International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Adopting Image Classification Using Pretrained Models with DCNN to Segment an Image in General 2-D Echo Cardiograph Images

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Submitted: 22/10/2023 **Revised:** 14/12/2023 **Accepted:** 22/12/2023

Abstract: The biggest cause of death worldwide is cardiovascular disease. Heart attacks and strokes can be avoided with early diagnosis and knowledge of the disease's trajectory. Early diagnosis of cardiac irregularities is made possible with the help of electrocardiogram (2D Echo) signals, which non-invasively monitor heart activity. Massive amounts of 2D Echo data can be difficult and error-prone to manually examine, which is why researchers are looking into automated interpretation methods to help clinicians make quick and correct choices. In order to monitor patients with cardiac disease and enable early detection and arrhythmia categorization, smart healthcare equipment are essential. However, because of non-linearity and weak amplification, categorizing 2D Echo recordings is difficult. The performance of traditional machine-learning (ML) classifiers when processing large-dimensional data with poorly modelled relationships is questionable. In order to address the limitations of ML classifiers, this study suggests an automated approach combining ResNet18, SegNet, Mobile-Net segmentation, and Feature extraction approaches with Dynamic CNN (D-CNN) classification. Tests using Stanford University's echo net-dynamic dataset show a considerable improvement in classifier performance, outperforming more sophisticated techniques with over 99.92% accuracy and 99.81% sensitivity. This strategy has the potential to help medical practitioners make quicker and more precise therapy decisions for individuals with heart disease.

Keywords: *Electrocardiogram, Arrhythmia monitors patient health 2D Echo classification guided learning*

1. Introduction

A primary source of morbidity and mortality worldwide, cardiovascular diseases (CVDs) will account for 18.6 million deaths in 2019—32% of all fatalities [1, 2]. Congestive heart failure (CHF), atrial fibrillation (AF), conduction disturbances (CD), hypertrophic cardiomyopathy (HYP), coronary artery disease (CAD), and myocardial infarction (MI) are all included in the category of CVDs [4]. These disorders frequently get worse with time, underscoring the significance of early detection and a greater comprehension of illness progression for efficient therapy [5,6].

Electrocardiography (2D Echo), echocardiography (ECHO), computerized tomography (CT) calcium scoring, CT coronary angiography, cardiac magnetic resonance imaging (MRI), coronary catheter angiography, and myocardial perfusion imaging (MPI) are diagnostic methods for assessing cardiovascular health [7]. Due to its ease of use and low cost in recording heart electrical activity, 2D echo is frequently used to diagnose cardiac diseases by spotting structural or electrophysiological anomalies [8,9]. A growing number of industries, including biomedicine, are using machine learning and deep learning (DL) models for data augmentation, denoising, detection, classification, and analysis [7]. This research focuses on the classification of 2D Echo signals in arrhythmia diagnostics using transfer learning-based deep learning models.

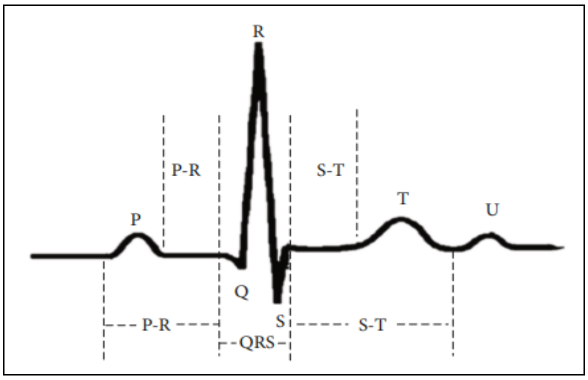

Fig 1: Single heartbeat waveform.

Due to the unpredictable and non-stationary nature of CVD indicators in the signals, clinicians must manually evaluate 2D Echo parameters to identify CVDs [8]. It takes a lot of time and effort to manually classify arrhythmic heartbeats, hence automated solutions are required for effective data analysis and classification.

