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Classification of Myocardial Infarction from Multi-Lead ECG Signals Using Hybrid Deep Learning

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***Abstract*—Myocardial Infarction, commonly known as heart attack is a serious condition that causes severe damage to the myocardium. Majority of the researches were engaged in preprocessing the ECG signals. This involved various steps such as reducing the noise, removing trends, segmenting beats and selecting relevant features before building models and classifying the data using machine learning methods. In this paper, the proposed model is an ensemble of 12 experts with predefined CNN architectures like AlexNet and GoogLeNet using the ECG signals without any complex preprocessing. Hyper parameters are tuned to give an accuracy of 98.78%, further tested with 6 datasets apart from the PTB database which gives an accuracy of an average of 75%. The model is significant compared with two other methods such as 12 lead scalogram collage method with an accuracy of 20.18% and concatenated raw signal method with an accuracy of 60.43%.**

Keywords— AlexNet, CNN, ECG, GoogLeNet, Myocardial Infarction, Scalograms.

I. Introduction

Electrocardiogram (ECG) can detect various d diseases. Electrocardiography employs a total of twelve leads, which are categorized into two groups. The first set consists of six leads known as limb leads, named I, II, III, aVL, aVR, and aVF. The second set comprises six leads known as precordial leads, named V1, V2, V3, V4, V5, and V6. Myocardial Infarction (MI) is a medical condition that occurs when the heart muscle's blood supply is obstructed due to the blockage of the coronary arteries. This could occur at various locations in the heart as mentioned in Table 1 [1].

TABLE I. LOCALIZATION OF MI

Localization of MI	**ST elevation**	**Reciprocal ST depression**
Anterior	V1-V6	None
Septal	V1-V4 (disappearance of septum Q in leads V5, V6)	None
Lateral	I, aVL, V5, V6	II, III, aVF
Inferior	II, III, aVF	I, aVL
Posterior	V7, V8, V9	High R in V1-V3 with ST depression V1-V3 in mirror view
Right Ventricle	V1, V4R	I, aVL
Atrial	PTa in I, V5, V6	PTa in I, II or III

Coronary artery disease stands as the predominant cause of mortality and disability both in Western nations and across the globe. Myocardial infarctions, commonly referred to as heart attacks, represent the primary contributor to fatalities in industrialized countries worldwide. Every year, there are 32.4 million myocardial infarctions and strokes globally. Survivors of MI have a higher risk of recurrent infarctions and a 5% yearly mortality rate, which is six times higher than in people of the same age who do not have coronary heart disease.

Therefore, it is essential to identify and diagnose MI early in order to prevent consequences such as cardiac failure, arrhythmia, and death. Fig.1 demonstrates the presence of three distinct waves within an ECG signal: the P wave, the QRS wave complex, and the T wave. ST elevation and depression, irregular Q wave, and T wave inversion are some of the MI characteristics.

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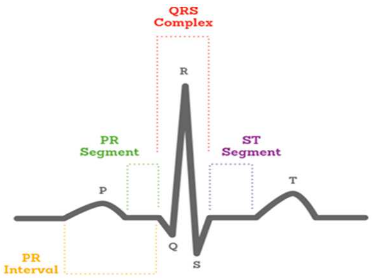

Fig 1. ECG wave

A convolutional neural network (CNN) is a deep learning model that can take an input, apply weights and biases to various features of the input, and differentiate between them. Originally designed for preprocessing 2D data, such as photos and videos, traditional CNNs have proven to be highly effective in image recognition tasks. In this paper, a CNN model is proposed to diagnose Myocardial Infarction and compared various CNN architectures to find out the best architecture to give an optimal result [1].

In the proposed research, ECG signals are directly input into a CNN model without the necessity for preprocessing. This is achieved by transforming the signals into scalograms, which are a time-frequency representation used for the analysis of time-varying signals. In this process, each scalogram is converted into an RGB format representation, where the amplitude of the coefficient corresponds to the intensity of each color channel.

II. Literature Survey

Early detection and diagnosis are vital to prevent these consequences. Electrocardiography (ECG) is commonly used for diagnosing acute MI, and advancements in technology have improved its effectiveness, particularly when computer-aided methods are employed for analyzing 12-lead ECG data [1]-[4]. To accurately detect beats and extract different features, it is necessary to pre-process ECG data since the signal recorded from different individuals are unique, heterogeneous, and can be easily distorted by noise during the recording process. Other than using scalograms, there are other ways to extract ECG features such as R-peak detection, QRS complex duration and PR wave duration [5][6].

