D-Resnet: Deep Resnet based approach for ECG classification

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Abstract: The ECG signal represents the electrical activity of the heart and reflects the health of the cardiovascular system. It also contains information that can be used to differentiate cardiovascular diseases. The automatic classification of arrhythmias is an important step in the development of monitoring equipment in the ambulatory or intensive care setting. In this work we propose a deep residual network (D-Resnet) model which allows a very deep extraction of the characteristics of the ECG signal in order to accurately differentiate between normal and abnormal signals. In the framework of an embedded system project for elderly automated diagnosis, we propose an approach that is designed to classify six types of cardiac rhythms: normal beats, ventricular premature beats, rhythmic beats, atrial premature beats, fusion of ventricular and normal beats or noise. The characteristics and depth of the proposed model make it possible to provide satisfactory precision in comparison with the work of the literature.

Keywords: Deep Learning, ResNet, Electrocardiogram ECG, Arrhythmia classification.

1. INTRODUCTION

The medical field requires new techniques and technologies in order to evaluate information objectively. Recent development in electronics and computing has enabled to have increasingly powerful machines capable of executing complex algorithms and to test new approaches in artificial intelligence. Today, machine learning algorithms are being used to prevent or detect heart disease. Early diagnosis of cardiac irregularities allows for prompt treatment and can help prevent complications. Several clinical features, such as age, sex, heredity, and blood pressure, can be used to define disease risk.

The electrocardiogram (ECG) signal is part of the data used by the algorithms for the detection of a possible heart disease. Several heart diseases, such as arrhythmias, coronary heart disease, heart attack, cardiomyopathy, can be detected by analyzing this signal. The ECG is therefore a standard test for monitoring heart activity and a powerful tool for diagnosis aid.

The ECG classification can be used for the early detection of diseases and abnormal heart conditions. Such application becomes essential due to the insufficient number of specialists in cardiology (Who, 2023). It is also useful in various medical scenarios, including pandemic outbreaks like COVID-19, where it is necessary to prioritize patients for vaccination and to identify high-risk groups, as explained by (Öğütcü et al., 2022). In this latter, authors present a decision-support system to start advanced medical support by training parameters that are relevant to one month mortality, through an Artificial intelligence Neural Network (ANN). However, it is crucial to avoid misdiagnosis that may lead to unnecessary treatment. Thus, two main points motivate our work:

- Improving automatic classification results is extremely important in several applications, but even more so in the health care field.
- Embedding a reliable CNN-based solution for tele-diagnosis applications would help to save efforts, time and resources. The medical team being far from the patient to confirm the classification result, the error probability should be infinitely small if not null.

In this work we present a simple but effective architecture based on Residual Network ResNet for the ECG signal classification. Our main contribution is to propose an automatic classification system based on an association of a CNN and ResNet architectures. This approach is based on three main blocks where the ResNet model constitutes the central block in such a way as to avoid overfitting and vanishing gradient issues while improving accuracy. This solution has been proposed in the framework of an embedded system project for telediagnosis. Thus, it was essential to ensure a low complexity of the proposed algorithm.

The rest of the paper is split into sections: In section 2 we present a brief review on classification of ECG signal based mainly on deep learning architectures. In section 3, we present some background knowledge on the Electrocardiogram signal, the Convolutional Neural Network and the Residual Network on which our solution is built. The proposed approach is detailed in section 4. Results are presented and discussed in section 5. Finally, conclusions and possible future work of the paper are given in section 6.

2. RELATED WORK

In dataset classification process it is important to take into consideration the number of dataset features. Having a large number of features can slow down the calculation speed and lead to overfitting. This issue has been discussed in (Kilic et al. (2023)) where authors proposed the implementation of the Anarchic Society Optimization algorithm, which is a human-inspired algorithm, as a feature selector to identify the most relevant features and improve the classification performance. Indeed, the motivation of the process of the feature selection (FS) is to reduce irrelevant feature while affecting learning performance. Another example in medical field is given in

(Öğütcü et al., 2022) where authors used factor analysis (FA) to select seven most relevant input parameters of an ANN from nineteen parameters in the context of Covid-19 pandemic as already mentioned in the introduction.

