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Enhanced Cardiac Arrhythmia Detection Utilizing Deep Learning Architectures and Multi-Scale ECG Analysis

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Abstract:-Cardiovascular disease is the leading cause of death globally, with arrhythmia being a particularly lethal condition. Efficient and accurate identification of arrhythmia through the analysis of ECG data is crucial for effective treatment. Arrhythmias must be assessed when examining ECGs. This study presents a novel approach to automatically diagnose arrhythmia and congestive heart failure from sinus rhythm. The proposed method involves utilizing a multi-scale filter bank with scalograms, which makes use of preprocessed ECG data and non-weighted, pre-trained convolutional neural networks. Temporal frequency textures provide two-dimensional representations of fundamental characteristics from single-lead ECG recordings. Subsequently, deep learning neural networks that are specifically designed for arrhythmia classification are used to label and classify collections of feature data. This study investigates the efficacy of deep learning models in classifying cardiac arrhythmias from ECG data. The study looks at how well different convolutional neural network architectures work by using a multi-scale filter bank and a scalogram-based representation. Pre-trained networks yielded classification models that were both 100% accurate and more effective than raw networks in terms of generalization. A comparison of models that have been trained and models that have not been trained shows that pre-trained networks, especially Vgg16, perform better in many ways, such as accuracy and precision. This suggests the potential for significant improvements in automated ECG-based diagnostics, paving the way for advanced, personalized healthcare solutions.

Keywords: *Multiclassification fusion (MSF), deep learning (DL), Convolutional Neural Network (CNN), Arrhythmias (ARR), Congestive heart failure (CHF), and Normal sinus rhythm (NSR).*

1. Introduction

Arrhythmias, irregular cardiac rhythms, affect many people worldwide and pose a substantial health concern [1]. In addition to harmless irregular heartbeats, severe aberrant heart rhythms can cause cardiac arrest or strokes [1]. Thus, early detection of such illnesses improves treatment [2]. Medical professionals rely on the electrocardiogram (ECG) to detect arrhythmic rhythms. Due to its subtlety, clinical symptoms often impede diagnosis [3]. Recent deep-learning algorithms have showed promise for accurate and automated medical diagnosis [4-6]. Identifying arrhythmias quickly allows for dietary changes and medication therapies to prevent sickness worsening. Preventing strokes and heart attacks requires accurately diagnosing arrhythmias like atrial fibrillation and ventricular tachycardia [7-8]. A correct diagnosis allows clinicians to prevent catastrophic clinical occurrences by providing anticoagulant treatment or employing implanted cardioverter defibrillators (ICDs) [9]. Arrhythmia categorization is essential for customized treatment [9-10]. Since arrhythmias have several causes and treatment demands, precisely recognizing and classifying them using ECG data helps tailor treatment [10]. This tailored approach ensures efficient anomaly treatments [10]. Remote arrhythmia monitoring could revolutionize healthcare. Traditional approaches that use transient ECG evaluations struggle to detect arrhythmic episodes due to their rarity [11]. Early detection and efficient treatment of abnormal cardiac rhythms can reduce emergency department, hospital, and long-term healthcare expenses [12]. Automated arrhythmia detection technologies streamline patient treatment, optimize resource distribution, and may minimize financial impact on individuals and healthcare systems [9]. Novel arrhythmia detection and categorization methods that increase accuracy, neutrality, and efficiency are needed due to conventional parameters [13]. The use of deep learning algorithms to automatically identify arrhythmias using electrocardiogram (ECG) measurements seems promising [13]. Artificial intelligence's deep learning has excelled in biomedical signal classification and protein detection [4-6]. Its capacity to autonomously extract complex patterns and features from raw data makes it excellent for ECG signal analysis and arrhythmia detection [14]. Deep learning can accurately classify arrhythmic ECG signals with complex temporal and spatial correlations [13]. Using deep learning algorithms with ECG readings can help diagnose arrhythmia. Deep learning models accurately identify arrhythmia patterns and characteristics in complicated ECG data. By including arrhythmia examples from big datasets, these models increase detection accuracy and generalization [13]. Deep learning models automate and immediately detect arrhythmias, reducing human interpretation and improving efficiency. After training, these models can scan ECG signals in real time, detect abnormal cardiac rhythms, and notify healthcare providers for further evaluation and treatment. Automating detection speeds up diagnosis and treatment [15]. Deep learning techniques on ECG signals can monitor and detect intermittent arrhythmias that brief ECG records miss [15]. Continuous monitoring helps identify and classify irregular heart rhythms, allowing for long-term cardiac rhythm study. Telemedicine and remote monitoring apps allow patients to access more healthcare services thanks to ongoing surveillance and powerful deep learning algorithms [15]. This study examines whether deep learning can automatically detect arrhythmias using electrocardiogram (ECG) data. The study's main goal is to develop and test improved deep-learning models that can accurately classify arrhythmias using electrocardiogram (ECG) data. Organization of the manuscript: Arrhythmia detection is crucial, and deep learning and ECG measurements can accurately and automatically detect it. The literature is then meticulously examined to determine past studies. The methodology section details the dataset, deep learning model structure, and performance evaluation criteria. After that, the findings and analysis sections compare the many DL models' effectiveness. The DL models detect arrhythmia using electrocardiogram (ECG) inputs well. With up to 100% accuracy, DL models function well. The study found that the model automates aberrant cardiac rhythm identification well. The results demonstrate the simplicity and operational efficiency of tiny DL models compared to larger ones.

