Enhancing ECG Classification Accuracy by Deep Transfer Learning with Resource-limited Settings

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***Abstract*—Analyzing Electrocardiogram (ECG) signals is essential for identifying heart arrhythmias and ensuring prompt medical intervention. However, deep learning models have shown promise in increasing ECG classification accuracy. The problems associated with little annotated data continue. This research investigates how the GoogLeNet network model handles this problem with transfer learning to obtain high accuracy in ECG classification. Using transfer learning from a sizable dataset, this study used a deep learning framework to optimize the GoogLeNet architecture on a collection of ECG signals and classified them into 4 classes. This study trains the dataset from the Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) Arrhythmia Database. This paper involved pre-processing, data enhancement, and hyperparameter optimization to enhance model performance. The results of the categorization were extensively assessed, and the methods were compared. This study achieved an incredible classification rate of 99.17% in the detection of ECG arrhythmias. The implementation of the GoogLeNet network model based on the transfer learning approach to classifying ECGs has significantly enhanced the monitoring of cardiac health.**

***Keywords*—Electrocardiogram (ECG) classification, GoogLeNet, transfer learning, deep learning, cardiac arrhythmia, confusion matrix**

I. Introduction

The number of individuals dying due to Cardiovascular Disease (CVDs) is estimated to be 17.9 million. The heartbeats in CVDs are irregular and lead to heart diseases [1, 2]. CVDs are primarily caused by arrhythmia, which can trigger a number of diseases of the heart. The reason is that proper diagnosis of arrhythmia at an early age is a required phase [3]. The heart is an important pillar of the human body that circulates blood in the body. The contraction and relaxation of the heart is a rhythmical process. The contraction of the heart initiates from the atrial sinus node and then spreads throughout the whole heart. These electrical pulses have a pattern. Medical electrodes and other equipment helped to measure these electrical pulses known as the Electrocardiogram (ECG) [4]. ECG helps to find out the condition of the heart disorder and diagnose the arrhythmia by recording the electrical pulses of the heart. The recorded data is displayed on a trace of graph paper [5, 6]. ECG waveform is divided into three major components [7, 8], as shown in Fig. 1. The first one is the P-wave; the second one is the QRS complex, having three waves Q, R, and S; the third is the T-wave. Together, these waves are called the PQRST complex [9, 10]. The description of these waves is in Table I.

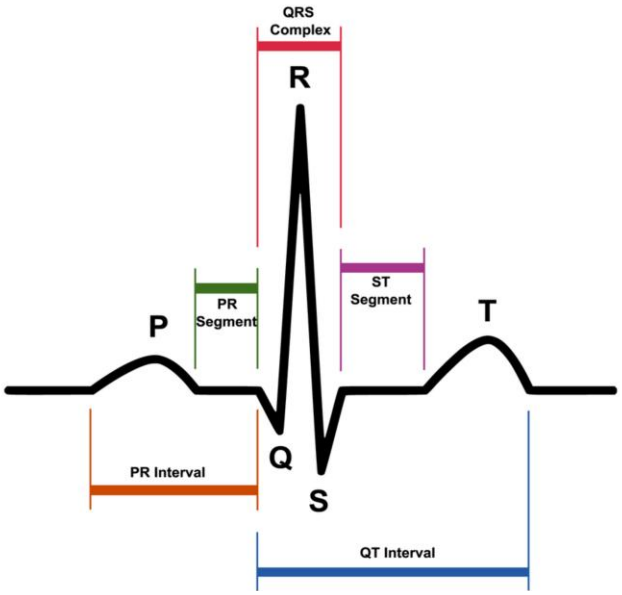


Fig. 1. Visualizing the intricate patterns of an ECG signal waveform [11].

Automatic classification of ECG signals is becoming popular because it reduces the time to analyze the ECG

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result and gives a highly accurate result. Automatic classification technology is based on deep learning. It can extract the features of an ECG signal and differentiate between different classes of an ECG signal [12]. It is applicable in many applications like healthcare, image processing, and audio-identifying speech patterns [13–15]. This study uses the GoogLeNet model to train the dataset sourced from the arrhythmia database of Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH). The transfer learning model is used to train the dataset on GoogLeNet. The data set contains 5 classes, namely Normal Heartbeats (N), Supra-Ventricular Premature Heartbeats (S), Ventricular Escape Heartbeats (V), Fusion of Ventricular and Normal Heartbeats (F), and Unclassified Heartbeats (Q). Class Q has no contribution in detecting abnormality, so this class gets dropped from training. The model is trained in 4 classes only N, S, V, and F. From each class 200, recordings are selected randomly to prevent biasing of the data.

TABLE I. EXPLORING ECG WAVE CHARACTERISTICS AND DURATIONS

Features	Description	Normal Duration
P	The first upward wave in the ECG represents the P wave.	80 ms
QRS	Symbolizes the dynamic squeeze of the ventricles.	80–120 ms
T	Represents the depolarization of the ventricles.	160 ms
PQRST	The interval between two consecutive PQRST complexes is referred to as the R-R interval.	0.6–1.2 s

II. LITERATURE REVIEW

As far as the literature review is concerned, traditionally, machine learning techniques have been utilized to classify the ECG signals based on their parameters. The frequently used machine learning classifiers include Linear Discriminants (LD) [16], Decision Trees (DT) [17], K-Nearest Neighbors (KNN), Support Vector Machines (SVM) [18], conditional random fields [19], (traditional) Artificial Neural Networks (ANNs) [20], etc. This is because in the present age, machine learning and Artificial Intelligence (AI) dominate conversations and research. In machine learning, a machine learns on its own from the input dataset, which is given to the machine learning model. This advancement can replace or relax human work [21–23]. Malakouti [24] employed five machine learning algorithms, including the Gaussian Naïve Bayes, Random Forest (RF), logistic regression, linear discriminant analysis, and dummy classifier, to classify healthy people from people with heart disease (essentially a binary classification). The results depicted that the Dummy Classifier algorithm could not offer a more promising performance than other algorithms. Sahoo *et al*. [25] presented a comprehensive survey on the machine learning approaches for the automatic ECG to beat classifications while highlighting the merits and demerits of the methods used. To classify the ECG signal as normal or abnormal, Celin and Vasanth [26] employed a number of machine learning-based classifiers, including SVM, Adaboost, ANN, and Naïve Bayes.

