An Intelligent Learning Approach for Improving ECG Signal Classification and Arrhythmia Analysis

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***Abstract*—The development of deep learning algorithms in recent years has shown promise in interpreting ECGs, as these algorithms can be trained on large datasets and can learn to identify patterns associated with different heart conditions. The advantage of these algorithms is their ability to process large amounts of data quickly and accurately, which can help improve the speed and accuracy of diagnoses, especially for patients with heart conditions. Our proposed work provides performant models based on residual neural networks to automate the diagnosis of 12-lead ECG signals with more than 25 classes comprising different cardiovascular diseases (CVDs) and a healthy sinus rhythm. We conducted an experimental study using public datasets from Germany, the USA, and China and trained two models based on Residual Neural Net-works-50 (ResNet-50) and Xception from CNN techniques, which is one of the most effective classification models. Our models achieved high performances for both training and test tasks in terms of accuracy, precision, recall, and loss, with accuracy, recall, and precision exceeding 99.87% for the two proposed models during the training and validation. The loss obtained by the end of these two phases was 3.38.10-4. With these promising results, our suggested models can serve as diagnostic aids for cardiologists to evaluate ECG signals more quickly and objectively. Further quantitative and qualitative evaluations are presented and discussed in the study, and our work can be extended to other multi-modal big biological data tied with ECG for similar sets of patients to obtain a better understanding of the proposed approach for the benefit of the medical world.**

***Keywords*—Electrocardiogram; cardiovascular diseases; classification; ResNet-50; Xception**

I. Introduction

Globally, one of the major causes of death is cardiovascular disease (CVD) as it represents about greater than 30% which 85% of it is a heart attack, it is expected that more than 130 million people will be suffering by 2035 [1]. CVD has caught the attention of many researchers as they have been studying to elaborate solutions for the prevention and detection of these diseases regarding their impact economically [2]. Every year, studies have shown that the impact of CVD on the American and European economies is estimated at $555M and €210M, respectively. Understanding how the heart's electrical system works is crucial before examining [20] the electrocardiogram (ECG). The heart is an organ that periodically contracts and relaxes. Its cells play a role in the propagation of electrical impulses to nearby cardiac cells [3].

The principle of the ECG is to record the electrical impulses at the origin of cardiac contractions. The electrical impulses are recorded away from the heart, through the skin, using electrodes [4]. There are two types of electrodes: six precordial electrodes implanted on the chest and three frontal electrodes (or four, to refine the signal) placed on the limbs. The accuracy of the diagnosis is influenced by the number of electrodes. In fact, the more there are, the more accurate and precise the diagnosis will be. The accuracy of an electrocardiograph with 4 leads will be less than one with 12 leads. the most common clinical use is with 12 leads [5]. If the electrical impulse moves toward one of these electrodes, it registers a positive signal; if it moves away, it registers a negative signal. The wrists and ankles of the patient are where the frontal electrodes are placed [6]. They enable the reconstruction of the patient's heart's electrical axis; the ECG is the tracing obtained. Numerous cardiac issues are highlighted by this diagram, including atrioventricular blocks (poor electrical impulse conduction), bradycardias, and tachycardias with a slowing or accelerating of these complexes on the drawing [7].

The interpretation of this schema enables the doctor to confirm whether the heart is functioning properly. The responsibilities of cardiologists are expanding along with the rise of cardiac problems. Cardiology variation both within and across radiologists affects the manual interpretation [8]. The result of the manual interpretation will also be influenced by other factors such as mood, exhaustion, and others. Doctors regularly analyze and interpret ECGs, the diagnoses are greatly influenced by the doctor's training, qualifications, expertise, and experience. However, even experts and specialists are unable to fully identify all ECG signals information. In actuality, the analysis of lengthy recordings, such as Holter examinations and ambulatory cases of continuous monitoring in intensive care and intensive care and resuscitation units, is difficult and time-consuming, particularly for the detection of characteristic waves of the ECG signal and the classification of heartbeats [9].

Nowadays, innovative technologies such as Artificial intelligence have been helpful in a revolutionary way. Computer-aided medical diagnostics (CAMD) are now crucial for the diagnosis of CVD due to developments in hardware and algorithms. Cardiologists can consult CAMDs based on ECG signals for guidance and interpret results within a few seconds by checking CVD-specific characteristics. Due to the enormous number of patients in critical care units and the requirement for ongoing surveillance, they can assist doctors in making the diagnosis in a simpler and quicker way, which appears to be essential [10]. This is how it appeared that DMAOs helped with the ECG signal-based cardiac diagnosis. These systems should be simple to use, scalable, precise, reliable, and solid. Several techniques have been suggested in the latest decades for the evaluation of CVD. Various approaches, such as Deep Learning (DL) techniques have lately become useful tools in complex applications such as computerized machine vision and natural language processing. Among DL technics, a convolutional neural network (CNN) is by far one of the most effective [11].