2. Literature Review

Recently, the medical industry has experienced a significant change in which advanced computational approaches are being used to enhance the accuracy of traditional medical practices [13]. An area of particular emphasis is the electrocardiogram (ECG), which is a non-invasive device that plays a crucial role in capturing variations in cardiac activity. The introduction of machine learning (ML) and deep learning (DL) technologies has completely transformed the analysis and interpretation of ECG data, namely in the identification and categorization of arrhythmias [7-8]. The ECG is essential for monitoring heart rhythm. It involves inserting electrodes on the patient's body to capture little electrical impulses produced by the heart muscle. Nevertheless, the examination of these signals is challenging due to the wide range of heartbeats, the small magnitude of the signals, and the complexities associated with differentiating between different signal elements [7]. The main difficulty lies in precisely identifying and categorizing various forms of arrhythmias, a process that demands a considerable level of proficiency and is susceptible to human fallibility [15]. Historically, researchers have mostly concentrated on diminishing noise in ECG signals through the use of diverse machine-learning techniques, such as signal segmentation, manual feature extraction, and support vector machines [17]. In order to overcome the constraints of conventional machine learning techniques, scientists have resorted to sophisticated deep learning architectures such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs) [4]. By preserving pertinent data that may be lost during pre-processing, these models yield a substantial enhancement in ECG signal analysis. The utilization of deep learning in medical diagnostics, namely in the automated detection of pulse and categorization of electrocardiograms (ECGs), represents a notable progression compared to prior machine learning (ML) methods [5]. The capacity of deep learning to abstract multi-level information allows it to accurately detect the inherent characteristics of ECG data. Multiple studies have demonstrated that deep neural networks (DNNs) outperform conventional neural networks and SVM classifiers in the classification of arrhythmias when utilizing raw ECG data as input [18]. Various datasets, such as the PhysioNet Challenge datasets and the MIT-BIH Arrhythmia Database, have played a crucial role in this research [19]. Interdisciplinary research will shape deep learning ECG analysis. Computer scientists, medical practitioners, data analysts, and ethicists must collaborate to overcome technological, practical, and ethical challenges of new technology deployment. These collaborations can help create technically skilled, therapeutically appropriate, and ethical models. To conclude, deep learning can transform ECG analysis greatly. To realize this promise, advanced models must be built, integrated into medical procedures, data privacy and security issues resolved, ethical issues addressed, and interdisciplinary partnerships promoted. Although these challenges remain, deep learning can dramatically enhance heart disease diagnosis and treatment. ECG analysis is complicated, traditional approaches are challenging, and deep learning algorithms have made great strides.