Various methods and approaches have been tested for the detection of heart disease. There are methods that use a single type of data (image, acoustic recording) and methods that use several inputs (age, blood pressure, cholesterol level, etc.). Several algorithms for the classification of heartbeats from ECG records have been proposed:

• The traditional ECG classification methods encompass several steps such as : signal preprocessing, segmentation of beats, feature extraction, and classification with techniques like Support Vector Machines (SVM) , ANN, k Nearest Neighbor algorithm (kNN) ,

• The ECG classification based on Deep Learning like the Convolutional Neural Networks (CNN) model.

The readers can refer to the work proposed by (Deepak et al., 2020) which presents a review of ECG signal classification using deep learning and traditional methods. In what follows, we present examples of literature related to the conducted research based on deep neural networks (DNN), convolutional neural networks (CNN) and Residual Network (ResNet)for the detection of heart disease.

The method proposed in (Brunese et al., 2020) detects heart disease using heart sound. This method only uses a mobile device equipped with the iStethoscope Pro mobile app to measure the heart sound then this sound is studied to extract the necessary features to put them into a feature vector used as an input to the deep learning algorithm. This method uses a DNN-like algorithm with a sequential model with 4 hidden layers. The output layer is enabled by the Softmax function because it can manipulate multiple classes into a single, then it gives the probability that an input value belongs in a specific class. conducting the tests, the algorithm reaches an accuracy of 98% , which shows the effectiveness of the proposed method. In recent years, there is a growing interest to residual networks in the classification area of biomedical signals.

In (Jing et al., 2021), authors have proposed an improved version of the Residual Network ResNet-18 model to identify arrhythmia classes. The approach consists on the following steps: a convolutional layer, a classic ResNet18 layer, an improved ResNet18 layer to be executed seven times, and a fully connected layer. the improved Resnet18 aims to accelerate the training of the neural network, increase the convergence speed, and to maintain the stability of the algorithm by adding a batch normalization before the classical ResNet-18. Tested on the MIT-BIH dataset, the proposed approach reached an accuracy of 96.5%, a precision of 97.44%, and a sensitivity of 93.83%.

In (Sakli et al., 2022) authors proposed a classification of the ECG signal based on the Residual Neural Network (ResNet-50). This approach proposes a classification of 26 types of cardiovascular disease and a normal sinus rhythm. In this architecture the input goes through a 1D convolution layer (Conv1d), a batch normalization layer (BatchNorm1d), a rectified linear unit (ReLU) activation layer, and a Max Pooling layer. Sixteen residual blocks have been used to extract deep features, in which two types of residual blocks are distinguished: One of them is composed of three Conv1d layers, three BatchNorm1d layers, and two ReLU activation layers, then one Conv1d layer and one BatchNorm1d layer which are used to match dimensions and skip connections, whereas the other block is composed on three Conv1d layers, three BatchNorm1d layers, and two ReLU activation layers. combined public databases have been used for tests. Results of the proposed model have achieved an accuracy of 97.63% and a precision of 89.67%. However, authors reported the high computational complexity of this model.

In this work, we propose a new ECG classification solution based on ResNet in the framework of an embedded system project, in particular because we have found that this architecture is relatively easy to build and gives good results to Time series problems as mentioned later. Reminders on basic knowledges on CNN and ResNet are presented in the next section.

3. BACKGROUD

3.1 The ECG basics

The electrocardiogram (ECG) is a tracing obtained by recording and transcribing the electrical currents that run through the heart during each cardiac contraction. As a reminder, the features of ECG signal, represented in Fig. 1, consist of waves, segments and intervals, mainly:

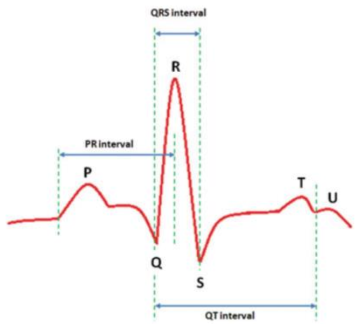

Fig. 1. ECG signal.

The P wave: It represents atrial depolarization. This wave can be positive or negative.

The complex QRS: corresponds to the ventricular depolarization preceding the mechanical effect of contraction.

The RR segment: This interval delimited by the peaks of two consecutive R waves makes it possible to evaluate the instantaneous heart rate.