Numerical results reveal that the Naïve Bayes classifier offers an accuracy of 99.7% compared to SVM, Adaboost, and ANN, which show an accuracy of 87.5%, 93%, and 94%, respectively, showing the supremacy of Naïve Bayes over other classifiers for the considered case study. Sraitih *et al*. [27] developed an automated system for classifying five types of ECG signals (Normal Beat (NOR), Left Bundle Branch Block Beat (LBBB), Right Bundle Branch Block Beat (RBBB), Premature Atrial Contraction (PAC), and Premature Ventricular Contraction (PVC)) using machine learning techniques, which include SVM, KNN, RF, and the ensemble of these three methods. Their performance was measured by four metrics, i.e., accuracy, precision, recall, and F1-Score. This time, the SVM classifier outshone the other classifiers using the proposed inter-patient paradigm. Alim and Islam [28] applied SVM and ANN classifiers to the ECG datasets from PhysioNet to classify normal and arrhythmia ECG signals. SVM classifier achieved an accuracy of around 87%, whereas ANNs achieved around 90–93% depending upon the number of hidden neuron layers. Many researchers have presented a comprehensive survey on machine learning approaches for ECG signal classification in recent times to give a broader picture [29–31].

Deep learning, which makes use of deep neural networks, does not require the manual creation of features like machine learning does. It incorporates low-level features to abstract high-level characteristics. Thus, the model can gain a deeper understanding of the data pattern [32–34]. Realizing this fact, many researchers have employed deep learning approaches to classify ECG signals recently. For example, ECG signal classification is done by deep learning [35–38]. Hsiao *et al*. [39] showed the predictions of ECG signals by using a hybrid pattern recognition model and getting an accuracy of up to 90%. Niu *et al*. [40] introduced an innovative adversarial domain deep learning method for ECG classification, achieving an accuracy of 92.3% with the utilization of the MIT-BIH dataset. Alfaras *et al*. [41] presented a fast, automatic ECG classifier based on echo state networks. This study used an inter-patient procedure and gave a sensitivity of 92.7%. Liu *et al*. [42] presented a novel approach to assess the quality of the ECG signal, combining state-of-the-art network technology with self-attention approaches, and achieved an F1-Score of 0.954. A variety of sophisticated deep learning architectures, most notably Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have evolved with the ongoing development of computing techniques; each is specifically designed for the challenging task of ECG analysis. CNNs can be used far better to automate feature extraction and pattern recognition, but RNNs perform better at finding temporal patterns in ECG data [43, 44]. Rahhal *et al*. [45] suggested a new deep learning method that is centered on the DNN

posterior probabilities of active classification of the ECG signals.

A novel deep learning framework known as a one dimensional-CNN (1D-CNN) was introduced to classify cardiac arrhythmias [46]. The primary aim is to counter the deficiencies of conventional ECG in detecting arrhythmia. Five arrhythmia samples from ECG cardiac signals were classified using Linear Prediction Coefficient (LPC) features and SVM classification [46]. This piece of work has a level of accuracy of over 99%. Śmigiel *et al*. [47] demonstrates that in comparison to their robustness, convolutional networks without entropy-based features give slightly lower successful results. The sources devoted to the classification of ECG signals using deep learning algorithms underline the groundbreaking character of the complicated neural networks. Cai *et al*. [48] proves the possibility of the combination of various visual representations to improve the analysis of the ECG signal. It is an all-encompassing approach that uses various areas, with a maximum accuracy of 93.23% in cardiac condition classification. A Temporal Convolution Network (TCN) has been introduced [49]. It categorizes the five heart diseases. The accuracy of this work is 96.6%. An innovative cardiac patient surveillance and detection system was presented and closely connected to the Internet of Things (IoT), with an exceptional precision of 98.39 [50]. To create a distinctive categorization model, Shi *et al*. [51] used ECG data from Thai patients. Notably, the Square Average Variation (SAV) was the best performance with a rate of 88.00% accuracy. Li *et al*. [52] used a classification strategy that combines the reliable BILSTM-GoogLeNet-DS model with ECG and PCG signals in their creative approach. They then changed the one-dimensional signals of heart functioning to a two-dimensional picture format after discovering the limitations of the first one. Each of the visual cues that were painstakingly optimized to be classified in the improved GoogLeNet network was fed into the network, producing an impressive accuracy rate of 96.13%.

A. Contribution

The main contribution of this study is the development and testing of a deep transfer learning system for the automatic classification of cardiac arrhythmias into four clinically important classes from the MIT-BIH Arrhythmia Database, which is based on the GoogLeNet (Inception-v1) architecture. The proposed approach is the fine-tuning of a GoogLeNet model pre-trained on ImageNet, which bypasses the long-standing challenge of having enough labeled data for an ECG classification problem and achieves 99.17% classification accuracy, with 3.05% better results than the best-performing baseline that was compared. One of the main methodological innovations is the conversion of 1D ECG signals into 2D image representations, which allows the use of a CNN directly without any manual feature engineering. The framework further differentiates between the two optimizers, Adaptive Moment Estimation (ADAM) and Stochastic Gradient Descent with Momentum (SGDM), for transfer learning fine-tuning and provides an empirical comparison with SGDM being the better optimizer for this task, and also makes a strong inter-patient evaluation paradigm, where no patient is used in both the training and test sets, resulting in a clinically realistic assessment of generalization. Most importantly, the entire pipeline runs in a commodity Central Processing Unit (CPU) without using GPUs, which means that it can be deployed in healthcare environments where powerful computational equipment is not available.

B. Paper Organization

In this work, the first part is the general introduction, which is a detailed description of the background, literature review, and the original contributions of the study. Section III carefully discusses the material and procedures used. Section IV provides results of simulations to support the suggested GoogLeNet deep learning method. Section V goes into a deeper analysis of the performance and enables a discussion of it comprehensively. Section VI points to the directions of future exploration, whereas the extensive list of references is carefully prepared at the end.