3. Materials and Methods

The present article adopts a meticulously designed methodology, as elucidated in the subsequent sections.

3.1 Dataset Overview

This study examines how to arrange ECG samples from ARR, NSR, and CHF patients. A range of ECG recordings from three PhysioNet databases—MIT-BIH Arrhythmia, Normal Sinus Rhythm, and BIDMC Congestive Heart Failure—are used in the study. 47 participants contributed 48 half-hour two-channel ECH recordings to the MIT-BIH ARR Database [19]. The MIT-BIH NSR Database includes 18 extended ECG recordings from arrhythmia-free patients from Beth Israel Hospital's Arrhythmia Laboratory. The BIDMC CHF Database contains comprehensive ECG recordings from 15 severe congestive heart failure (NYHA class 3–4) individuals [19]. ECG recordings from 96 ARR-diagnosed, 30 NSR, and 36 CHF patients were included in the study. In a table [19], they listed database types, data collection methods, subject demographics, recorded parameters, annotations, geographical context, technical details, sample rates, goals, obstacles, practical usage, and scholarly references.

3.2 Preprocessing of ECG Signals

ECG signals must be preprocessed for accurate analysis and interpretation, especially in automated diagnostic systems. Best-practice ECG signal preprocessing includes several crucial steps. Noise reduction comes first. Finite Impulse Response (FIR) filtering maintained sign forms throughout noise removal. Electromyographic noise and baseline drift are reduced by bandpass filters [7-9]. Moreover, a notch filter eliminates powerline interference. Artifact reduction is crucial for addressing spikes or rapid variations generated by electrode movement or other external interferences [8-9]. Signal normalization reduces recording variability after noise and artifact reduction. Segmentation prepares signal segments for further steps, and the first 7.8125 s are utilized to test the detection algorithm's signal prediction accuracy. This stage is necessary for feature extraction, classification, and anomaly detection. Effective preprocessing enhances diagnostic algorithm efficiency and reduces automated ECG analysis system false positives and negatives. In addition, wavelet transform techniques were used decades ago to extract features from ECG signals, providing a time-frequency portrayal that is beneficial for recognizing transitory characteristics and non-uniform elements [20]. This article uses the Continuous Wavelet Transform (CWT) and filter banks to capture signals at various scales and frequencies. This allows for detailed visualization of non-stationary ECG data. ECG data are transformed into scalogram images for visual and time-frequency representation. Scalograms help diagnose heart ailments by showing the signal's frequency content over time in a more targeted and exact manner. This enhanced representation improves ECG analysis and helps identify and classify signal anomalies. A 10-s NSR ECG signal and scalogram are shown in Figure 1.

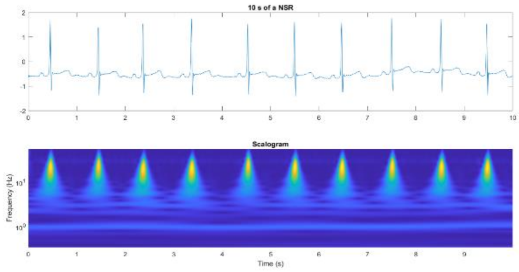


Figure 1 (a) 10 s of a NSR signal (b) Scalogram of the signal in (a)

3.3 Deep Learning Methods

The paper discusses following deep learning architectures that combine additional deep learning network properties [14]: ResNet18 is an iteration of the Residual Network (RESNet) architecture, notable for its deep layers. It has 18 layers and is popular for picture identification. It has leftover blocks with skip connections or shortcuts for layer traversal. These blocks help solve the vanishing gradient problem and train more complicated networks. Batch normalization improves convergence and generalization by re-centering and rescaling the input layer. Global average pooling instead of entirely connected layers makes it computationally efficient despite its complexity.

The Inception model, known for its fast calculation time and accurate image classification, has been improved in Inception-V3. Larger convolutions are factorized into smaller, more efficient processes to simplify processing. Auxiliary classifiers improve gradient flow during training. Grid size decrease allows higher-dimensional representation at the same computing cost.