The ST segment: During this interval, the ventricles remain in a state of active depolarization.

The T wave: It corresponds to the depolarization of the ventricles, which can be negative, positive or biphasic.

The PR interval: measured between the beginning of the P wave and the beginning of the QRS complex, it corresponds to the auricle-ventricular conduction and represents the interval between the beginning of the depolarization of the atria and the beginning of the ventricular depolarization.

The QT interval: It represents the time between the beginning of the QRS complex and the end of the T wave. This interval reflects the duration of ventricular depolarization and repolarization.

ECG signals can be affected by noise from different sources, and are particularly susceptible to noise from sources such as the powerline interference, the beseline wander (caused by breathing) and noise caused by the Electrical equipments (Jing et al., 2021). It is necessary to consider the noise that affects the ECG signal during the classification process in order to obtain reliable classification results.

3.2 Convolutional Neural Network

The convolutional neural network (CNN) is one of the most famous and commonly employed deep learning network. The main benefit of CNN compared to its predecessors is that it automatically identifies the relevant features without any human supervision. The basic concepts of CNN networks are related to fundamental data transmission and its components. It is based on the concept of perceptron inspired from the biological neuron. The multilayer perceptron (MLP) consists of the input layer, the hidden layer (one or more) and the output layer. The CNN architecture is then composed of a number of different function layers. They are presented as follows (Alzubaidi et al., 2021; Chen et al., 2021):

Convolutional Layer The convolutional layer has several convolution kernels with learnable parameters. The input, expressed as N-dimensional matrices (generally 3×3, 5×5, and 7×7), is convolved with filters (or kernels) to generate the output feature map.

Pooling Layer The main task of the pooling layer is to create a smaller feature map by sub-sampling the feature maps. This dimensionality reduction aims to reduce the burden of network Among the frequently utilized pooling methods are the max, average, and global average pooling (GAP) as represented in Fig. 2. For the proposed approach we adopt the max pooling technique.

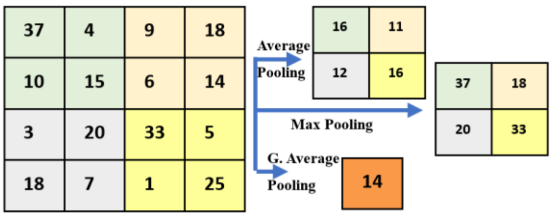

Fig. 2. Pooling techniques.

Activation Function (non-linearity) The activation function (such as ReLu) aims to map the input to the output through functional relationship. The input to this function is the weighted sum of the neuron's input with its bias (if any). A suitable nonlinear activation function can significantly improve the performance of the network. ReLu function is the mostly commonly used function. It converts the whole values of the input to positive numbers as represented in equation (1).

$$f(x)_{ReLu} = \max(0, x) \quad (1)$$

Fully Connected Layer (FC) Located at the end of each CNN architecture, each neuron of the fully connected layer (FC) is connected to neurons of the previous layer. It is utilized as the CNN classifer. Its input, which comes from the last pooling, is in the form of a vector. The output of the FC layer represents the final CNN output.

Loss Functions The loss function (such as Softmax or Cross-Entropy) are used to calculate the predicted error created across the training samples in the CNN model. This error represents the difference between the actual output (Label) and the estimated one (predicted). Mathematically, the output vector a = {a1, ...ak} is transformed into a probability (pi or p(a)i) as represented in equation (2).

$$p(a)_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}} \quad (2)$$

k represents the number of neurons; e is the exponential function. Finally, the cross-entropy loss function is represented in equation (3).

$$H(p, y) = -\sum_i y_i \log(p_i) \,, i \in [1, N] \quad (3)$$

Regularization and optimization are important concepts in deep learning area. The regularization (such as Dropping and normalization techniques) provides basically techniques to address the overfitting issue and guarantees the performance of the output activations. For instance, Batch Normalization is applied to the output of the layers to mainly stabilize the network. It consists of modifying the input data of a neural network so that the mean is zero and the standard deviation equal to one. However, the optimizer process, such as Stochastic gradient decent (SGD), provides essentially a way to make entire network may converge faster with cheaper calculation.