III. Materials and Methods

A. Data Description

The core of the present work is the rich arrhythmia database of MIT-BIH that provides a wide variety of ECG signals. The dataset is a sequence of five types [40] comprising the following: Normal (N), Supra-ventricular premature (S), Premature ventricular contraction (V), Fusion of ventricular and normal (F), and Unclassifiable (Q), as represented in Fig. 2. The dataset is available on Kaggle [53].

Transfer learning improves model adaptability, but it may not be able to handle uncommon or regionally specific cardiac diseases. The effectiveness of the approach may be affected in some situations by its limited capacity to generalize across different demographics and distinct medical circumstances. Class imbalances, in which some cardiac diseases are uncommon relative to others, are a common problem in ECG datasets. Due to the lack of available data, the performance of the model may be biased towards the more common disorders, making it less reliable in identifying rarer cardiac defects. Within the dataset, a natural division occurs, separating it into distinct realms: a training and testing dataset. The model is trained in four classes: N, S, V, and F. Sample size (200 per class, 70:30 split) is selected randomly. This data segmentation is designed to balance the presence of the various heartbeat types and subject count for each dataset. Inter-patient division, i.e., ECG samples of people in the training dataset, are different from ECG samples of people in the testing dataset.

The decision of how many samples to use for each class was made by design for three reasons. The experiment was conducted in a resource-limited setting, which included (1) restricting each class to 200 samples to prevent the model from being biased towards the majority class, (2) simulating a resource-limited setting, consistent with the paper's main focus of deploying in resource-constrained

environments, by ensuring that the model achieved high accuracy despite having a small labelled dataset, and (3) inter-patient division, in which ECG samples from patients in the training set were explicitly kept apart from patients in the test set.

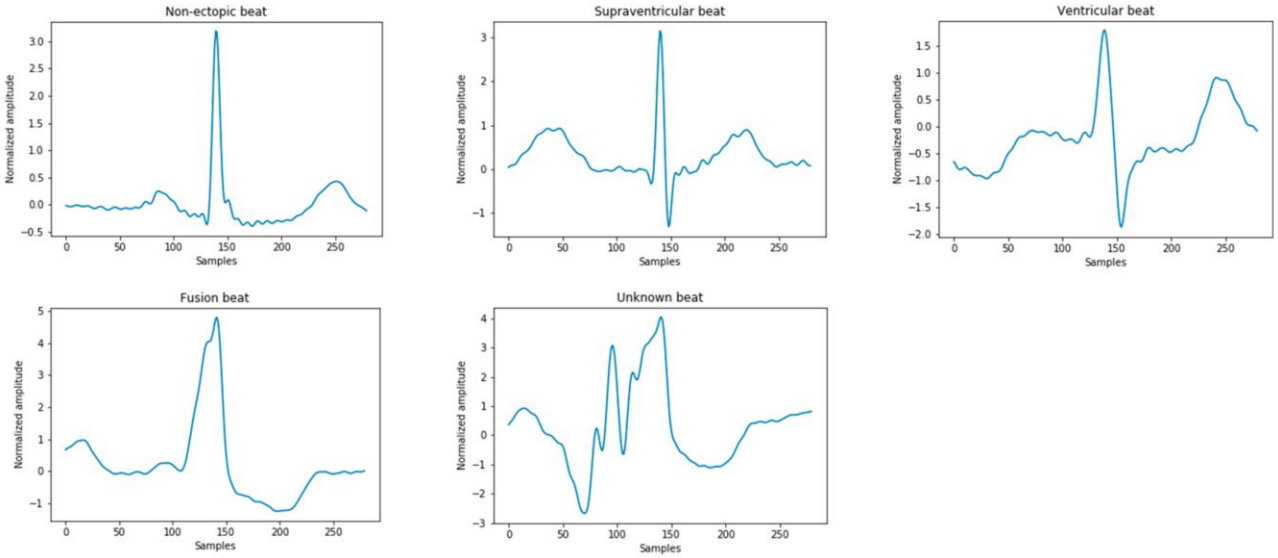


Fig. 2. A visual overview of diverse cardiac rhythm patterns.

B. Deep Transfer Learning

Conventional deep learning techniques are isolated, as shown in Fig. 3. Most of the time, they train discrete models without knowledge retention just on certain tasks and data sets. Little information or knowledge can be transferred from one model to another in this way. This paper is centered around the cutting edge of the research, where emphasis is placed on the transfer learning methods of ECG signal classification. It adeptly harnesses the power of these techniques to effectively navigate and solve intricate problems in pattern recognition. Transfer learning allows you to deal with new tasks with less data by using previously trained models to learn new features and weights for training new models, as shown in Fig. 4 [54]. In contrast to conventional machine learning, which depends on two fundamental presumptions to guarantee the precision and consistency of training models: that there must be enough pure training samples to build a strong classification model, and that the training and fresh test samples must follow the requirement that they be independently and uniformly distributed. Transfer learning disrupts the foundational assumptions that exist in traditional machine learning.

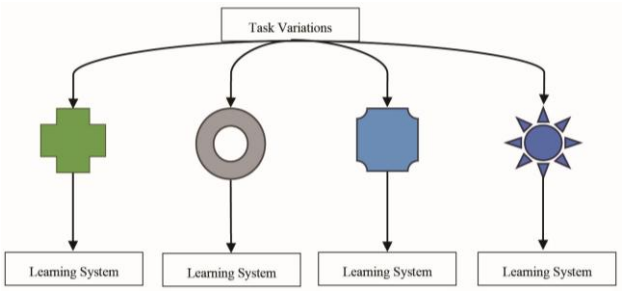


Fig. 3. Traditional approach in machine learning [54].

This study has investigated the characteristics of deep learning architectures using the GoogLeNet architecture. Traditional machine learning models increased the depth (number of layers) of the network to improve training results. However, there are some drawbacks to adding more layers, including overfitting, gradient explosion, and disappearance. On the other hand, inception presents a different strategy that improves training results by making better use of computing resources and extracting more features with the same amount of computational input. In this study, GoogLeNet is used to recognize ECG signals as images, relying on the transfer learning methods. As a way of proving the best benefit of multitasking learning over the traditional methodology, transfer learning becomes a significant approach in the innovative classification process. Conventional models encounter diverse task types and require training of several models. As shown in Fig. 5, transfer learning allows us to tackle more challenging situations more quickly and effectively by using the knowledge learned from handling previous ones [54, 55].