VggNet16: Convolutional neural network with 16 layers. Its simplicity and network-wide implementation of small 3x3 convolutional filters are well-known. Implementation and comprehension are simplified by its simple and uniform structure. Core networks with three completely connected layers might be resource-intensive. Transfer learning often uses pre-trained models that performed well on ImageNet.

SqueezeNet, a powerful CNN framework, provides AlexNet-like accuracy with far less parameters. This makes it excellent for memory-constrained settings. It uses 'fire modules' with a compressed layer of 1x1 filters and an enlarged layer of 3x3 and 1x1. Compressing models is a simple way to optimize them for wearable applications. Its memory-efficient structure makes it suitable for peripheral devices with limited memory.

AlexNet outperformed other convolutional neural network architectures in the 2012 ImageNet Large Scale Visual Recognition Challenge. AlexNet was known for its vast design, with five convolutional layers and three totally connected layers. The ReLU activation feature was innovative and accelerated training. Overlapping maximum pooling reduces network size and prevents overfitting. By intentionally building the architecture to use GPUs, it pioneered deep learning research.

3.4 Implementation Approach

The datasets categorized ECG samples into ARR, NSR, or CHF groups. We employed MATLAB for development. Figure 4 illustrates the arrhythmia detection process using ECG signals, comprising the following steps:

A. The preprocessing steps include:

1. Filtering of ECG signals to eliminate noise and abnormalities.
2. Generating scalograms through a 12-octave continuous wavelet transform for time-frequency analysis.
3. Optimizing time-frequency analysis parameters for improved visibility of specific frequency components.
4. Utilizing scalograms as a visual tool for identifying irregularities in temporal frequency distribution.

5. Employing DL networks for the detection of abnormal ECG patterns indicative of cardiac arrhythmias.

B. Dataset division: 80% for training, 20% each for validation and testing, utilizing 10-fold cross-validation.

C. Design the none trained and pre-trained DL networks in (3.3) for automated detection of ARR, CHF, and NSR.

D. Utilize the same loss function and optimizer with all DL networks to achieve the classification task.

E. Model Evaluation: Utilizing the test set for performance assessment using the following performance assessment metrics including accuracy, error, recall, specificity, precision, false positive rate, F1 score, Matthews correlation coefficient, and Kappa.

3.5 Performance Assessment

Performance metrics employed include the confusion matrix, accuracy, error, recall, specificity, precision, false positive rate, F1 score, Matthews Correlation Coefficient, and Kappa. These metrics offer nuanced insights into the model's classification performance.

A. Accuracy: It measures the proportion of true results (both true positives and true negatives) among the total number of cases examined.

$$ACC = \frac{\text{True Positives (TP)+True Negatives (TN)}}{\text{Total Population (TP + TN + False Positives (FP) + False Negatives (FN))}} \quad (1)$$

B. Error Rate: It represents the proportion of all incorrect predictions out of the total number of cases.

$$ER = ER = \frac{FP+FN}{Total\ Population} = 1 - ACC \quad (2)$$

C. Recall (Sensitivity or True Positive Rate): It measures the proportion of actual positives that are correctly identified.

$$Recall = \frac{\text{TP}}{\text{TP+FN}} \quad (3)$$

D. Specificity (True Negative Rate): It measures the proportion of actual negatives that are correctly identified.

$$SPE = \frac{\text{TN}}{\text{TN+FP}} \quad (4)$$

E. Precision (Positive Predictive Value): It measures the proportion of positive identifications that were actually correct.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (5)$$

F. False Positive Rate: It measures the proportion of actual negatives that are incorrectly identified as positives.

$$FPR = \frac{\text{FP}}{\text{FP+TN}} = 1 - \text{Specificity} \quad (6)$$

G. F1 Score: The harmonic mean of precision and recall, providing a balance between them.

$$\text{F1 Score} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision+Recall}} \quad (7)$$

H. Matthews Correlation Coefficient (MCC): It is a measure of the quality of binary classifications, providing a balanced measure even if the classes are of very different sizes.

$$\text{MCC} = \frac{\text{TP}\times\text{TN}-\text{FP}\times\text{FN}}{\sqrt{\text{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}} \quad (8)$$

I. Kappa: It measures the agreement between two raters who each classify items into mutually exclusive categories.

$$Kappa = \frac{P_o - P_e}{1 - P_e} \quad (9)$$

Where Po is the relative observed agreement among raters (i.e., the accuracy), and Pe is the hypothetical probability of chance agreement.