Many researchers have shown interest in this topic and numerous approaches have been put out by various researchers to address it. There are several types of CVDs surpassing 100 types. This study aims to classify 27 heart rhythm types using ECG data including 26 different varieties of CVDs and normal sinus rhythm. The four merged used datasets to train, validate, and assess models in this classification, which comprises 42511 ECG records. The dataset utilized comprises 12-lead ECG signals, which is a common ECG category used in hospitals and clinical situations. It is trained with two models based on Residual Neural Networks-50 (ResNet-50) and Xception from CNN techniques, which is one of the most effective classification models.

The remainder of this investigation is organized as follows. Section II provides a review of comparable publications in the literature, while Section III described the suggested model and the simulation methodologies. A discussion and evaluation of the proposed ECG classification models' findings are provided in Section IV. Test phases are given in Section VI. Finally, Section VI discusses the conclusion and future projects.

II. Related Works

For ECG diagnosis, the Uni-G analysis tool, developed by the University of Glasgow, used rule-based criteria on signal processing and medical characteristics [3]. Datta et al obtained the best score in the Physionet/CinC Challenge 2017 [4] that have as its objective the single-leads ECGs classification. They applied a feature-oriented technique that includes a two-layer cascaded binary classifier. Another SP was employed in [6], Aziz et al used a Discrete Wavelet Transform (DWT) and SVM to detect R peaks and classify ECG signals.

Lately, DL models have been used on ECG data for a variety of applications such as denoising signals, pathology diagnosis [12], annotation or detection, and so on. The application of Deep Neural Network (DNN) in the classification of single or multiple ECG leads had shown a wonderful outcome [13]. Moreover, the results obtained by the em-ployment of a DNN on 91,232 ECG records are more performant than cardiologists when trying to diagnose 11 types of CVDs [14].

There are a variety of datasets used to train DL models. Most publications employ public databases such as MIT-BIH Databases and the Phsysionet/CinC Challenges da-taset. For example, the first dataset is MIT-BIH Arrhythmia Database [15] which comprises 48 2-leads ambulatory ECG recordings. Each one has a duration of 30 min. These were acquired from the BIH Arrhythmia Laboratory's 47 patients investigated between 1975 and 1979. This dataset includes five classes. In addition, MIT-BIH Atrial Fibrilla-tion Database [16] contains 25 ECG records. The duration of all the recordings is 10 hours. Most of the investigation dedicated to the Atrial Fibrillation (AFib) automated detection used this dataset. In addition, PTB is a widely used dataset that includes 54912-leads ECG signals from 290 subjects. This contains nine various diagnostic classes. Also, Ones of the most utilized dataset in the task of ECG classification are China Physiological Signal Challenge datasets [17]. Actually, the CPSC 2017, includes 8528 single lead ECG recordings. Their duration varies from 9s to 61s, and this comprises four classes: AFib, Normal, Noise and other MCVs. Whereas the CPSC 2018, it is a series of 6877 10s 12-leads ECG records. This comprises 9 diagnostic classes [18].

Ribeiro et al [19] used 2,322,513 ECG recordings, collected from 1,676,384 various patients, containing 6 types of CVDs as the training and the validation set. Their model is based on a Deep Neural Network (DNN) Architecture. DNNs outperformed cardiology resident clinicians in detecting six categories of anomalies in 12-lead ECG recordings, with F1-score over 80% and specificity exceeding 99%. These findings show that ECG diagnosis using DNNs, which was before examined in a single-lead scenario, generalizes effectively to 12-lead tests, bringing the technique closer to mainstream clinical practice. Besides, Zhu et al. [23] established their work on private dataset counting 180,112 12-leads ECG from 70,692 patients, including 21 classes. To classify these CVDs, they employed a CNN. The suggested CNN model consists of fifteen alternating layers for multilabel classification of the 21 heartbeats varieties. Shortcut connections in residual blocks were utilized to skip intermediate layers to avoid gradient vanishing difficulties. Rectified linear unit (ReLU) nonlinearity with dropout was utilized in the network to improve the performance and avoid the overfitting of the model. Similar to Zhu et al., Zhang et al. [21] used CNN to classify 6877 12-leads ECG provided by the CPSC 2018 to nine heart rhythm types. The suggested 1D-CNN has a similar overview to the original residual neural network for image recognition with 2D CNNs [22]. Actually, the proposed model has 34 layers. To capture deep characteristics, four residual blocks are stacked, then employed. Moreover, they used SHapley Additive exPlanations (SHAP) [23] to interpret the prediction of the model. This was used to interpret the patient level and the population level. Otherwise, this clarifies the attitude of the model against the single input, 12-lead ECG, and the whole used dataset. The SHAP method is based on game theory. In simple terms, it measures the impact on the prediction of adding a variable (all else being equal) by permuting all possible options.