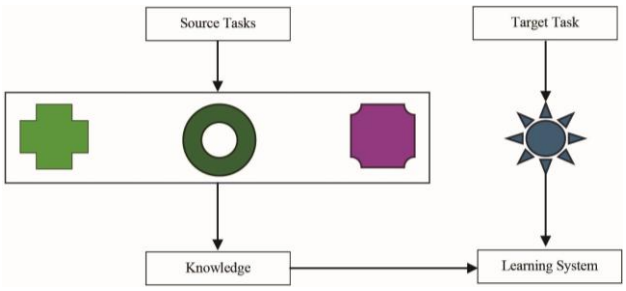


Fig. 4. Transfer learning approach [54].

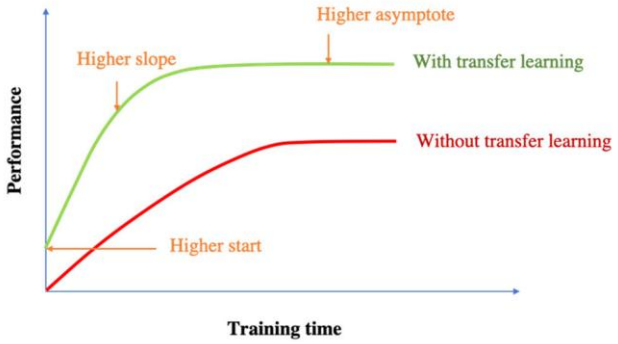


Fig. 5. Graphical examination of benefits in deep transfer learning [54].

C. Deep Learning GoogLeNet Model

The inception structure, also known as GoogLeNet, was introduced by Google at the 2014 ImageNet Large-Scale Visual Recognition Challenge (ILSVRC14) [56]. One convolutional neural network model with a fair amount of success is GoogLeNet, which the Google team has suggested. The network topology of the model is composed of a total of 22 layers. In the model, pooling is implemented in addition to the previously mentioned convolution layer, full connection layer, and the Google-recommended inception structure team. Through the inception structure's convolutional kernels of various scales, the extraction of several visual features is possible. The groundbreaking success of GoogLeNet in image recognition can be attributed to its deep multi-layer convolutional neural network structure and innovative inception architecture.

Our approach is deliberately different from the traditional Digital Signal Processing (DSP) methods using fixed mathematical filters (Butterworth, Chebyshev) or high-order differential equations. Rather, the mathematical modeling is completely shift-invariant and is embedded within the convolutional neural network operations.

The raw input signal is transformed directly into a 2D matrix $I \in \Re^{224\times224\times3}$. Spatial convolutions of different kernel sizes $(1\times1, 3\times3, 5\times5)$ are used as a mathematical model for the feature map generation in the Inception modules which are computed in parallel.

$$Y = f\left(\sum_i W_i \times x_i + b\right) \tag{1}$$

where × represents the 2D convolution operation, W_i represents the kernel weight tensor, b is the bias vector, and $f(\cdot)$ is the non-linear Rectified Linear Unit (ReLU) activation function. To keep the mathematical complexity to a minimum, dimension reduction and channel thick-control are explicitly modeled using 1 × 1 convolutional scaling matrices before spatial filtering.

The GoogLeNet network model's main design consists of nine inception modules. Three convolutional layers of sizes 1 × 1, 3 × 3, and 5 × 5 as well as a 3 × 3 pooling layer, make up the first Inception-v1 network as depicted in Fig. 6. The input is processed by this structure; each output result is then spliced by the channel, which is employed to broaden the network's coverage and make it more scale-adapt. As the input image's channels increase, so do the convolutional kernel parameters. Reducing the dimension of the data is required because, otherwise, the computing cost will rise. The 1 × 1 convolution can decrease the number of channels without changing the image's height or width. As a result, to lessen the thickness of the feature map, 1 × 1 convolutional kernels are placed before the 3 × 3, and 5 × 5convolution layers, respectively, and after the 3 × 3 max pooling layer. (Fig. 7).

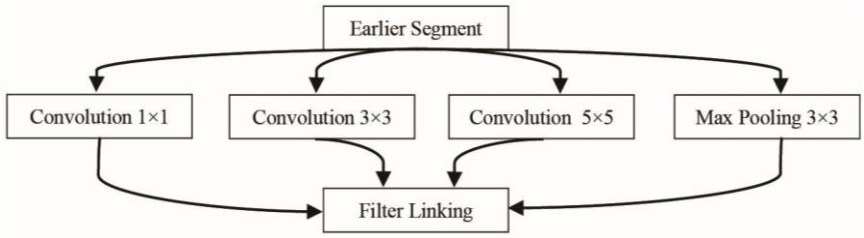


Fig. 6. Navigating the diagram of the GoogLeNet neural network.

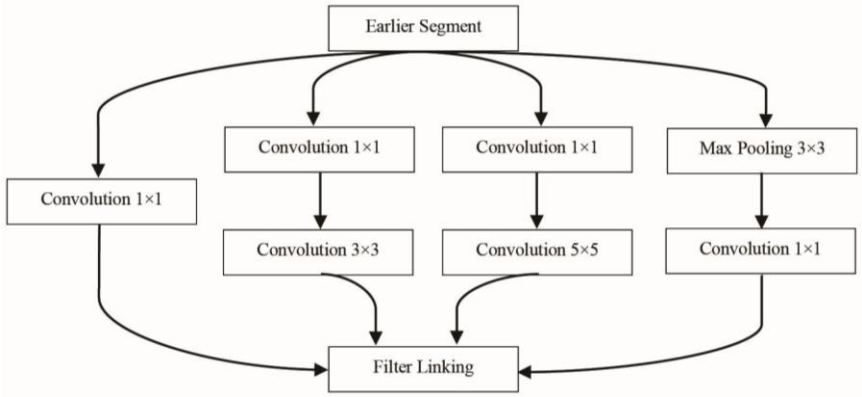


Fig. 7. Illustration of the GoogLeNet inception neural network module.