The paper utilizes Tan ford University School of Medicine's echo net-dynamic research dataset for investigating the benefits of early arrhythmia diagnosis using artificial intelligence (A.I) models [7]. It presents a

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transfer learning-based approach for 2D Echo signal categorization using deep learning.

The Literature review information on 2D Echo signals, deep convolutional neural networks (DCNNs), and residual networks (ResNet) is presented in Section 3 while related work in 2D Echo monitoring in the ML/DL region is discussed in Section 2 of this paper. The parameters and training process of the proposed model are described in Section 4. The importance of automated procedures in 2D Echo monitoring is shown in Section 5 by performance comparison test results that are provided and discussed. The essay is concluded at Section 6.

Background:

The goal of this effort is to diagnose various cardiac conditions that affect heart rhythm for effective treatment and prevention. Using changes in cardiac rhythm and demographic information, the focus is on classifying different problems. The wavelet dispersed data of arrhythmic electrocardiograms (2D Echo) are categorized using pre trained convolutional neural network models.

Methods:

The Tan Fork University School of Medicine's echo net-dynamic dataset was resampled and segmented into 2D Echo signals with various abnormalities. After sample data points underwent linear interpolation, interdependence variances were recovered using wavelet scattering. The one-dimensional signal data was transformed into two-dimensional scalogram images using a continuous wavelet transform. We extracted features from training deep learning models and classified them with a support vector machine classifier. Performance parameters like precision, specificity, recall, F-measure, and accuracy were analyzed, as well as the impact of network depth and accessibility on model performance.

Results:

In the classification findings, ResNet18-DCNN achieves higher accuracy with raw data (98.01% and 98.81%) and scattered data (96.92% and 97.05%). Performance, network parameters, and model depth are independent. DCNN shows better accuracy, recall, specificity, and F-measure values (96.45%, 96.49%, 96.42%, and 98.24%) for wavelet dispersed data.

Conclusion:

DCNN achieves accurate and computationally efficient results by categorizing dimensionality-reduced data. For unstructured data, Dense Net outperforms ResNet18, while for structured data, ResNet18 performs better than Dense Net.

2. Related Work

AI has emerged as a valuable tool for analysing 2D Echo signals, particularly in anomaly recognition and heart rhythm estimation. Various ML and DL algorithms have been employed to improve the detection of heart-related conditions. One approach involves treating 2D Echo signals as one-dimensional data and analysing them using textual data analysis methods. In one study, D-CNN (deep-convolutional neural network) was created using extreme gradient boosting trees to enhance heart rhythm estimation accuracy. The system was trained using a CNN with data from the Physio Net dataset, achieving 82% accuracy for the test sample. Another novel mechanism, DDL (deep deterministic learning), integrates predefined heart activities and uses an artificial neural network (ANN) classifier for pattern recognition and classification, achieving an overall accuracy of about 98%. Researchers have also developed a network to categorize cardiac problems, achieving satisfactory results with the proper and wrong relationships using a back-propagation method with a feed-forward neural network.

For long-term monitoring and studying non-stationary behaviour in 2D Echo signals, an automated system using time-frequency-based feature extraction and PCA for dimensionality reduction was developed. SVM classifier with optimized parameters achieved enhanced accuracy of 98.82% using the Tan ford dataset. Investigating the use of mobile services to connect wireless body sensor networks with healthcare social networks, researchers worked on a secure way to transmit 2D Echo signals. Although there were some inaccuracies, the method proved effective with an overall accuracy rate of about 82%.In conclusion, AI-driven techniques in 2D Echo signal analysis show promising results for improved heart disease diagnosis and monitoring.

3. Literature Review

The inter-patient heterogeneity in 2D Echo signals and the increasing volume of data can limit the effectiveness of standard approaches [15] [13-16]. Most existing techniques have been tested on smaller datasets and need validation on larger datasets to generalize results. Converting 1-D 2D Echo signals into 2D images for use in 2-D CNN models has not been explicitly explained. This study proposes a method to create 2-D spectrograms from 1-D 2D Echo signals using Short-Time Fourier Transform (STFT) and data augmentation. The suggested technique combines CNN and 2D spectrograms as inputs, achieving advanced capability in 2D Echo arrhythmia detection.