In other papers, researchers opted to combine Neural Networks to boost models' performance. Zheng et al. [24] developed model formed by a combination of CNN and long short-term memory (LSTM) which belong to the Recurrent Neural Network (RNN) and trained it on the MIT-BIH databases. CNN is best suited for analyzing spatial or locally linked data, whereas LSTM excels at collecting time series data properties. Concerning the CNN, they used two models. The first is a simple CNN. The model's layers 1-9 are convolutional layers connected to the highest collection layer, while layer 10 is the LSTM layer. To predict the output, the network's end employs a fully - connected layer. Whereas the second is VGGNet belonging to the deep CNN. By combining convolution and pooling layers, the model can successfully collect ECG deep information.

To enhance the robustness of models, investigators used data augmentation technics which are usually figured when there is an imbalance in training data. Wu et al. [25] utilized shifting test data. Moreover, Nonaka et al. [26] applied 13 data augmentation method on ECG signals to improve the efficiency of their DNN model. For example, they used erasing, scaling, squaring and so on.

III. METHODS

Fig. 1 depicts the process of the proposed methods, which were used in this investigation. The next subsections will discuss each phase of this workflow. Actually, this starts with the fundamental steps which is data preparation. This step comprises data cleaning, data preprocessing, data partition and data augmentation. The next step is the training and validation of the proposed models using the training and validation data already split. Lastly, the test of the trained and validated model. This requires the test data.

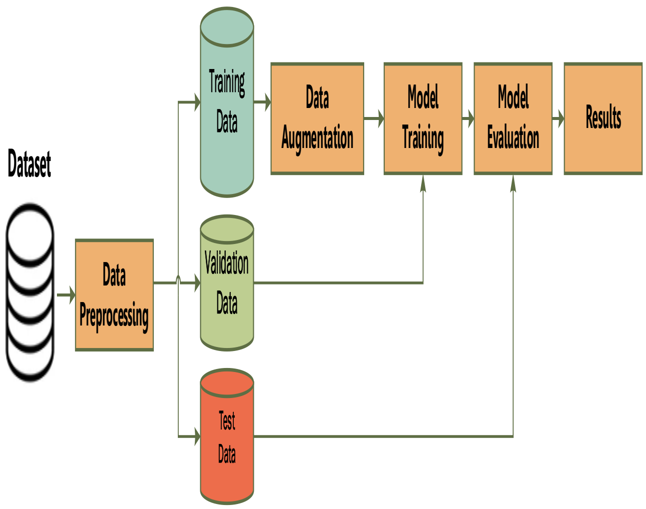

Fig. 1. Workflow of the proposed methods.

A. Dataset

The utilized dataset in this study contains four combined open source and free databases from George B. Moody PhysioNet Challenges which aims to classify 12-leads ECGs. This dataset contains 42 511 ECGs, 500 Hz-sampled, recorded from patients for a duration of 10 seconds. They come from three various countries, the USA, China, and Germany. Table I details the characteristics of these databases.

TABLE I. CHARACTERISTICS OF THE USED DATABASES

Database	Source	Records	Length
CPSC [21]	China Physiological Signal Challenge in 2018	6877 M: 3699 |F: 3178	6 s ~60 s
CPSC EXTRA [21]		3453 M: 1843 |F: 1610	6 s ~60 s
PTB-XL [26]	Physikalisch Technische Bundesanstalt	21837 M: 11379 |F: 10458	10s
Georgia [27]	Georgia	10344 M: 5551 |F: 4793	10s

The database is annotated with more than 110 diagnostics. In this study, due to the delimited annotations scored by the SNOMED-CT organization, which is a standardized multilingual clinical terminology vocabulary, only 27 classes will be considered, divided into normal sinus rhythm (NSR) and 26 categories of CVDs. Fig. 2 presents these classes.

Fig. 2. Distribution of classes in each database.

B. Data Preparation

The data preparation starts with the extraction of the patient's personal information from the header files such as ID, age, gender, and anomalies codes. The following paragraphs detail the rest of the data preparation steps of training, validation, and testing. As indicated in paragraph 3, this work focuses on the 27 scored classes. For that, any annotated signal from the unscored classes will be removed. As a result, the number of ECGs will decrease from 42511 to 21724. The final distribution of the classes is presented in Fig. 3.

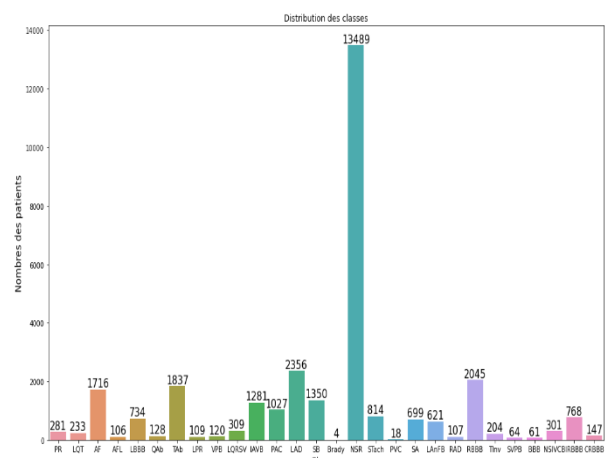

Fig. 3. Dataset classes distribution.