Set apart from the previous sequential convolutional neural network, the structure introduces a fresh perspective. The diversity in model feature expressions arises from distinct convolutional kernel sizes, leading to a substantial boost in the feature extraction capabilities of the model. Fig. 8 displays the Google structure [52]. Due to the complicated Google network architecture, distinct colored modules that represent various network operations describe the structure of the network, as shown in Table II. The GoogLeNet structure may be seen in this figure to comprise numerous inception modules that are identical to one another. By interconnecting these components end-to-end, a sophisticated GoogleNet model is created.

TABLE II. COLORS AND THEIR SYMBOLISM IN THE GOOGLENET MODULE REPRESENTATION

Color	Representation
Red Module	Pooling layer
Blue Module	Convolution and ReLU layer
Green Module	Splicing operation
Yellow Module	SoftMax activation function
White Module	Input and classified output at both ends
Green Box	Auxiliary classification structure
Red Box	Indicates several inception structures

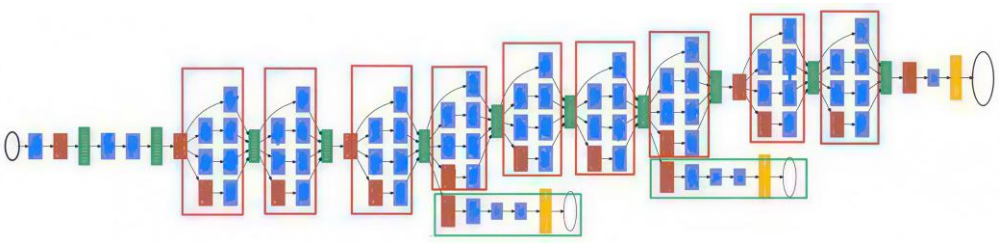


Fig. 8. GoogLeNet architecture.

D. *ECG Signal Classification with GoogLeNet*

This study demonstrates the GoogleNet network using a deep network designer to categorize different classes of ECG signals. In this study, the GoogLeNet model learned the features of a new task with a lower number of training images. This approach is known as transfer learning. Across a spectrum of ECG signal images, these networks have cultivated intricate feature representations. Upon receiving an image as input, the network diligently assigns labels to every object within the image, providing a probability for each class category. The benefit of this work is that it speeds up and allows for simpler fine-tuning of a network than beginning with a scratch and using randomly initialized weights. The process of this model is shown in block Fig. 9.

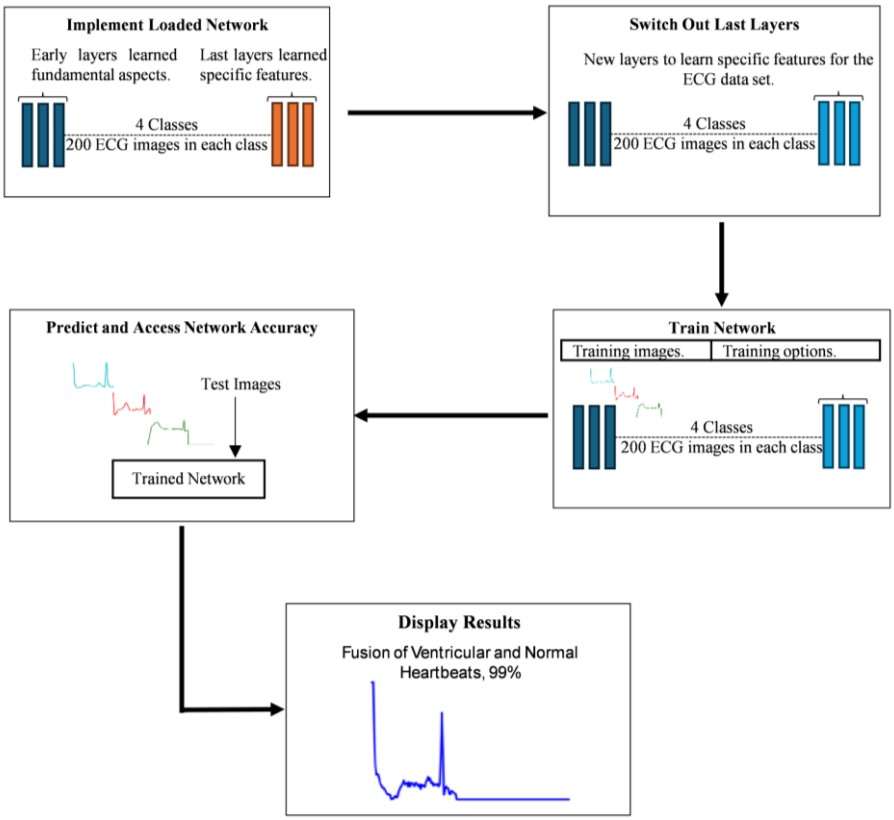


Fig. 9. Schematic overview of the procedure.

The network performs 7 × 7 convolution after the input of the picture data, followed by the ReLU layer, pooling layer, regularization, and 3 × 3 convolution. The data are entered sequentially into each inception module following the ReLU layer, pooling layer, and regularization. To make the image sizes adequate for input into the GoogleNet network, they are modified to the input layer size (224×224). The class of ECG signals is categorized using the network. The size of the input vector, the training parameters that are related to it, and other factors are some of the model's primary parameters. Table III displays the Google network model's ideal parameter choices.