In (Alzubaidi et al., 2021), authors explained that the key upgrade in CNN performance occurred principally due to the processing unit reorganization, to the development of novel blocks and to the use of network depth. In (Chen et al., 2021) a proposition of a classification is presented, mainly: Classic CNN Models: such as LeNet Network, Alex Network and VGGNet; GoogLeNet/InceptionV1 to V4 : such as Inception V1 and improved versions; Residual Learning Networks: such as ResNet. This latter was the Residual Network presented by (He et al., 2016) as an ultra-deep network free of the vanishing gradient issue. It was the winner of ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2015. Indeed, motivated by the success of these CNN architectures in various domains, researchers have started adopting them for time series analysis. A review of the deep learning for time series classification (TSC) presented in (Fawaz et al., 2018) shows that end-to-end deep learning can achieve the current state-of-the-art performance for TSC with architectures such as Fully Convolutional Neural Networks and deep Residual Networks. In the next section we present the ResNet architecture.

3.3 Residual Network

Residual network (ResNet) is a CNN architecture whose core building element is a residual block. A residual block makes the use of skip connection to improve learning and to prevent the problem of gradient diminishing as mentioned in the previous section. Connections (skip or shortcut connections) can skip one or more layers. Indeed, Experiments showed that even if the network performance is linked to the network depth, increasing the network depth within a certain depth range cannot effectively improve network performance due to the disappearance of the gradient problem. In the training process, the residual shortcut guarantees the network integrity if the regular connections coefficients converge to zero. The alternative connections improve the network by providing the option of choosing these shortcuts when required. The residual connection in ResNet is a method to break degradation and enable deep neural networks to achieve high accuracy. Another advantage of the Resnet architecture is the lower computational complexity, even with enlarged depth.

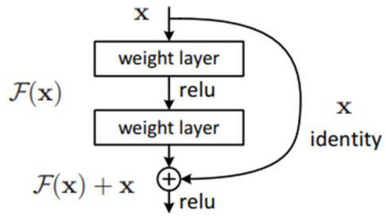

Fig. 3. Residual learning: a building block (He et al., 2016).

The desired underlying mapping denoted H(x), such as H(x)=F(x)+x, can be realized by feedforward neural networks with shortcut connections as illustrated in Fig. 3. In this case, the shortcut connections perform identity mapping, and their outputs are added to the outputs of the stacked layers. The entire network can still be trained end-to-end by SGD with back propagation, and can be implemented using common libraries. Notice that, the equation H(x) = F(x) + x can be used when the input and output are of the same dimensions. Otherwise, it is possible to use extra zero entries padded to increase dimensions, or to perform a linear projection to the shortcut (done by 11 convolutions) (He et al., 2016).

4. PROPOSED MODEL

4.1 Project context

The classification model is proposed in the context of Smart Wristbands for the elderly project developed in (CERIST-ALGERIA) research center lab, which provides an ECG AD8232 sensor connected directly to Arduino card. Fig. 4 illustrates the hardware used in the project.

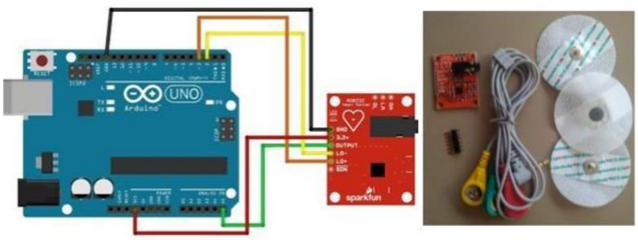

Fig. 4. ECG Sensor with Arduino board.

The proposed model can be deployed in the cloud using internet of things (IoT) as shown in Fig 5. The customer ECG signal is acquired using ECG AD8232 sensor. This ECG signal is sent through Bluetooth of device (e.g., Arduino, Raspberry) for processing and fusion with other sensors to the cloud. Our model control elderly people by sending real time data to doctors. In this paper we focus particularly on the ECG signal classification step.