Each of these metrics serves a specific purpose in evaluating the performance of a classification model, providing a comprehensive understanding of its strengths and weaknesses. The emphasis in cardiac arrhythmia detection is on minimizing both false positives and false negatives, ensuring precise and reliable diagnostic outcomes.

4. Results and Discussion

The described study presents a comprehensive analysis of deep learning models for cardiac arrhythmia classification, highlighting the effectiveness of various architectures. The training process was conducted on an i-core 3 Acer tablet using MATLAB, comparing five different deep learning (DL) models. Key aspects of the training process included:

Learning Rate and Optimizer: An initial learning rate of 0.0005 was set for all models, with the use of an SGDM optimizer.

Data Augmentation: Image sizes were adjusted to fit the DL networks, with no other augmentation techniques employed.

Dropout Layer: To mitigate overfitting, a dropout layer with a probability of 0.6 was embedded in the networks.

Model Performance and Comparisons

Accuracy and Loss Function Graphs: Figures 2 illustrates the accuracy and loss functions of the pre-trained DL models, using training data in color and validation data in dotted black lines.

Metric Performance: Table 1 shows metrics of the non-trained DL networks and Table 2 shows the metrics for the pre-trained DL networks.

Comparative Analysis

Analysis of Non-Trained DL Networks (Table 1):

Table 1 Performance metrics of the non-trained DL networks

Net\Metric	ACC	Err	Recall	Specificity	Precision	FPR	F1_score	MCC	Kappa
AlexNet	0.8438	0.1562	0.8759	0.9100	0.7982	0.0900	0.8045	0.7297	0.6484
SqueezeNet	0.9375	0.0625	0.9167	0.9556	0.9649	0.0444	0.9339	0.9042	0.8594
Vgg16	0.8750	0.1250	0.8690	0.9340	0.8158	0.0660	0.8333	0.7619	0.7188
Iception-V3	0.7188	0.2812	0.7403	0.8386	0.7661	0.1614	0.7326	0.5999	0.3672
ResNet18	0.8125	0.1875	0.7941	0.8833	0.8187	0.1167	0.8016	0.6959	0.5781

SqueezeNet shows the highest performance in terms of accuracy (0.9375), precision (0.9649), F1_score (0.9339), MCC (0.9042), and Kappa (0.8594). It also has a low error rate (0.0625) and FPR (0.0444). This suggests a balanced and robust model for ECG signal classification.

AlexNet and Vgg16 perform moderately well, with Vgg16 slightly better in terms of specificity and MCC.

Iception-V3 and ResNet18 show lower performance compared to others, particularly in accuracy, precision, and MCC. *Iception-V3* has the lowest Kappa score, indicating less agreement in its predictions.

Analysis of Pre-Trained DL Networks (Table 2):

Table 2 Performance metrics of the pre-trained DL networks

Net\Metric	ACC	Err	Recall	Specificity	Precision	FPR	F1_score	MCC	Kappa
AlexNet	0.9375	0.0625	0.9408	0.9620	0.9269	0.0380	0.9299	0.8943	0.8594
SqueezeNet	0.9375	0.0625	0.9278	0.9744	0.8968	0.0256	0.9103	0.8797	0.8594
Vgg16	1	0	1	1	1	0	1	1	1
Iception-V3	0.9062	0.0938	0.9000	0.9475	0.8713	0.0525	0.8834	0.8268	0.7891
ResNet18	0.8750	0.1250	0.9420	0.9556	0.7778	0.0444	0.8016	0.7646	0.7188

Vgg16 stands out with perfect scores across all metrics, indicating exceptional performance in the pre-trained scenario.