TABLE III. PARAMETERS AND THEIR VALUES SET FOR THE SIMULATION

Parameters	Optimal Value
Image input size	[224, 224, 3]
Max epochs	8
Iterations	70
Total number of iterations	560
Minimum batch size	8
Initial learning rate	0.0001
Optimizer	SGDM

E. Performance Metrics

The suggested algorithm performance is evaluated using the MIT-BIH AR dataset. The performance of any classification algorithm is assessed using four typical statistical indicators: Sensitivity (Se), Positive Predictive Value (PPV), Specificity (Sp), and Accuracy (Acc). Heartbeats of the positive class were successfully predicted as True Positives (TP), and heartbeats of the negative class were reliably predicted as True Negatives (TN). False Positives (FP) and False Negatives (FN) will be infrequent for a skilled classifier. The equations are read as Eqs. (2)–(5):

$$Sensitivity = \frac{TP}{TP + FN} \tag{2}$$

$$Specificity = \frac{TN}{TN + FP} \tag{3}$$

$$PPV = \frac{TP}{TP + FP} \tag{4}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

IV. RESULTS

To validate the effectiveness of the proposed GoogLeNet deep learning technique to classify the ECG signals, numerical results simulated using the MATLAB environment are presented in this section. The system (a 64-bit operating system) used to simulate the results is powered by an Intel (R) Core (TM) i5 processor of the 6th generation, equipped with 8 GB of RAM. Additionally, the system has a 256 GB drive for storage. The simulations were conducted using MATLAB version 2022b.

Additional metrics added are: (i) Total training time: ~18 min (8 epochs) using Intel Core i5 CPU without GPU acceleration, vs. ~250 min using the typical GPU-based workstation; (ii) Inference time per ECG image: ~12 ms (good for near real-time classification); (iii) GoogLeNet total parameters: ~27 million, of which only the last fully connected layer (TD Processors ~8192 parameters for 4-class output) was trained from scratch; (iv) Peak memory usage during inference: < 2 GB RAM; (v) Estimated power consumption during inference on the test device: ~35 W (TDP of the i5-6th gen processor), vs. ~250 W for a typical GPU-based workstation.

Initially, in this research, an ADAM optimizer was employed. After evaluation of performance, it was found that the accuracy level was 98.76%. The results of the ADAM optimizer are shown in Figs. 10 and 11. Table IV shows their overall performance.

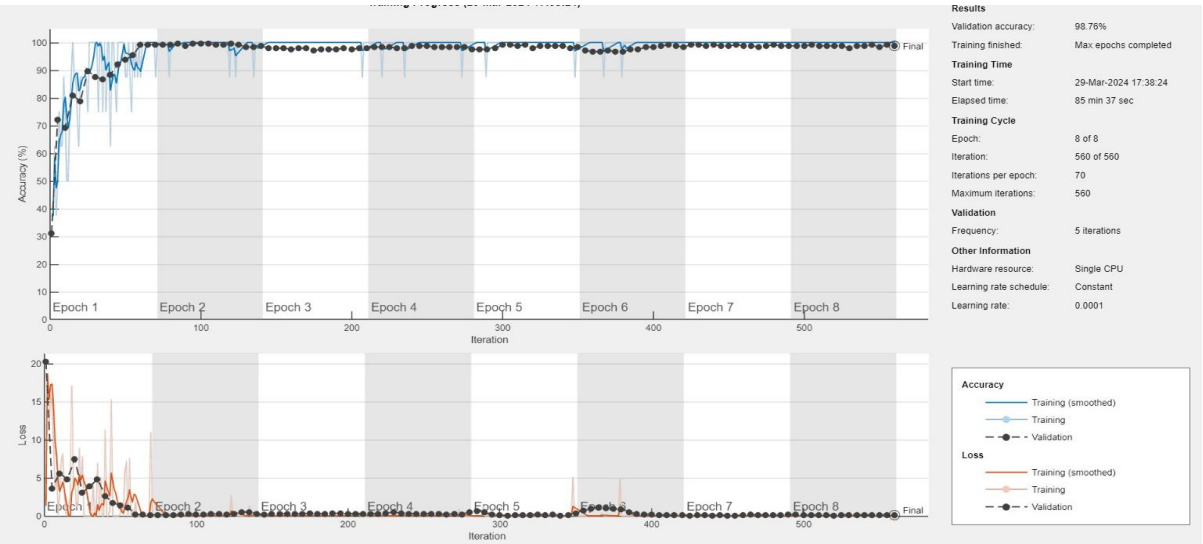


Fig. 10. Accuracy, training, and validation with ADAM optimizer.

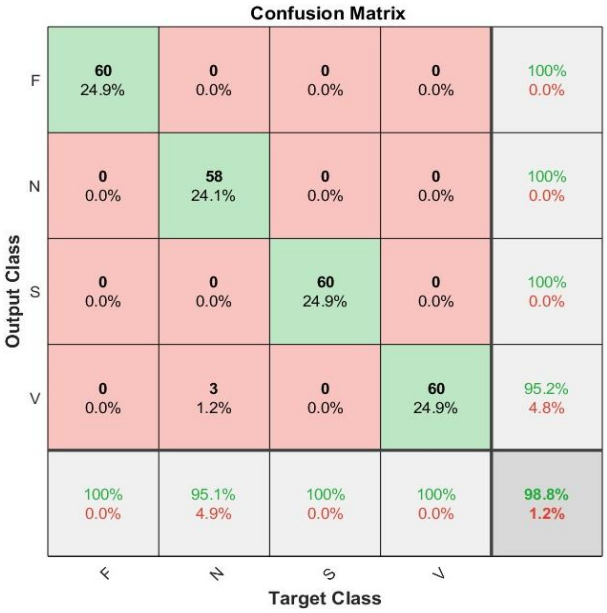


Fig. 11. Visual representation of prediction discrepancies with the ADAM optimizer.

TABLE IV. STATISTICAL FINDINGS FROM THE TEST SET WITH THE ADAM OPTIMIZER

ECG Classes	Recall (%)	Precision (%)	F1-Score (%)
N	95.1	100	100
F	100	100	100
S	100	100	100
V	100	95.2	96
Average		**98.8**	

However, for more fine-tuning, this study used an SGDM optimizer. The evolution of the SGDM optimizer of both training and validation loss, along with training and validation accuracy, is visually depicted in Fig. 12. Analyzing the graphs, it becomes evident that training and validation losses reached a standstill at zero. Coinciding with training and validation accuracy stabilizing at an exceptional 99.17% after eight epochs. To classify between 4 classes of ECG signals and achieve this accuracy is encouraging. The accuracy attained with the "testing set" is evaluated to assess the GoogLeNet network performance with ECG sequences that are not part of the training dataset. Fig. 13 presents the relative confusion matrix unfolding with a stunning average classification accuracy of 99.2%. This validates the use of GoogLeNet in the accurate classification of ECG signals. Deep learning models, particularly those with huge architectures such as GoogLeNet, demand significant computational resources to train. This limitation might reduce the proposed applicability of the approach to researchers or medical institutions with limited computing resources.