C. Data Preprocessing

The dataset includes 12-lead multi-label ECGs with diverse lengths between 6 s and 60 s. Considering DL needs inputs to be the same length, the dataset has been preprocessed to guarantee that all inputs have the same length. A variety of lengths were tried, and it was discovered that proceeding with lengths equal to 5000 (10 s duration, 500 Hz sampling rate) gave the best performance. Regarding ECGs with full length longer than 10 s, they will be shortened, and the first 10 seconds of the ECG signal will be kept. Otherwise, they are padded with zeros until they have 10 seconds of recording. Fig. 4 shows the techniques used in the preprocessing of the data.

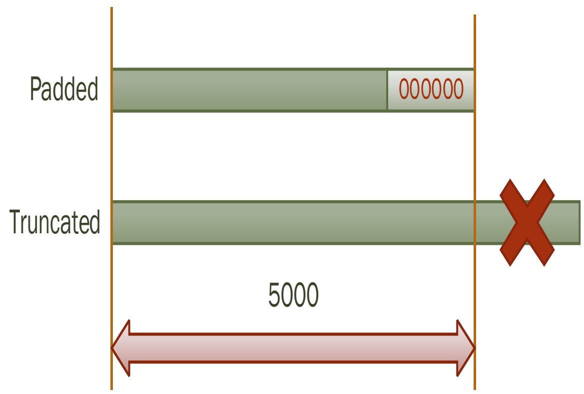

Fig. 4. Data preprocessing techniques.

D. Data-Split

To start with, the dataset is partitioned into two sets with a 0.75/0.25 ratio: the Training and Validation (TV) set and the test set. After that, the K-Fold stratified multi-class cross-validation technique was used, with 10 folds for the training and validation sets. As a result, ten stratified folds were generated by keeping each class samples rate constant. This ensures its existence at all stages. The training set is used to ensure the training of the model. The validation set is set aside for model optimization. As a result, a search for the appropriate parameterization is done without utilizing test data. This aims to determine the model's performance and evaluate its generalization potential. To resume this step explained in Fig. 5, the data was split into a TV set and a test set containing 16293 and 5431 ECG records, respectively. For the TV set, each training and validation fold includes 14655 and 1638 ECG recordings, respectively.

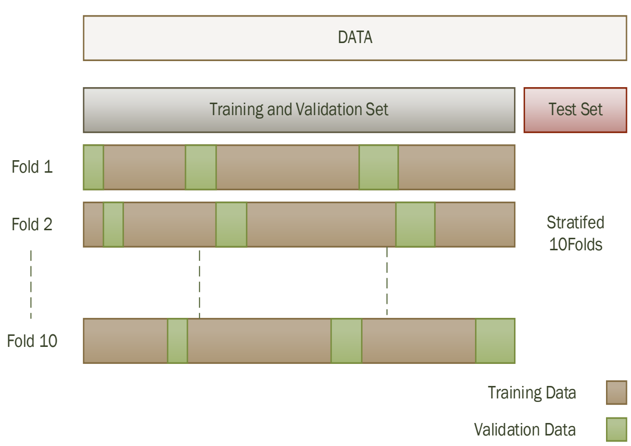

Fig. 5. 10-Folds stratified used in data split.

E. Data-Augmentation

As shown in Fig. 3, the problem of imbalance and insufficient data is very severe for the diagnosis of these cardiac arrhythmias. To solve this problem, Amplitude Scaling was applied to augment the data during the training phase. Data augmentation consists in generating realistic data to avoid data insufficiency. To extend or compress the amplitude, amplitude scaling method amplifies ECG signals by a random coefficient generated from a normal distribution N (1, 0,1). Although this da-ta augmentation technique introduces noise, it can assist prevent model overfitting and enhance resilience against bad cases [30].

IV. Models Architectures

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A. Model 1

The first proposed model is ResNet-50 which belongs to the residual neural networks. At the conclusion of its layers, this network learns numerous low/medium/high level characteristics. Instead of trying to train features, residuals are trained in residual training. The residual may be easily defined as input for that layer minus the trained features. ResNet employs shortcut connections for this purpose (directly linking the nth layer's input to the (n+i)th layer). The training of the model is made possible thanks to the residual blocks with shortcut connections. The input of the models is a patient ECG recording $x \in \mathbb{R}_{n}\text{samples}\times 12$, and the output is $\hat{y} \in \mathbb{R}_{1}\text{x}27$ which represents the multi-label classification outcome. These inputs were subjected to a 1D convolution layer (Conv1D), a batch normalization layer (BN1D), a rectified linear unit (ReLU) activation layer, and a Max Pooling layer. As well as, for the extraction of wide features, 16 residual blocks were used. In this model, there are two types of residual blocks:

1) Res_Block_1 consists of 3 Conv1D layers, 3 BN1D layers, 2 activation layers ReLU, 1 Conv1D layer and 1 BN1D layer, while it is utilized to adjust dimensions and skip con-nections. Res Block 2 is just 3 Conv1D layers, 3 BN1D layers and 2 ReLU activation layers.