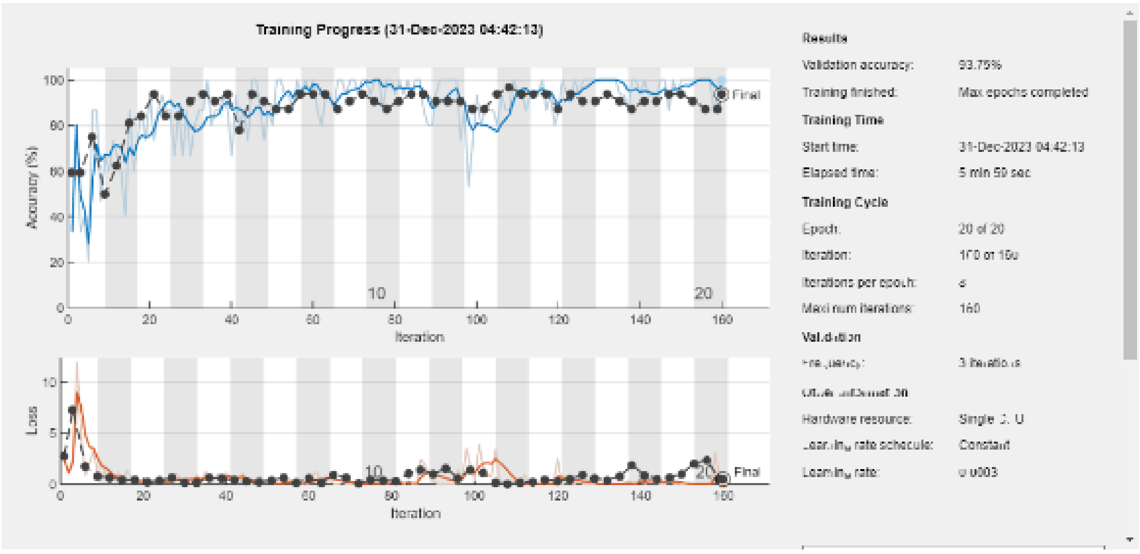
Both AlexNet and SqueezeNet show high performance, similar in accuracy, precision, F1_score, MCC, and Kappa. *SqueezeNet* has slightly better specificity but a lower recall than AlexNet.

Iception-V3 shows improved performance in the pre-trained setting compared to its non-trained counterpart, particularly in accuracy, precision, and MCC.

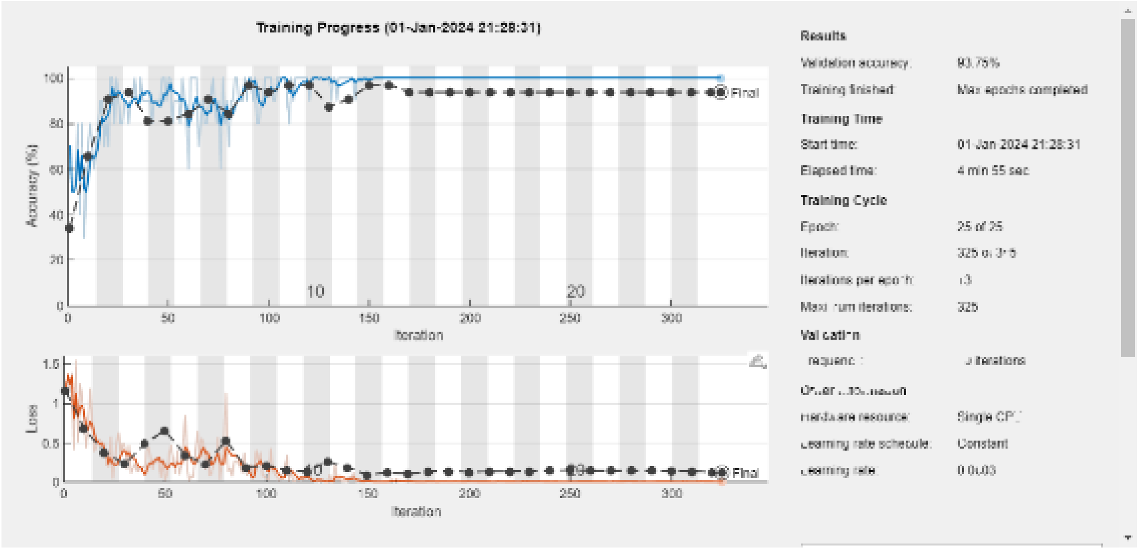
ResNet18 also improves in the pre-trained setting, with notable increases in recall and specificity, but its precision and MCC are lower than other pre-trained networks.