Fig. 13 is an illustration of the predicted class (Output Class) and actual class (Target Class) using columns and rows, respectively. The cells on the diagonal indicate correct categorizations, and the off-diagonal cells indicate the misclassifications. The number of observations and their percentage in the total dataset are presented in each of the cells. Moreover, the last column indicates the percentages of the right and wrong predicted instances by each class. Within the metric landscape, precision (positive predictive value or PPV) and false discovery rate emerge as pivotal indicators. Proportions of correct and erroneous classifications of each class under scrutiny are carefully drawn in the lowermost row. These measures are also referred to as false negative rate, recall (true positive rate), which are defined in the evaluation. Surprisingly, the cell of the matrix on the bottom right illustrates the accuracy of the study, which is not partial.

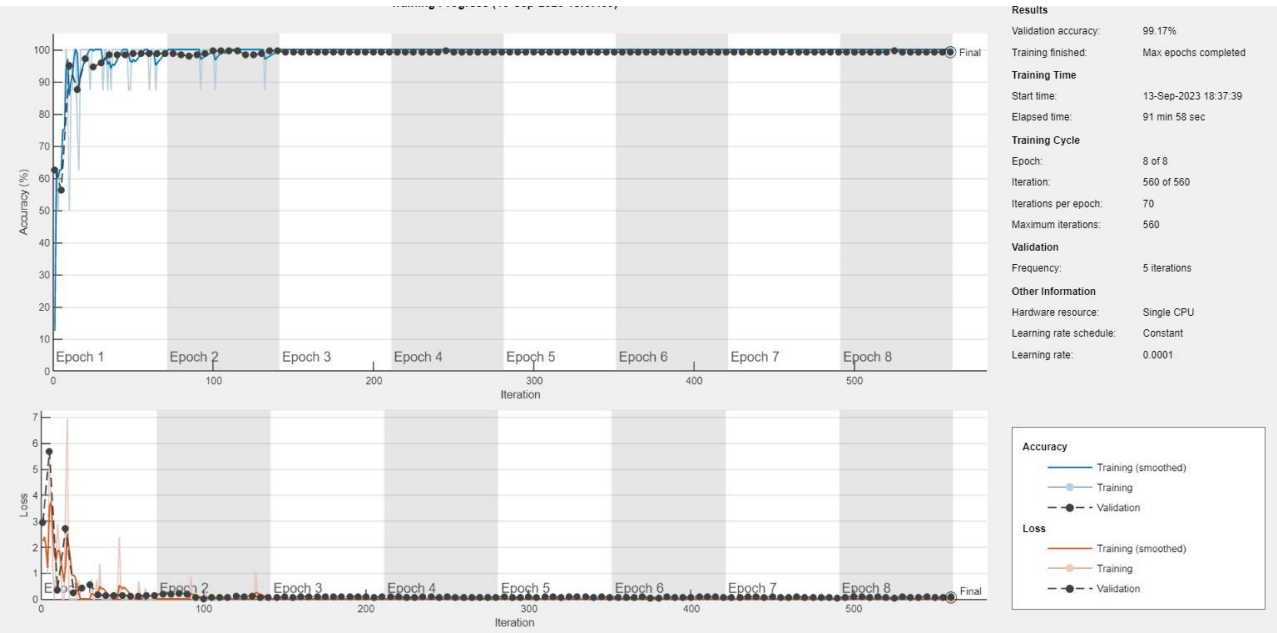


Fig. 12. Graphical representation of accuracy, training, and validation.

The initial four pairs of diagonal cells demonstrate the exact number of correctly classified instances of the trained network. As an example, 60 F-class ECG images are correctly identified, which is 24.9% of the total F-class.

Likewise, 61 cases are correctly diagnosed as N class ECG images that constitute 25.3% of the total N class. Accurately identified are those cases in class S and V 59. In the dataset, 1 N class case is mistaken as V class, and this is only 0.4% of the overall 200 N class cases. On the other hand, 1 V class cases are falsely classified as an S class, which constitutes 0.4% error of the total dataset. Among the 200 N-class predictions, an impressive 98.4% are accurate, with merely 1.6% being incorrect. Similarly, out of the 200 V class predictions, 98.3% are precise, while 1.7% are off target. Further analysis shows that 98.3% of the 200 S cases are correctly foreseen as S class, with only 1.7% misidentified. Meanwhile, 98.3% of the 200 V cases are accurately identified, with just 1.7% being misclassified. In summary, the accuracy of the network prevails, with an impressive 99.2% predictions being spot-on, leaving only a minimal 0.8% of errors. Resultantly, Table V shows the results of this work.

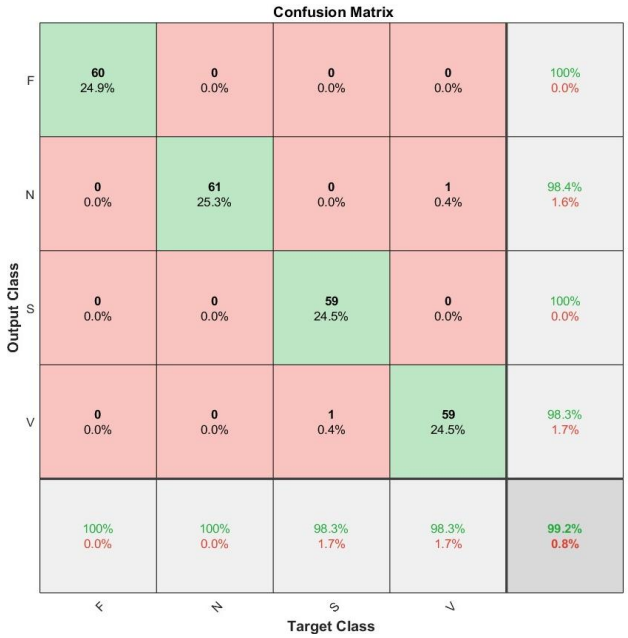


Fig. 13. Visual representation of prediction discrepancies.