3.1 Problem Statement

Automated cardiac irregularity detection using ResNet18, Seg Net, Mobile-Net, and D-CNN classification on 2D Echo signals improves accuracy to 99.92%, enhancing early diagnosis and treatment of cardiovascular disease for better patient outcomes.

The following are the study's primary contributions:

1. A two-dimensional approach for transforming multi-channel time-series signals, where each column represents a time-series of a single lead and 2D Echo data is represented as 2D greyscale-like images.

2. Using ResNet18 and a two-dimensional DCNN model, processing multi-channel time series in 2D Echo signals is made possible. Internal and inter-lead properties are captured during training.

3. Using orthogonal experiments and a slicing rule to widen the training set and choose the hyper-parameters.

4. Applying group learning for categorization outcomes in the evaluation model stage based on the voting technique.

3.2 Pre-Processing

Electromyographic noise, baseline drift, and power line interference are the three main types of noise in the 2D Echo signal. We utilized wavelet-based threshold and decomposition to remove noise from the initial 2D Echo signal and produce a de noised signal for further processing [17].

3.3 Generation of 2-D Image:

As a result of using 1-D feature kernels, 1-D CNN applications are restricted. The computational and data requirements for 3-D CNNs are greater. However, 2-D CNNs with 2-D kernels are more flexible and provide representational properties for time series data in a 2-D format. For the purpose of capturing non-stationary data changes over time, 1-D 2D Echo signals are converted into 2-D time-frequency spectrograms using the short-time Fourier transform (STFT). A brief period of reliability is anticipated for non-stationary transmissions. One-dimensional data is converted into two-dimensional spectrograms using STFT on 2D Echo signals, and log values are shown as (256x256) images.

3.4 Optimization Process:

The optimization cycle involves predators identifying the best option or match. During the discovery phase, predators aim to move quickly. Levy motions are represented by vector RL, and the elite position mimics prey movement. The suggested CNN model uses 2-D pictures of 2-D Echo signals as input data, allowing actions like cropping to change the image's size and augment the training data.

$$stepsize_j = X_{STFT}(\overline{R}_L \otimes (\overline{E}_j - R_L \otimes p\overline{y}_j)$$
$$\overline{Py}_j = \overline{Py}_j + P.R \otimes stepsize_j \qquad (1)$$

Data augmentation helps avoid over fitting and maintains balance between classifications for unbalanced data. Cropping was used to amplify seven types of 2D Echo beats, resulting in smaller spectrograms fed into the CNN. This process increased the training data tenfold, improving the effectiveness of arrhythmia classification using 2D Echo signals.

3.5 Deep Neural Network:

This article proposes a supervised CNN method to automatically classify arrhythmias based on 2-D Echo signal data. Cardiology experts labelled the data, and the class of arrhythmia was added to each spectrogram representation. CNN models have shown remarkable results for image classification, utilizing spatial proximity of pixels through filtering techniques. Down sampling is used to filter and extract spatial distance in 2D Echo images. The 2D CNN algorithm accurately classifies arrhythmias, making automatic taxonomy for 2D Echo waves possible.

4. Proposed Methodology

This article explores de noising techniques for 2D echo signals, using wavelet transform to remove disturbances like electromyographic noise and power line interference. A supervised CNN model based on ResNet-18 architecture is proposed for accurate multi classification of 2D echo data. Intra patient and inter patient techniques for data classification are compared, favouring inter patient approach for accuracy.

$$WT(a,\tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) * \psi\left(\frac{t-\tau}{a}\right) dt \qquad (2)$$

CNNs with local connections and weight sharing are effective for feature extraction and classification. Alex Net with SVM achieves 97.89% accuracy in 2D echo scalogram picture classification using the Image Net database. ResNet offer solutions to issues with deep CNNs, optimizing design and performance. The noise reduction results on patient record 100 from the Database show the elimination of high-frequency noise in the 2D Echo signal [18].