Overall Observations:

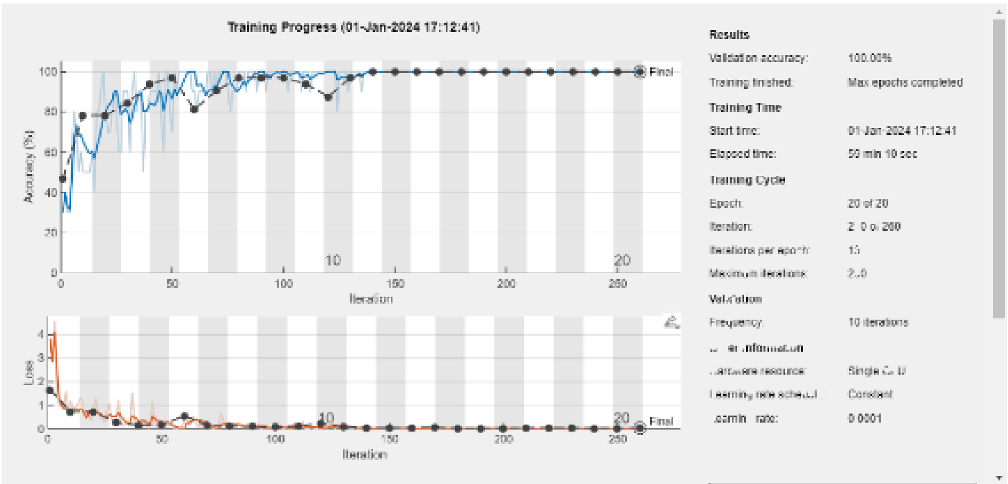
Pre-training generally improves the performance of DL networks in ECG signal classification. Vgg16, particularly in its pre-trained form, appears to be the most effective model. SqueezeNet is consistently high-performing in both non-trained and pre-trained forms. There is a significant improvement in the performance of Iception-V3 and ResNet18 when pre-trained. The choice of the network might depend on the specific requirements of the task, such as the emphasis on recall (identifying all positives) vs. precision (ensuring positives are correct) or the need for a balance as indicated by the F1 score and MCC.



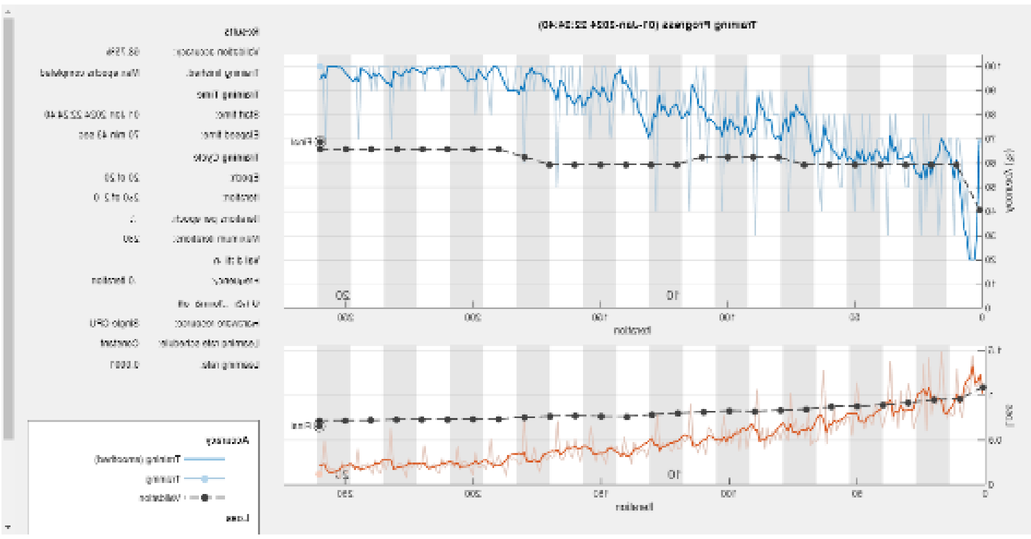
(a)