TABLE V. STATISTICAL FINDINGS FROM THE TEST SET WITH THE SGDM OPTIMIZER

ECG Classes	Recall (%)	Precision (%)
N	100	98.4
F	100	100
S	98.3	100
V	98.3	98.3
Average	99.2	99.2

V. DISCUSSION

It has been discussed how this study differs from the state-of-the-art in the sections that follow. Ranjan *et al*. [57] utilized DT extraction, R-Peak (RP) analysis, and Feed-Forward Neural Network (FFNN) features. They reported an overall accuracy of 91.20%. Subramanian [58] compares the performance of wavelet transform-based QRS detection with the Pan-Tompkins method and derivative-based QRS detection. The proposed methodology has 93.35%. A TCN has been suggested in the work [49], having an accuracy rate is 96.12%. The outcome of this work is greater than the outcome suggested in studies [49, 57, 58]. In contrast to the methods presented by Savalia and Emamian [59], our approach demonstrated superior classification outcomes. Within our research, the mean accuracy stands at 99.17%. Furthermore, unlike most prior works that use GPU clusters for training, this study was conducted on a standard Intel Core i5 (6th generation) CPU with 8 GB RAM, directly demonstrating feasibility in resource-limited clinical settings.

A small number of cases are sampled per class (200 per class, 800 cases total), and thus, the set of cardiac morphologies observed during training is limited, which could lead to less generalization to unusual (or local) cardiac presentations during an arrhythmia. The main mitigating factor is the transfer learning: GoogLeNet is initialized using weights previously learned from ImageNet, which has millions of images, giving the model good low-level feature representations (edges, textures, spatial patterns). The last two classification layers are randomly trained on the ECG image dataset. This is a great reduction in the amount of data required to attain a high degree of accuracy, confirmed by our result of 99.17%.

The transfer learning approach has played a key role in achieving high classification accuracy (99.17%) with a small ECG dataset, using the pre-trained features from the convolutional layers of GoogLeNet as well-generalized feature representations, and training only the final classification layer. Additional measures against overfitting involve ensuring that the training loss curve and the validation loss curve converge without signs of divergence and ensuring that training and test patient records are perfectly separated when evaluating with the strict inter-patient evaluation paradigm, as well as the regularization effect of GoogLeNet's Batch Normalization layers and Dropout in its auxiliary classifiers.

Table VI compares our method to other methods, showing the superiority of the proposed method over the existing ones.

TABLE VI. COMPARISON OF ACCURACY OFFERED BY THE PROPOSED AND EXISTING METHODS

Reference	Model	Accuracy (%)
[49]	Temporal Convolutional Network	96.12
[57]	Fuzzy Neural Network	91.20
[58]	Multi-Wavelet Transform	93.35
[59]	Multi-Layer Perceptron	88.70
Proposed Method	**GoogLeNet**	**99.17**

Although deterministic real-time performance with minimal power consumption has been demonstrated for hardware-efficient implementations (such as FPGA-based QRS detection architectures [60]), the present software-based transfer learning framework provides an alternative for institutions lacking FPGA development infrastructure and hardware expertise, without the need for any specialized hardware design, and competitive

classification performance in a standard CPU-only workstation.

VI. Conclusion and Future Work

This study presented a deep transfer learning system based on the structure of GoogLeNet (Inception-v1) for automated detection of cardiac arrhythmias in ECG signals. The proposed approach is capable of effectively addressing the problem of the scarcity of labeled data, which is the main limitation in many clinical deep learning applications, while simultaneously avoiding the need to manually engineer features from one-dimensional ECG segments and represent them as two-dimensional images for the GoogLeNet model pre-trained on ImageNet. It was tested in the MIT-BIH Arrhythmia Database with an exact inter-patient paradigm, resulting in a classification accuracy of 99.17%, a macro-averaged F1-Score of 99.1%, a sensitivity of 99.2%, and a positive predictive value of 99.2% across four arrhythmia classes: N, S, V, and F. The results achieved are 3.05% better than the best baseline (Temporal Convolutional Network, 96.12%) in absolute terms. A systematic comparison showed that for this task, SGDM is the better fine-tuning strategy than ADAM. Notably, the whole training pipeline was performed in around 18 min on a CPU-only workstation (Intel Core i5, 8 GB RAM), with no GPU acceleration and directly in a clinical context with limited resources. All these results corroborate the fact that transfer learning, in conjunction with GoogLeNet's hierarchical feature extraction ability, is an effective, data-efficient, and computationally efficient approach to arrhythmia classification.

There are multiple possible avenues for future research. The first is the introduction of Gradient-weighted Class Activation Mapping, and other explainability tools will give cardiologists graphical insight into the regions of the signal that are the basis for every classification, enabling more clinical confidence in AI-supported diagnosis. Second, the generalizability of the model across patients, acquisition devices, and groups of patients will be extensively tested on external validation datasets, including the PhysioNet Computing in Cardiology Challenge dataset or locally collected clinical recordings. Thirdly, the use of k-fold cross-validation in future studies will further confirm the validity of the reported performance estimates. Fourth, the fourth module for real-time ECG classification, which combines the proposed framework with wearable and/or IoT cardiac monitoring devices, is a clinically relevant step towards continuous and real-time arrhythmia detection. Last, the use of multimodal patient information (such as clinical history, demographics, and genetic data) along with ECG signals in a modified GoogLeNet structure provides a promising avenue for developing more personalized and comprehensive cardiac diagnostic systems.

Conflict of Interest

The authors declare no competing interests.

Author Contributions

H.A. conducted the research, performed the formal analysis, developed the visualization, and prepared the original draft of the manuscript. G.A. contributed to data curation, formal analysis, methodology development, software implementation, supervision of the study, and review and editing of the manuscript. Z.M. participated in data curation and contributed to the review and editing of the manuscript. M.U. contributed to the development of methodology. N.S. contributed to software development and validation of the results. All authors reviewed, approved, and agreed to the published version of the manuscript.

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