Electromyography noise, power line interference, and skeletal artifacts are some examples of this noise. The fundamental properties of the 2D Echo waveform are preserved when this noise is removed, which is important for successful model training and diagnosing various 2D Echo arrhythmias, such as atrial arrhythmia with reduced P wave distortions [21].

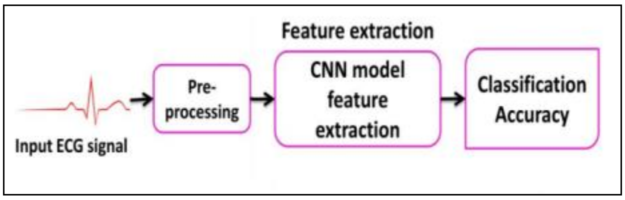

Fig 2: Complete procedure of electrocardiogram (2D Echo) signal classification.

Our research focused on classifying 2D Echo signals using a deep learning (DL) technique like image classification. We modified the ResNet-18 model for 2D Echo multi classification, resulting in an improved version. This model effectively sorted single lead 2D Echo from the Tan ford database, outperforming existing models in classification accuracy and computation time.

Using inter patient approaches, it is possible to categorize certain traits shared by a number of patients without relying on data from the testing stage to create an algorithm. Although less reliable, intra patient approaches are frequently utilized and divide the data from a single patient into training and test sets at random. Although inter patient data categorization is more significant and reliable, the majority of recent research still employs intra patient methods. Since the model is evaluated using the same data it was trained on, this method is inconsistent and unworkable and produces inaccurate results.

ResNet and CNNs use local connections and weight sharing, which distinguish them from standard neural networks. This dramatically enhances their ability to collect functions, improve efficiency, and reduce the need for trained variables. A standard CNN consists of input, convolutional, pooling, and fully connected layers, the input for the following layer is the output of the previous layer (Figure 5). Convolutional and pooling layers are often alternated in the structure.

In a CNN's convolutional layer, multiple feature maps containing multiple neurons are present. When categorizing images using a CNN, the layer uses a convolution kernel to analyse the image and gathers information from the surrounding region to determine its characteristics. This results in a map of features created by activation.

$$X_j^{l+1} = f\left(\sum_{i \in Mj} X_i^l * k_{ij}^{l+1} + b_i^{l+1}\right) \tag{3}$$

In the context of feature input maps (Mj), Xl+1 J represents the jth characteristic of the (l+1)th convolutional layer. Xl is the input feature, and f is the activation function, usually a ReLU. The operation denoted by [25] involves convolution using the kernel and b as the "offset" term.

Its role in picture classification is to emulate the human visual system and condense the amount of information. It depicts the picture with the traits listed below: If available, explain the traits; otherwise, use the word "features" to be broader.

$$X_i^l * k_{ij}^{l+1} + b_i^{l+1} \tag{4}$$

Maximum likelihood is used in the fully connected layer of CNN-based classification to calculate the probability for each test. After mapping the newly acquired features to their associated labels, the classification result is arrived at by choosing the label with the highest probability.

Deeper CNNs are more effective, but they face issues like diminishing gradients and saturation. ResNet, proposed in [99], provide an efficient and optimized solution by handling gradient problems and performance losses associated with increasing depth. They allow significantly greater depth in network design and optimization.

Alex Net consists of 8 layers, including 5 convolutional, 1 max pooling, and 3 fully connected layers. It uses ReLU activation for better results and dropout to address over fitting. Optimized for 2D Echo scalogram image classification, Alex Net has 60.9 million learnable parameters, pre trained on Image Net's 1.2 million photos in 100 categories. The SVM classifier achieves 97.89% accuracy using learned features for classification.

4.1 ResNet

The extended ResNet-18 model accurately identifies and classifies diseases. ResNet's deep architecture with residual and identity blocks mitigates vanishing gradient issues. Batch normalization enhances network performance. ResNet-50 achieves 98.3% accuracy in classifying arrhythmias, while ResNet-18 identifies 2D Echo signals with 98.81% accuracy using raw data scalogram.