2) The Conv1D layers extract features, the BatchNorm1D layers speed up and stabilize the model, and the ReLU layers do non-linear activation. The residual blocks' extracted characteristics are pooled by Average Pooling. The findings are gathered and transferred to the output layer (dense layer) for prediction utilizing the sigmoid activation function.

Fig. 6 presents the architecture of the first proposed model is presented.

B. Model 2

The second proposed model is Xception. It is a deep convolutional neural network architecture incorporating depth-separable convolutions [31]. This is a powerful architecture that relies on its two main points of: Depth-separable convolution and Shortcuts between convolution blocks as in ResNet. Depth-separable convolution is said to be an alternative to classical convolution and much more computationally time efficient [32]. As in the first model, the Xception model has the same input and output. Xception comprises 36 layers of convolutions that form the basis for extracting network features. They are divided into 14 modules with linear residual connections around all but the last and first modules. The Xception architecture is essentially a linear stack of depth-separable convolution layers with residual connections. Data is routed via the Entry flow first, then via intermediate flow 8 times, and lastly the Exit flow. A batch normalization layer follows all convolution (Conv1D) and separable convolution (Sep-Conv1D) layers (BN1D). These modules' collected characteristics are pooled using Global Average Pooling. The pooling results are gathered and forwarded to the dense layer, which uses the sigmoid activation function to make predictions. Fig. 7 details the architecture of proposed model 2.

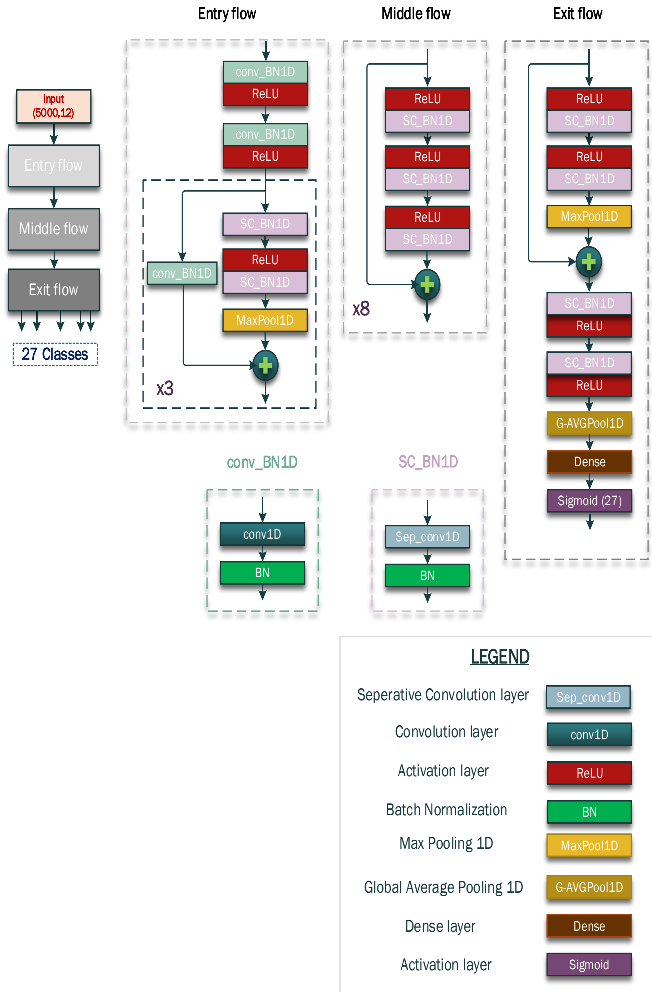

Fig. 7. Architecture of the proposed model 2.