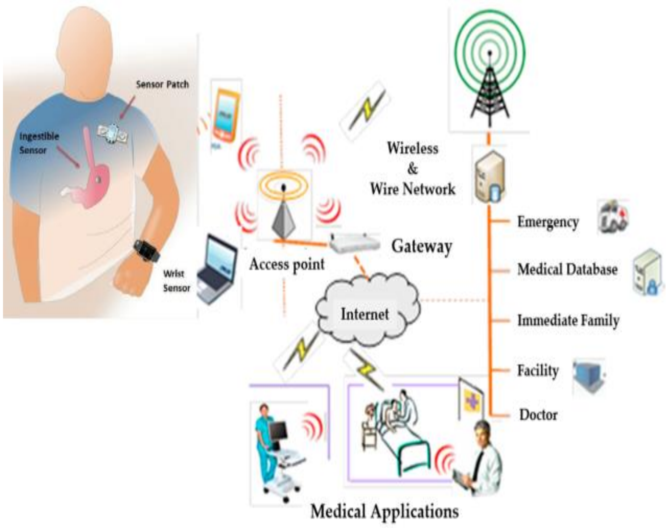

Fig. 5. Smart Wristbands using Internet of things.

4.2 Architecture

The Core of our model includes inputting ECG signals, preprocessing step, followed by the classification as illustrated in Fig. 6.

4.2.1 ECG database The proposed D-ResNet is trained and tested using MIT-BIH, containing a total of over 4,000 Holter recordings obtained by the Beth Hospital Arrhythmia Laboratory (Physionet, 2017), of which approximately 60 were from inpatients, and 40 were from outpatients. The subjects were 25 men aged 32-89 and 22 women aged 23-89.

4.2.2 Data preprocessing The preprocessing step is applied to ECG signals, which could improve the learning efficiency and reduce the computational complexity. It consists on overlapping, segmenting the ECG signals and labeling each segment. Then denoising and Z-score standardization are performed on each segment.

4.2.2.1. ECG Data Segmentation In the MIT-BIH database, there are 15 heartbeat types mapped to the five main classes of the American Association of Medical Instrumentation (AAMI) standard (AAMI, 2023). The ECG signals have been categorized into five essential groups (N: Normal beat; S: Supraventricular ectopic beat; V: Ventricular ectopic beat; F: Fusion beat; Q: unknown beat) following AAMI standards.

4.2.2.2. ECG Signal Denoising The denoising step could clean the ECG signals to prevent overwhelming micro features in signals and help our model to focus more on the ECG features. Wavelet transform has better effect on filtering time-sensitive data. We use wavelet transform to decompose the original ECG signal data into wavelet components to the selected level.

After filtering, the ECG signals is reconstructed into different scales. Wavelet transform is defined in equation (4).

$$W(l,n) = 2^{\frac{s}{2}} \sum_{n} x_n \psi(2^s n - l) \tag{4}$$

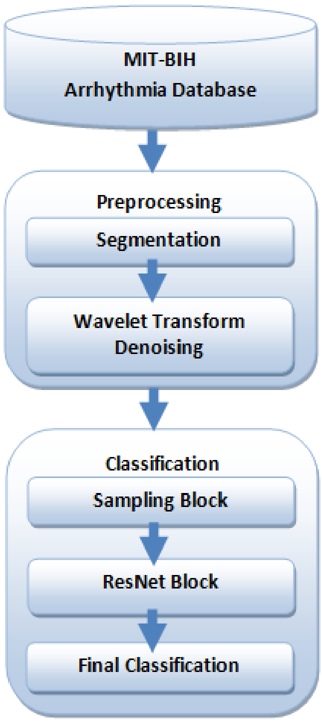

Fig. 6. Overall structure of the proposed model.

M where n = 1, 2, ..., N and N is the total number of samples. x_n is the signal, l describes the shifting, s is the wavelet(scale) and ψ is the mother wavelet. The aim of the denoising Wavelet transform is to decompose a signal into different resolutions using high pass filter (HPF) and low pass filter (LPF) as illustrated in Fig. 7.

Discrete wavelet transform uses a set of dyadic scales and it is translated from the wavelet function to form an orthonormal basis for the signal analysis. The wavelet base selected in this paper is Symlet wavelet (Aqil et al., 2017). This modified version of Daubechies wavelet has significant contribution in signal and image processing and can better preserve spectral information.