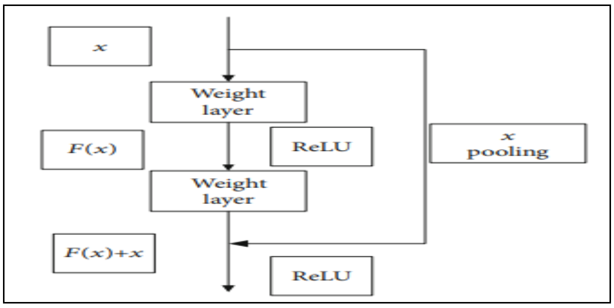

Fig 3: The ResNet building block

The ResNet construction block employs a rapid connection to find the remaining input F(x) + x in real time, preventing performance degradation and accuracy loss. Straight links perform identity mapping within two layers, avoiding learning specific functions with references (X). This enables easier optimization of the residual function and allows for deeper network layers.

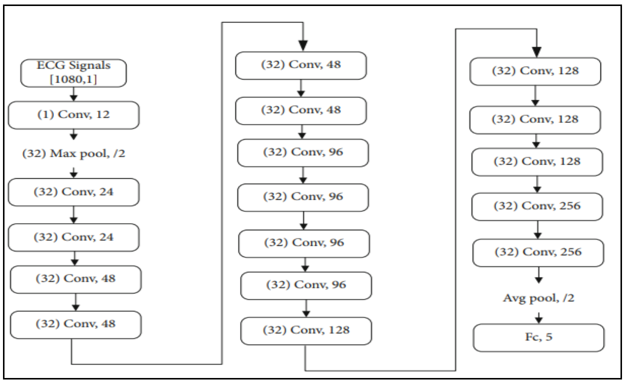

Fig 4 : Layer-specific parameters for the upgraded ResNet-18 model

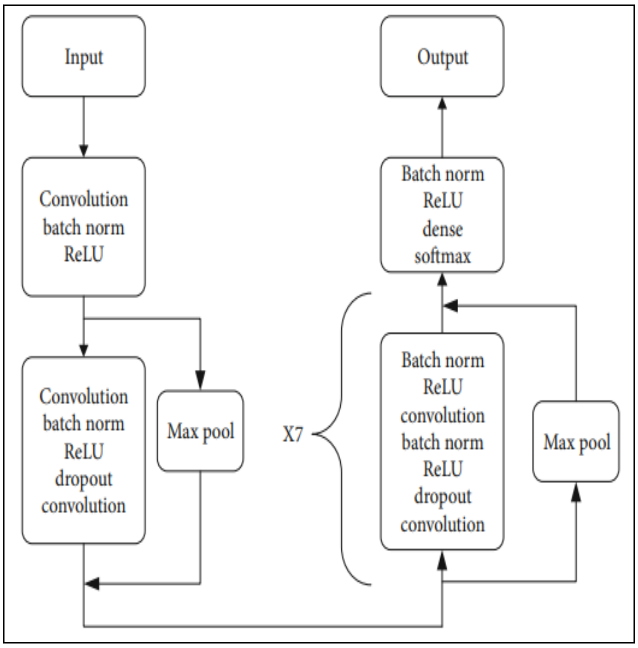

Fig 5: The structure of improved ResNet-18 model

Proposed Algorithm –Pseudo code:

Data: processed Signals from 2D echo

Result: different heartbeats

Start:

Step 1: Layers should be started with learning rate A, maximum iterations per epoch, minimum error, and total batch.

Step 2: Determine what is the most valuable

Step 3: Weights in ResNet-18 should be randomized

Step 4: ResNet-18 model = Init ResNet-18 model(th);

Step 5: When error > emin, and iteration > epoch

Step 6: Initialize error = 0;

Step 7: For batch = 1 to the Total Training for batch is:

Step 8: The = ResNet 18 Model: Train administration the countersignature

Step 9: Updating the th

Step 10: error = error + mean

Step 11: End of the day for.