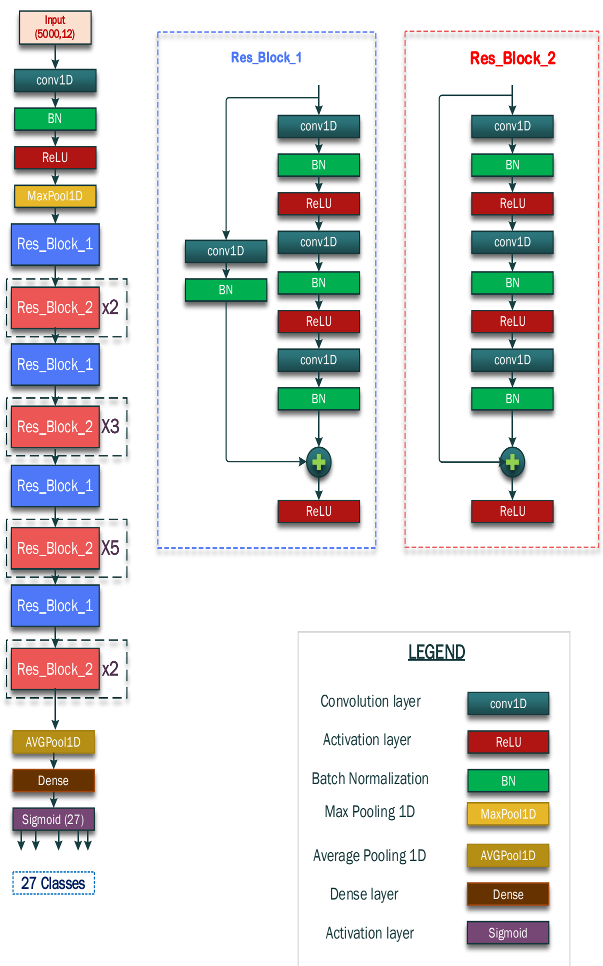

Fig. 6. Architecture of the proposed model 1.

V. Results & Discussions

In the Training and Validation phase, there are many introduced metrics. In fact, this paragraph details the evolution of the accuracy, recall, precision, and loss during these two phases for the two proposed models.

A. Accuracy

At the end of the training and validation, for the model N°1, ResNet-50, the accuracy obtained is 99.99% and 99.98% respectively. For the model N°2, Xception, it reached 100% in both phases. Fig. 8 and 9 represent the development of the accuracy during the two phases for the ResNet-50 and Xception respectively.

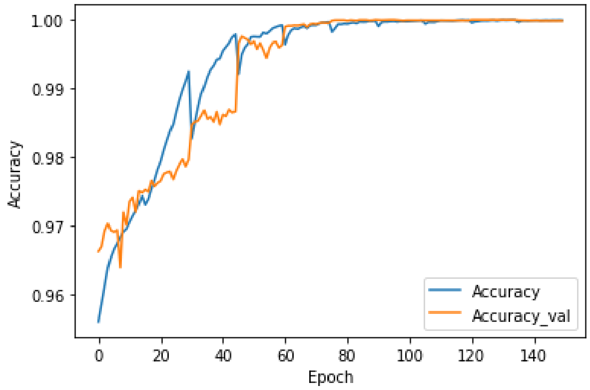

Fig. 8. Evolution of accuracy during the training of two models.

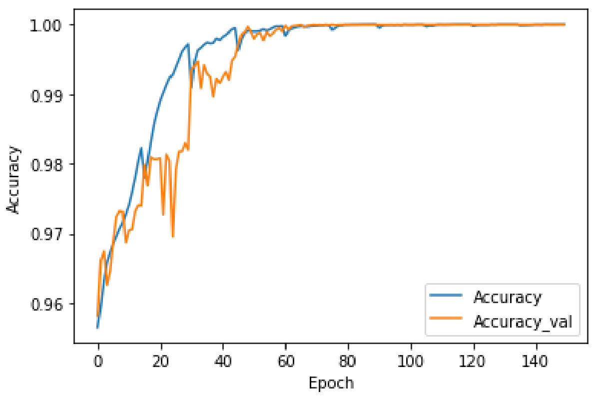

Fig. 9. Evolution of accuracy during the validation of two models.

B. Precision

Fig. 10 and 11 illustrate the evolution of the precision in the two steps for the two proposed models. Indeed, for model 1, it reached 99.99% in the training and 99.87% in the validation. Concerning the model N°2, the precision obtained in the two phases is 100% and 99.96%.

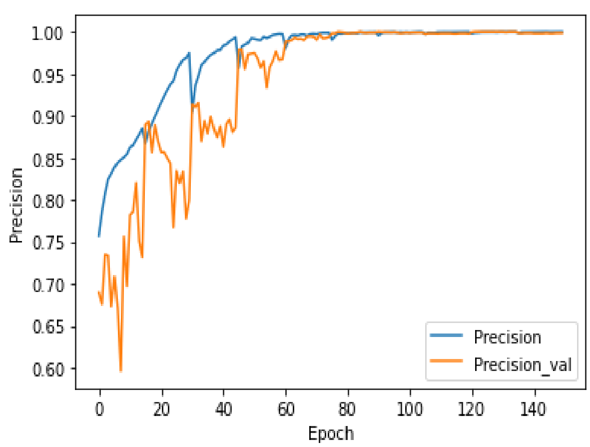

Fig. 10. Evolution of the precision during the training of two models.

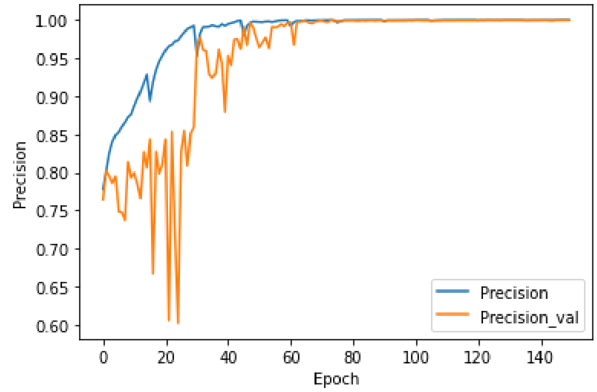

Fig. 11. Evolution of the precision during the validation of two models.