RMSE can be computed using equation (5).

$$RMSE(n) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2} \tag{5}$$

where x is the original signal, y is the reconstructed signal and n is the length of the signal. The choice of threshold plays a crucial role in the wavelet denoising method. Equations (6) and (7) define two types of thresholding, namely soft and hard thresholding, which are employed in wavelet denoising.

$$Softthreshold : y = sign(x)(|x| - T) \tag{6}$$

$$Hardthreshold: \begin{cases} y = x, & if \ |x| > \mathrm{T} \\ y = 0, & if \ |x| < \mathrm{T} \end{cases} \tag{7}$$

Where x is the input signal, y is the signal after applying threshold and T is the threshold value. This step is repeated for different threshold points. The threshold value which gives low RMSE is found to be the optimum value.

Data preprocessing algorithm is described in Algorithm. 1.

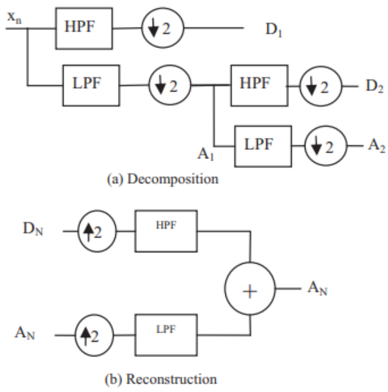

Fig. 7. Data preprocessing stage based on Wavelet transform

Algorithm 1 : Data preprocessing	
1	Input: ECG Data;
2	Output: Classification results;
3	Read the original ECG signal from MITBIH arrhythmia database;
4	Generate noisy signal including power-line noise, baseline drift, electromyogram (EMG) noise and abrupt shift to form noisy signal;
5	Compute the Root Mean Square Error (RMSE) of the noisy signal;
6	Decompose the noisy signal into wavelet coefficients using forward DWT;
7	For each level calculate RMSE and select the level with low RMSE to be the optimum level;
8	Compute and select the threshold with Soft and hard threshold using equations (6) and (7).
9	Choose optimal level for S-median thresholding technique (Awal et al. (2014));
10	Compute signal reconstruction using the thresholded wavelet coefficients by calculating inverse DWT.
11	Compute RMSE of the reconstructed signal then compared with the values obtained in step 5 for evaluating the performance.

4.2.3 *ECG Signal Classification* Fig. 8 presents the flowchart of ECG Signal Classification step in the proposed deep residual network. A ResNet 1D Convolutional Neural Network with skip connections to classify the ECGs signals. One of the key advances of the proposed is the improvement of information transfer throughout the network. Skip connections led to a significant increase in the feature learning capabilities of the CNN as well as speeding up the training time. The model layer-wise architecture is explained as follow.

4.2.3.1. *Sampling Block* The ECG data is passed to down sampling block, which consists of one-dimension convolution kernel with 32 filters and stride of 1, Batch Normalization layer, a ReLU activation function, and MaxPool. The convolutional layer is used to perform basic feature extraction on the input data in order to prepare these for the next deeper level.

4.2.3.2. *Residual Convolutional Block* The three residual blocks are constituted from series of two sets of convolutional layer with ReLU applied as an activation function and Batch Normalization(BN). ReLU activation function is used to reduce over-fitting. After that, BN is used to accelerate CNN training process by reducing internal covariate shift. The maximum-pooling is added, which computes the maximum value in each patch of the feature map and enables to diminish the size of the feature. Maxpool1D with pool size of 5 and strides of 2 is used to perform max-pooling operation on spatial domain signal.

4.2.3.3. *Classification Block* Finally, the classification stage has a flatten layer that aims to translate the multidimensional information into 1-D information. Following flatten layer, there are 2 fully connected dense layers with ReLU function and one dense layer with Softmax for five heartbeats classification. The training set was randomly split into 80% training and 20% validation for 10-fold cross validation. To find the optimal values for the network parameters (learnable weights) that minimize the loss function in DL model, the categorical cross entropy loss function and the Adam (Adaptive moment estimation) optimizer (Kingma and Ba, 2017) were employed. A learning rate of 0.001 was chosen for the optimization process.