Step 12: Iteration i = i + 1;

Step 13: Close while.

Step 14: Return: Output at least th.

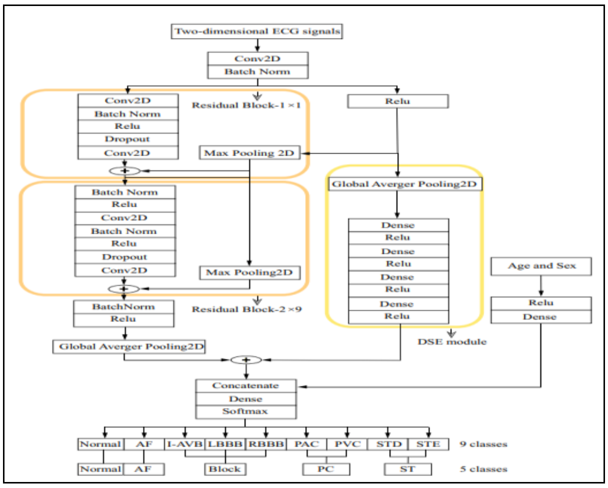

Fig 6: Structure of DCNN-ResNet.

Signals with abnormal 2D echo show waveform shape and periodic rhythm changes. Others are recurrent and show up practically every cycle, while some are sporadic and only happen occasionally. For feature extraction, DCNN-ResNet combines ResNet and DCNN, including age and gender information. To deal with difficult non-linear circumstances and prevent gradient problems, the model makes use of residual blocks, Conv2D layers, and shortcut connections. Over fitting is avoided via batch normalization and dropout.

5. Experiment and Results

2D Echo images were transformed into 2D scalogram pictures using segmentation and fed into D-CNN networks. Pre trained networks like ResNet18, Seg Net, and Mobile-Net achieved classification accuracies of 97.89%, 98.81%, and 95.61% respectively. The research used PyCharm development software, a GeForce GTX 1060 GPU, 8GB RAM, and an Intel(R) Core i5 processor. The Windows 10 OS was employed together with Python 3.7 and Tensor Flow. The upgraded ResNet-18 model outperformed other models in overall precision for classifying heartbeats with 100 iterations in the testing phase.