C. Recall

Concerning the recall parameter, at the end of the training and validation of ResnNet-50 model, it reached 100% and 99.87%. For the Xception model, it is 100% in both phases. Fig. 12 and 13 show the evolution of recall for the two models.

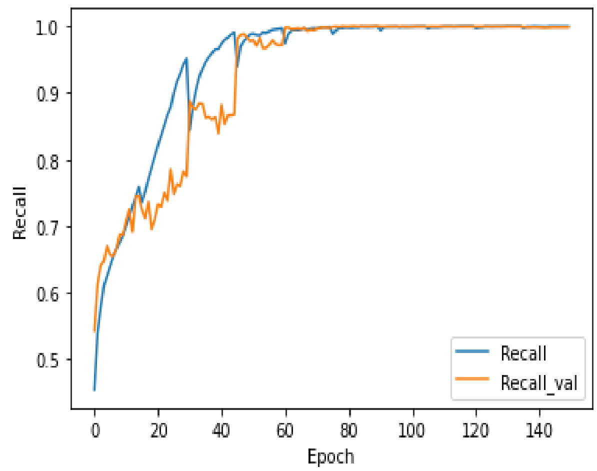

Fig. 12. Evolution of the recall during the training of two models.

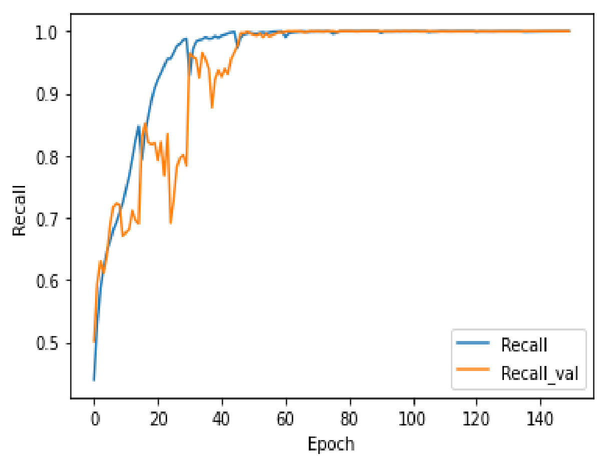

Fig. 13. Evolution of the recall during the validation of two models.

D. Loss

In terms of loss, the first model reached $7{,}89.10^{-05}$ and $3{,}83.10^{-04}$ in the two phases. For the second model, at the end of learning and validation, it reaches $4{,}37.10^{-05}$ and $2{,}05.10^{-04}$, respectively. Fig. 14 and 15 present the declination of the Loss function for the two models.

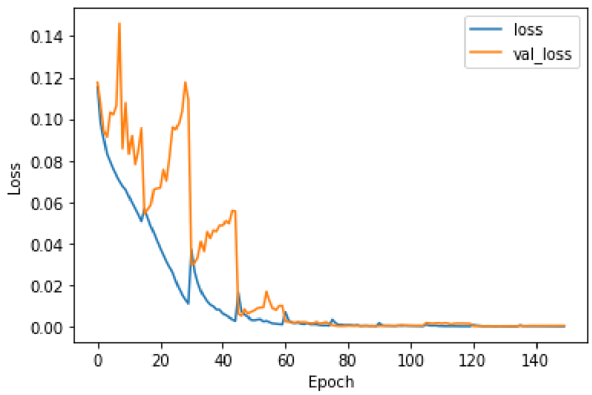

Fig. 14. Evolution of the loss during the training of two models.

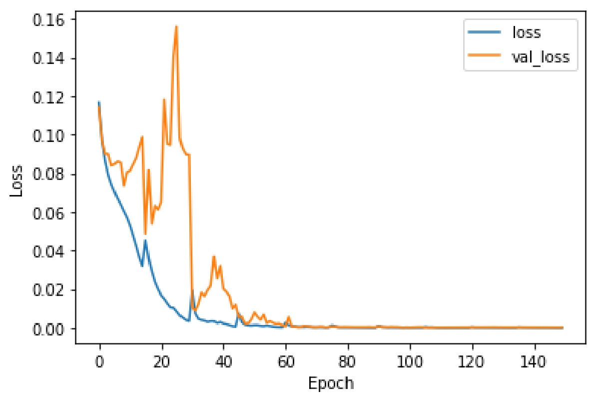

Fig. 15. Evolution of the loss during the validation of two models.

Globally, for both models, the evolution of the performance parameters is generally similar to a faster stabilization of the Xception model. Indeed, the model N°2 has converged since the 60th epoch (beginning of fold N°5) whereas the model N°1 has converged only after the 90th epoch (beginning of fold N°7). Also, the evolution of the validation curves of the performance parameters for the ResNet-50 model is more stable than that of the Xception model. Moreover, the saw teeth noticed in these curves are less severe for the model N°1.

