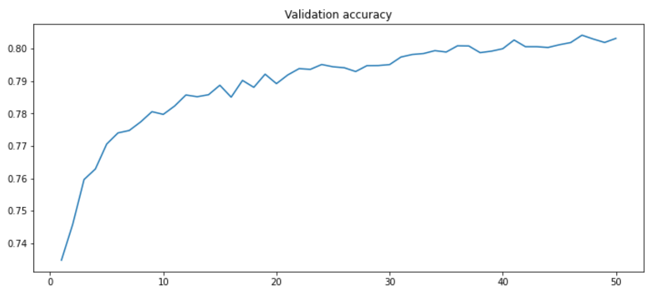

Fig. 4. Validation accuracy vs epochs.

Then, the confusion matrix for the validation set is shown in Fig 5, since that model was proposed for 3 classes using the test data for the validation set. The CNN-BiLSTM network correctly classified 1279 out of 8258 fragments belonging to the 3 classes during the test phase, resulting in an overall accuracy of 81%. In terms of individual cardiac arrhythmia diagnostic classes (aFib, Normal, and Other), the recognition system provided a classification accuracy of 75% or higher for all. While the predicted values are always between 0 and 1, we observed that all correct predictions are on the diagonal of the matrix, with accuracy greater than 75% for each class. Any values outside the diagonal represent incorrect predictions.

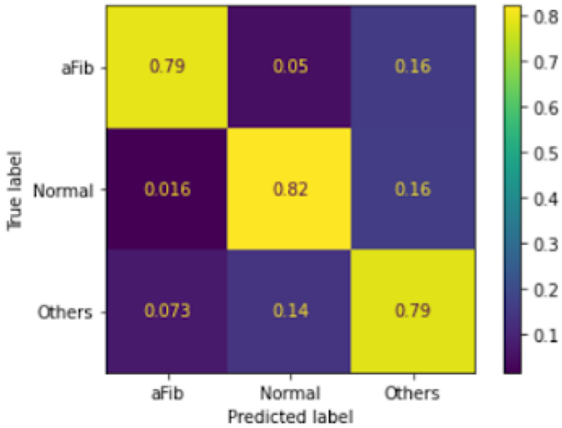

Fig. 5. Confusion matrix for test set.

On the other hand, the results obtained from training the signal images with the hybrid MobileNetV2-BiLSTM model are illustrated in Fig 6.

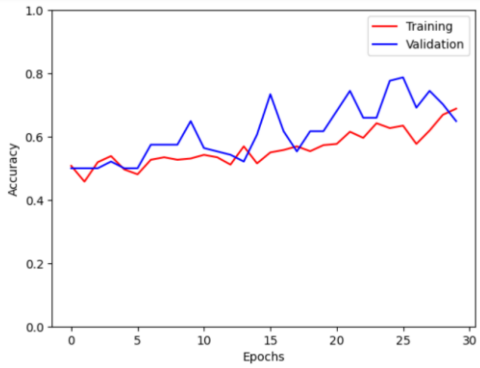

Fig. 6. Training and validation accuracy of MobilenetV2-BiLSTM.

Figures 6 and 7 reveals that, at the beginning, the loss is relatively high and accuracy is around 50%. As training progresses, there is some fluctuation in both loss and accuracy. Toward the end of the training, the loss starts to decrease and accuracy improves. These results indicate that the model was able to learn and adapt to the patterns present in the training data. However, it is essential to highlight that these improvements were not consistently linear. Additionally, fluctuation in validation accuracy is shown in figure 6. These fluctuations can occur because the model is too complex relative to the available data, which may lead to overfitting and, consequently, fluctuations in validation accuracy. Later, after 30 epochs, the accuracy values of the training and validation set were 69% and 65% respectively.

In addition, the results of training and validation loss are shown in Fig 7., specifically, training loss started at approximately 0.6979 in the first epoch and gradually decreased over subsequent epochs. By the end of training, the training loss reached a value of approximately 0.5895. On the other hand, the initial validation loss was around 0.6967 and also experienced fluctuations in subsequent epochs. At the end of training, the validation loss stabilized at approximately 0.6282.

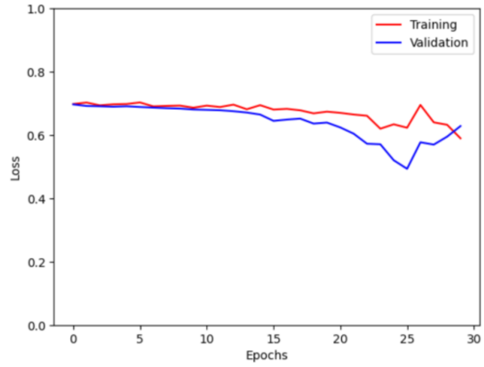

Fig. 7. Training and validation loss of MobilenetV2-BiLSTM.

In general, the training loss demonstrated that the model learned from the training data, as indicated by the decreasing trend. While the model performed reasonably well on the training data, it did not consistently generalize effectively to unseen data. The validation loss fluctuations may signify overfitting or model instability.