Training Progress (01-Jan-2024 21:28:31)
Accuracy (%)
Iteration
Loss
Final
Results
Validation accuracy: 93.75%
Training finished: Max epochs completed
Training Time
Start time: 01-Jan-2024 21:28:31
Elapsed time: 4 min 55 sec
Training Cycle
Epoch: 25 of 25
Learning rate schedule: Constant

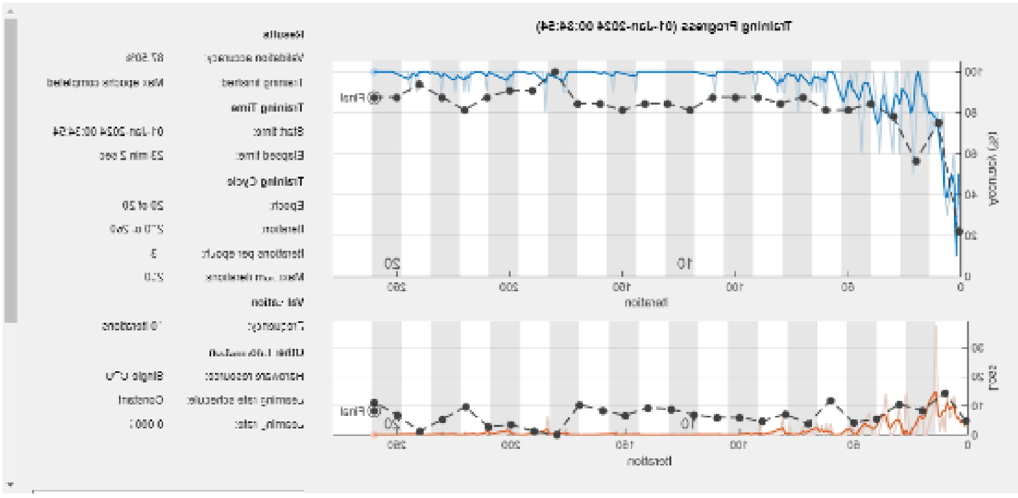
(b)


Training Progress (01-Jan-2024 17:12:41)
Accuracy (%)
Iteration
Loss
Final
Results
Validation accuracy: 100.00%
Training finished: Max epochs completed
Training Time
Start time: 01-Jan-2024 17:12:41
Elapsed time: 59 min 10 sec
Training Cycle
Epoch: 20 of 20
Frequency: 10 iterations
Constant
0.0001

(c)



(d)



(e)

Figure 2: the accuracy and loss functions of the pre-trained: (a) AlexNet, (b) SqueezeNet, (c)Vgg16, (d) Iception-V3, and € ResNet18

5. Conclusions

Deep learning can detect arrhythmias in electrocardiogram (ECG) readings, underscoring its usefulness in healthcare. This highlights the importance of these healthcare practices. The work shows how deep learning methods revolutionize arrhythmia therapy, a vital element of cardiac healthcare. Comparing five DL networks was crucial to our investigation. The findings strongly show that model complexity does not directly affect efficacy. Contrary to model complexity and efficiency norms, the tiny DL network model found arrhythmias better. Its potential as a robust and effective automated arrhythmia detection method could have major clinical ramifications. The study validates the potential of deep learning for automating the detection of cardiac arrhythmias using ECG signals. It showcases the effectiveness of pre-trained models over non-trained ones, with Vgg16 outperforming other architectures. These findings could revolutionize arrhythmia therapy, underscoring deep learning's expansive role in healthcare. The research encourages the integration of these technologies into clinical practice, offering a path toward more accurate and rapid diagnoses and, consequently, improved patient outcomes in cardiovascular care.

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