VI. Test Phases

In the test phase, the metrics presented are the confusion matrices of the proposed two models as well as their classification reports. Fig. 16 presents the normalized confusion matrix obtained. The model N°1 is performing for the classes CRBBB, RAD, Brady, PR, NSR, RBBB, AF, IRBBB, STach, IAVB, PAC, LBBB. Indeed, their percentages of correct determinations are greater than 80%. Moreover, its performance is moderate for the PVC, SA, TInv, SB, and AFL classes where their percentages of correct predictions are higher than 60%. For lasting classes, such as QAb, LPR, and LAD, ResNet-50 has a bad performance.

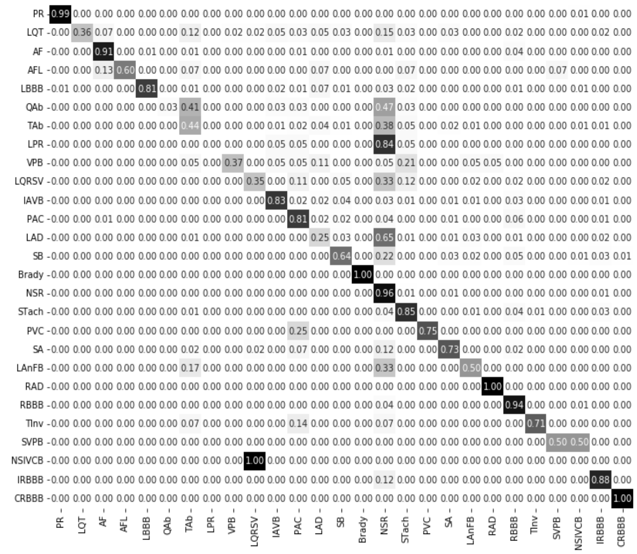

Fig. 16. Confusion matrix of the proposed model 1.

Fig. 17 illustrates the normalized confusion matrix obtained from model N°2. It performs well for the classes NSIVCB, CRBBB, SVPB, NSR, RBBB, PR, IRBBB, AF, AFL, IAVB, STach. Moreover, their percentages of correct predictions exceed 80%. Moreover, its performance is moderate for the classes PAC, SB, SA, TInv, and LQRSV where their percentages of correct predictions are above 60%. For the remaining classes, like LPR, QAb, Brady and RAD..., Xception has a bad performance.

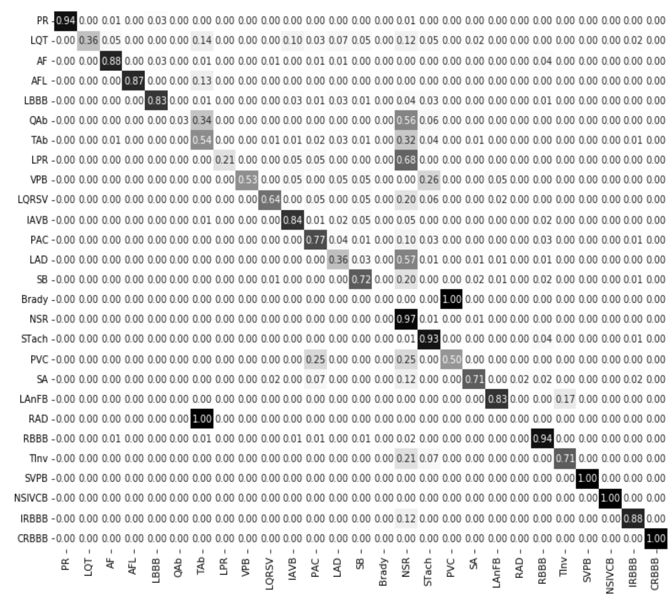

Fig. 17. Confusion matrix of the proposed model 2.

VII. Conclusion

This study showcases a successful application of deep learning (DL) techniques for the accurate diagnosis of cardiovascular diseases (CVDs) using ResNet-50 and Xception models. The study considered 27 heartbeat rhythms, where one belongs to normal sinus rhythm (NSR), and the remaining 26 belong to cardiac abnormalities. The dataset utilized in this research was created by aggregating four distinct datasets from three different nations, providing a diverse range of cardiac conditions. The results demonstrate the effectiveness and high performance of the proposed methods, which were also validated against recent literature. However, it is essential to acknowledge the limitations of the suggested methods. Firstly, the high complexity of computation required for the deep learning models may hinder their implementation in some medical settings. Additionally, the limited interpretability of some of the classes in the global dataset used may pose challenges in diagnosing and treating certain cardiac conditions. To address these challenges, future studies will focus on enhancing the proposed techniques to make them more accessible and interpretable for a broader range of medical applications. Overall, this research provides promising insights into the potential of deep learning models for CVD diagnosis, and with further development, they have the potential to revolutionize the field of cardiac medicine.

ACKNOWLEDGMENT

This work was supported by Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2024R393), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia.

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