Fig 7: Pre-processing of the image

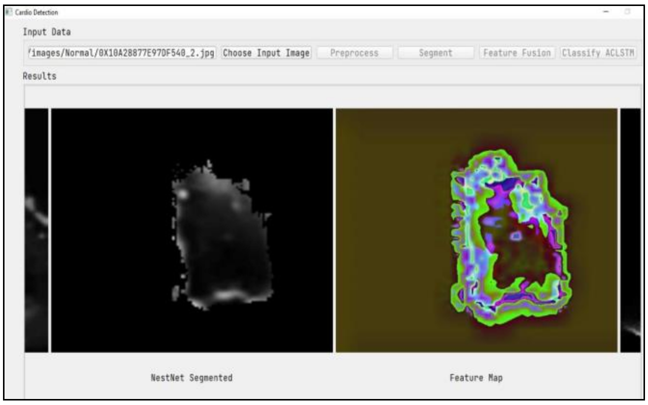

Fig 8: Feature extraction of the 2d 2D Echo image using the segmentation model

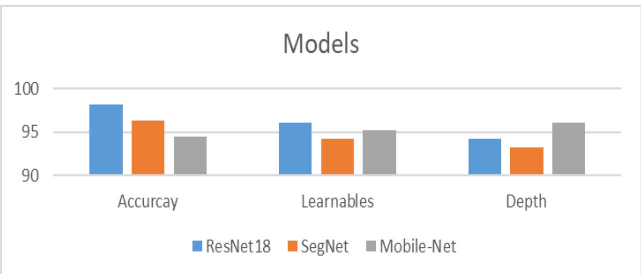

Fig 9: Graphical representation of model performance

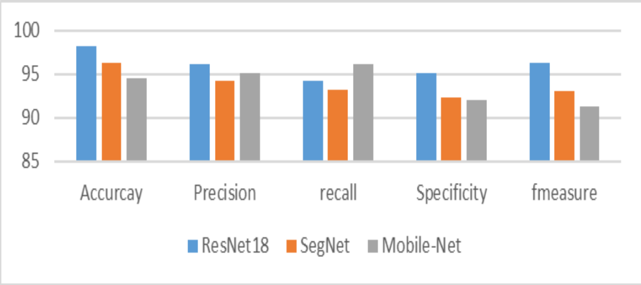

Fig 10: The core values of the models evaluated using the DCNN as the neural model

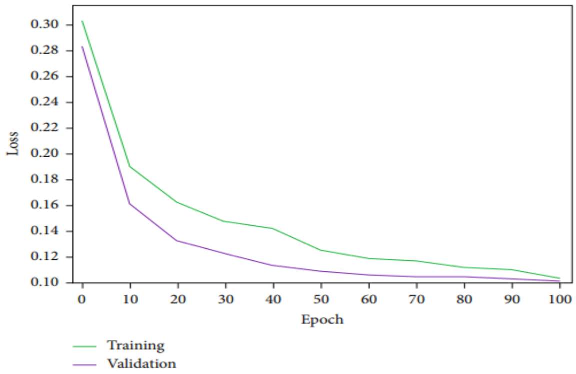

Fig 11: Loss of the enhanced ResNet-18 with DCNN model as a function of iterations.

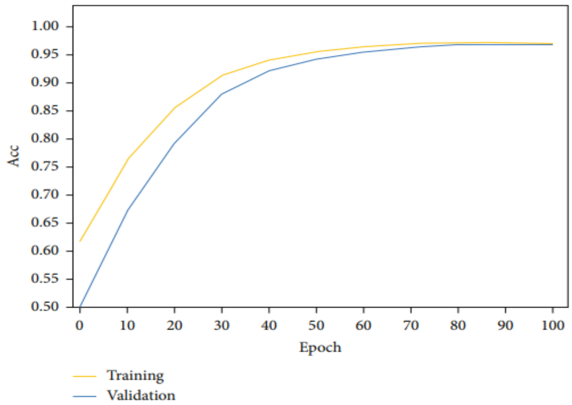

Fig 12: Accuracy of the enhanced ResNet-18 with DCNN model as a function of iterations.

During the model's training phase, many indicators are carefully considered, and trial results are logically analysed. It is usual practice to evaluate the model's performance in multiclassification issues using sensitivity (Se) and precision (P+). Precision indicates the percentage of pertinent cases among the anticipated ones, whereas sensitivity measures the model's capacity to categorize true positives properly. Raising sensitivity in disease detection is essential for correctly identifying cardiovascular illnesses (CVDs).

The study utilized CNN architecture to extract features from 2D Echo scalogram pictures, achieving good classification accuracy. The ResNet18 model performed well, outperforming previous efforts in accuracy, with the Dense Net model showing superior results for wavelet-scattered data. The use of transfer learning for classifying wavelet-dispersed values is a novel approach that improves the model's generalization. ResNet18 achieved 98.81% accuracy for raw data and 97.05% for wavelet-dispersed data in identifying 2D Echo sounds. These findings indicate that frequency domain CNN designs are more effective than time domain structures for this task.

6. Conclusion

A CNN-based algorithm for 2D Echo signal classification was developed, offering automated categorization and classification of cardiac arrhythmias. Deep CNN has proven to improve diagnostic accuracy for cardiovascular diseases (CVDs). The proposed method achieved high values for sensitivity, specificity, accuracy, and precision (97.91%, 99.61%, 99.11%, and 98.59% respectively) using 2D spectrograms. The automatic categorization of 2D Echo signals can assist professionals in CVD diagnosis. Further research will explore the impact of various lead 2D Echo data to enhance experimental instances.

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