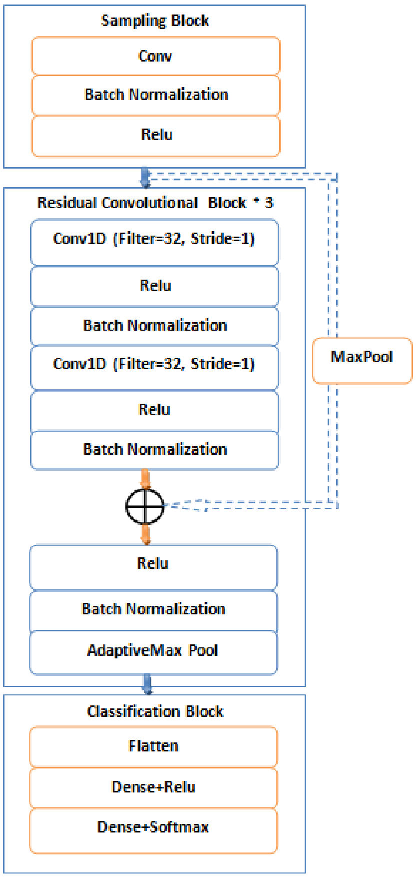

Fig. 8. Overall structure of the proposed model.

5. TESTS AND DISCUSSION

The ResNet model is built using the Keras framework with the Tensorflow GPU backend.

5.1 Training

Use The Model is trained in Google Colab (Colab, 2017) using several functions : Expand dims to read and process data. Three callback objects to perform actions at different stages of training namely: EarlyStopping to stop learning if accuracy does not improve after 10 learning periods. Tensor Board to enable visualizations and ModelCheckpoint to save the model. Fit function is used to start the training. By selecting the batch size to be 32 and epochs equal to 100, the plots for training and testing loss were obtained as shown Fig. 9.

Initially, the testing loss shows abrupt characteristics but after 30 th epoch the testing loss becomes steady with no abnormal fluctuations. 10-fold cross validation is employed to evaluate the model performance.

The training and testing accuracy plots, depicted in Fig. 10, clearly demonstrate an increasing trend with the progression of epochs. Initially, some fluctuations were observed in the testing accuracy, but starting from the 30th epoch, both curves converge and stabilize, indicating a consistent level of accuracy.

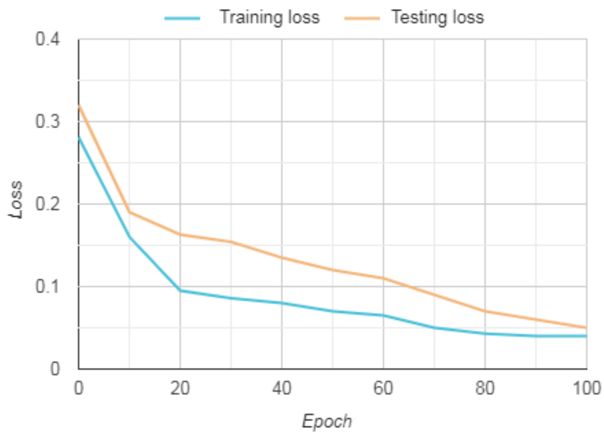

Fig. 9. The D-ResNet models loss as a function of the number of iterations.

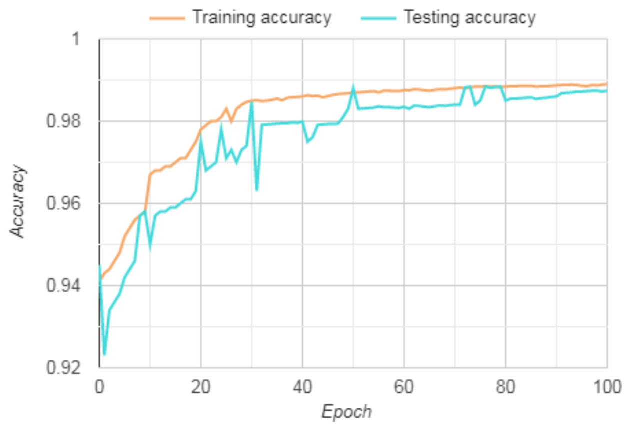

Fig. 10. The D-ResNet models accuracy as a function of the number of iterations.

5.2 Prediction

Table 1 provides the performance of the proposed model using confusion matrices for all five classes with normalization. The diagonal elements reflect successfully categorized classes, while the others indicate improper categorization. The averaging of the diagonal values in the normalized confusion matrix provides the average accuracy of the classification system. 10-fold cross validation has been used on ECG test dataset.