Figure 8 shows the normalized confusion matrix.

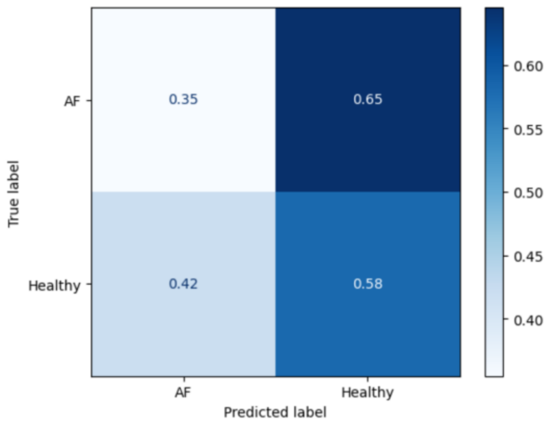

Fig. 8. Normalized confusion matrix of MobilenetV2-BiLSTM

Results revealed in Fig 8 highlights that the relatively high true positive rate (0.65) indicates that the model has a reasonable ability to correctly identify cases of atrial fibrillation, which is crucial for accurate diagnosis and timely intervention.

The true negative rate (0.35) shows that the model is effective at correctly identifying cases without atrial fibrillation, contributing to reducing unnecessary concerns or treatments for individuals who do not have the condition.

The false negative rate (0.42) is a concern as it suggests that the model occasionally misses cases of atrial fibrillation. This could potentially result in underdiagnosis and delayed treatment for patients who need it.

Finally, the false positive rate (0.58) indicates that the model sometimes incorrectly predicts atrial fibrillation in cases where it is not present. While this may lead to additional testing or treatment for some patients, it is generally safer to have a higher false positive rate than a high false negative rate in a medical diagnosis context.

IV. DISCUSSION

TABLE III. COMPARISON RESULTS OF THE HYBRID MODELS

Model	Epochs	Total data	Acc	Sen	Spec
1D-CNN and BiLSTM	50	8528 recordings	81%	82%	79%
MobilenetV2 and BiLSTM	30	416 images	65-69%	61%	38%

In Table 3 it is illustrated that the CNN-BiLSTM-based model achieved high accuracy of 81% on the validation set, which indicates that the patterns were learned well without overfitting [16]. The categorical cross-entropy function was used to calculate the loss, which was 0.385 for the validation set. Additionally, a confusion matrix was constructed for the validation set, which showed that the model correctly classified 1279 out of 8258 fragments belonging to the 3 classes during the test phase, resulting in an overall accuracy of 81%.

Furthermore, the confusion matrix shown in figure 6 also revealed that the recognition system provided a classification accuracy of 75% or higher for all individual cardiac arrhythmia diagnostic classes (aFib, Normal, and Other). The diagonal of the confusion matrix showed all correct predictions, with accuracy greater than 75% for each class, while values outside the diagonal represented incorrect predictions. These results demonstrate the effectiveness of the CNN-BiLSTM-based model for accurate classification of cardiac arrhythmia diagnostic classes.

Comparatively, our findings on the metrics shown in table 3 about the Mobilenetv2-BiLSTM model showed contrasting results compared to Model 1. This model was trained for 30 epochs, using a much smaller data set, consisting of only 416 images. This represented a significant challenge in terms of the amount of data available for training. Moreover, although the accuracy ranged from 65% to 69%, the sensitivity value (Sen) was 61%, indicating that the model had difficulty in accurately identifying PA cases. This could be due to data limitation and image complexity compared to the 1D signal recordings used in Model 1. On the other hand, the specificity (Spec) was 38%, suggesting a high number of false positives, which could be due to the difficulty of the model in discerning between AF and non-AF cases in the images.

V. CONCLUSION

To sum up, the utilization of CNN-BiLSTM machine learning algorithms for classification tasks can deliver precise outcomes if trained and verified properly. The presented investigation indicates that the proposed model obtained an 81% overall accuracy and a 75% or higher classification accuracy for each of the three diagnostic classes. These outcomes imply that the CNN-BiLSTM-based model could be a valuable instrument for accurately categorizing cardiac arrhythmias. Nonetheless, additional research and validation are required to determine the universality and usefulness of this model in clinical environments.

Similarly, model 2, which used MobileNetV2 images, experienced difficulties compared to Model 1. With a smaller and more complex data set of 416 images, it obtained variable accuracy (between 65% and 69%) but performed poorly in terms of sensitivity (61%) and specificity (38%). This suggests that image processing for AF detection can be challenging, especially when there is limited access to training data.

To further enhance the performance of the models, future work could include hyperparameter tuning to explore the effect of different parameters and features on the accuracy of the models. This analysis could provide insight into potential improvements or modifications to the existing models. Additionally, it would be beneficial to evaluate the performance of the models on a larger and more diverse dataset to determine their generalizability in clinical settings. Furthermore, an important area for future research would be to investigate the feasibility of implementing the models in real-time monitoring of atrial fibrillation, which remains a challenging task.

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