Table 1. The confusion matrix of D-ResNet model.

True Label \ Predicted Label	N	S	V	F	Q
N	0.994	0.003	0.001	0.001	0.000
S	0.160	0.826	0.007	0.005	0.002
V	0.026	0.003	0.958	0.012	0.001
F	0.080	0.000	0.068	0.852	0.000
Q	0.007	0.001	0.002	0.000	0.990

5.3 Performance Evaluation

A numerical analysis with Python (Python, 2023) in embedded systems is presented in this section. The performance of the proposed model is evaluated using various metrics which are accuracy, precision, and F1-Score (Physionet, 2017).

5.3.1 Accuracy The Accuracy is indicated as the total number of correctly classified ECG beat images divided by the total number of test images, as defined in equation (8).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

True positive (TP) is the count of examples for which the actual label is true and the model made a correct prediction. False negative (FN) is the count of examples for which the actual label is true but the model made an incorrect prediction. True Negative (TN) means the number of examples for which the actual label is false and the model made a correct prediction. False Positive (FP) means the count of samples for which the actual label is false but the model made an incorrect prediction.

5.3.2 Precision The precision is referred to as the proportion of classified positive cases that are correctly real positives, as defined in equation (9).

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

In our work, the weighted average of the precision of each class is considered as the precision of the model. The weight of a class is computed as the ratio of count of examples of that class to the total count of examples in the test set. table 2 shows the accuracy of the network models used by several scholars on the MITBIH dataset.

5.3.3 F1-Score The F1-Score metric is calculated by evaluating the harmonic mean of precision and recall values.

Comparison of performance of ResNet with that of Improved ResNet-18 (Jing et al., 2021) and ResNet-50 (Sakli et al., 2022) is done on the basis of three metrics accuracy, precision (Teijeiro et al., 2017), and F1-score as presented in table 2.

In addition, six machine learning algorithm classifiers are used to train and predict the above dataset. Table 3 shows the classification results of these classification algorithms: K-Nearest Neighbor (KNN) (Cover and Hart, 1967), Logistic Regression (LR) (Elkadiri et al., 2014), Random Forest (RF) (Breiman, 2001), Decision Tree (DT) (Loh, 2011), Gradient Boosting Decision Tree (GBDT) (Ma et al., 2017), and Adaptive Boosting (AdaBoost) (Yoav and Robert, 1997).

Table 2. Test set accuracy and precision of each network under the MIT-BIH database.

Model	Accuracy	Precision	F1-Score
Improved ResNet-18	96.50	83.87	96.36
ResNet-50	97.58	88.85	97.12
D-ResNet (Proposed Model)	98.92	92.89	98.81

It can be observed from Table 3 that the machine learning algorithm LR exhibits the highest performance, followed by GBDT, KNN, RF, and DT. Conversely, AdaBoost demonstrates relatively poor performance.

Table 3. Accuracy of each classifier on all datasets.

Model	Accuracy
AdaBoost	73.67
DT	86.87
RF	92.72
KNN	93.43
GBDT	93.47
LR	94.26
D-ResNet	97.83

However, D-ResNet achieves the highest accuracy compared with all machine learning classifiers. The results show that our model has strong generalization. We note that the introduction of the ResNet block in the heart of our model allowed a very deep extraction of the characteristics of the ECG signals and the improvement of performance. Besides, the denoising step played a crucial role in obtaining these results.

6. CONCLUSIONS

In this work we address the problem of ECG signal classification with a new solution. For this quasi periodic signal we adopted a solution that takes advantage of the accuracy offered by a CNN network and the depth offered by a Resnet network in order to extract signal characteristics in a very deep way. The preprocessing phase helps considerably to prepare the signal for the classification stage, in particular that the choice of the wavelet transform is suitable for non-stationary signals (Mahmoodabadi et al., 2014). the evaluation carried out through several parameters showed that D-Resnet can accurately detect and classify disease from images of ECG. The proposed model has achieved classification accuracy of 0.9892 on the MITBIH database. Obtained results, compared with other techniques from the literature, present higher accuracy and precision values demonstrating the superiority of this approach for the ECG signal classification. further work should be curried to optimize the solution and adapt it for hardware implementations and telemedicine applications.

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