The accurate analysis of ECG data involved several phases, including pre-processing, feature extraction, feature reduction, classification, and output [7]. In another study [8], three neural classifiers (BPNN, FFN, and RBFNN) were employed to differentiate between normal and pathological ECG signals based on beat counts. After eliminating noise, statistical and morphological characteristics are obtained by applying wavelet transformations with different wavelet families. The results indicate that the Daubechies wavelet family produces the most optimal outcomes. The most accurate classifier was determined to be RBFNN, which outperformed FFN and BPNN with 100% accuracy, specificity, positive predictivity, and sensitivity. The study demonstrated that Daubechies, Symlet, Biorthogonal, and reverse biorthogonal wavelets are effective when used with RBFNN, a fast-learning neural network for classifying ECG signals with high accuracy[9]. Further, the performance of two algorithms—the SVM and 1D-CNN model—for the task of rhythm classification is assessed and contrasted in another exploratory study [10] using a combined public dataset. SVM and 1D-CNN algorithms produced accurate results, with similar F1 scores, precisions, and recall for the classification of heart rhythms. SVM requires a difficult process of trial and error, whereas CNN algorithms can significantly lighten the workload. In other study, CHF is detected using DCNN and LSTM [11][17]. In order to extract deep features, CNN is incorporated. LSTM is then used to accomplish the aim of CHF detection utilising the extracted features. CNN uses fewer parameters because of its weight sharing and local perception abilities. Convolution, pooling, and full connection layers make up the CNN. A pooling layer is added to the network to reduce the size of the extracted features. This increases the effectiveness of the network training phase. LSTM was developed to address the gradient vanishing and gradient explosion issues. Getting the data needed for classification and identification is the first step. The data was then standardized in the second step. The third step involves using the trained CNN-BiLSTM-AM model to determine the potential output value. Restoring the standardisation of the data to its initial value is the fourth step. Finally, the output of the classification issue is the restored value, which divides ECG data into normal and CHF signals [11]. A 12-lead ECG was used to perform an automated MI identification and localization process. The ECG signals were divided into four levels using the wavelet transform, and 12 nonlinear characteristics were identified using the k-nearest neighbour (KNN) algorithm [12]. Ten distinct spatial myocardial infarction (MI) locations were determined by analyzing the presence of MI-related ECG abnormalities in various sets of continuous ECG vectors. To enhance the quality of the ECG data by removing noise and baseline drift, a wavelet transform was employed as a preprocessing step. The study introduced an automated ECG classification approach that leveraged the Continuous Wavelet Transform (CWT) in conjunction with a Convolutional Neural Network (CNN). The Continuous Wavelet Transform (CWT) is a signal analysis method that yields a time-frequency representation known as a scalogram.

Reference [14] introduces a distinctive approach with the objective of transforming one-dimensional ECG data into two-dimensional scalogram images. This technique effectively reduces data loss and mitigates the risk of beat loss, as illustrated in Fig 2. To address the limitation of limited training datasets, transfer learning is employed, leveraging the pre-trained GoogLeNet model on ImageNet to extract distinctive features associated with abnormal heart conditions. The Naive Bayes classifier is chosen due to its low dimensionality and independent features, facilitating simplified calculations. The results exhibit improved performance compared to previous methods, showcasing high recall, precision, and F1 measure. In another cited work [16], arrhythmia was classified using a 2-D convolutional neural network. Using scalograms negates multistep pre-processing approaches which are very complicated This study simplifies the diagnosis process in real-world medical practice and reduces noise impact on ECG data by using a simplified model. Furthermore, this approach allows for comprehensive training and classification of 12 sets of ECG images obtained from each lead, yielding results on par with those of healthcare professionals.The 12-lead ECG data was converted into grayscale images with 256 levels and 64x64 pixels. This transformation was applied to W milliseconds of the ECG data, and repeated by window shifting in steps of 1000 milliseconds(W was configured to 1000 millisecond, average ECG beat is 1 beat per second) to produce 12 ECG images per lead, referred to as "ECG image set" in the study [15]. The proposed CNN model is unique in its use of convolution and pooling layers to learn ECG image features separately for each lead. The extracted features from each lead are then combined and thoroughly learned by the fully connected layer. The output of the fully connected layer is transformed into a probability vector using the SoftMax function, and the weights and bias are updated using the backpropagation algorithm [17]. This study has suggested a classification method that outperforms conventional approaches in terms of accuracy and performance. However, the study has identified two limitations: ECG images with significant noise or trends may lead to misclassification, and ECG images with multiple beats or missing beats may also be misclassified [18]. Thus, there is a need for a suitable approach to overcome this limitation which is discussed further in this paper.

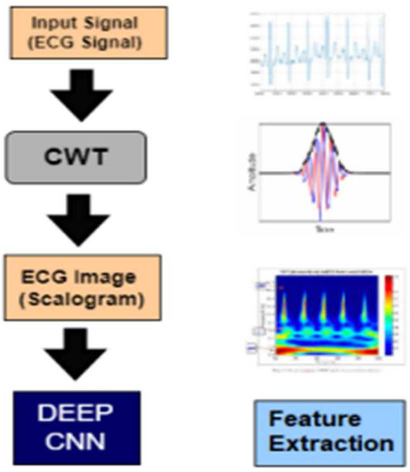

Fig 2. Feature extraction using scalogram

III. Methodology

Before getting into the experiments, lay a common ground between these methods for the purpose of comparing and contrasting fairly. A few settings are maintained the same for all the methods which is mentioned in Table II. And with addition to it, no signals are pre-processed also to ensure normality, since the idea of this paper is to get more accuracy with less effort and time. Scalograms are used as input to our model. In comparison to a 1-D ECG signal, they offer better time-frequency localization and provide a multi-resolution view of the signal. Here in order to find a good representation of the actual signal in the scalogram image, 1- second, 2-second, and 5-second segregation of the 1min signal are compared. Fig 3. indicates that 1-second signal scalograms are too distorted and 5.22-second scalogram has fewer datasets. But in a 2-second scalogram, the signal is intact and able to get more datasets to train since for localization, the need for more datasets is crucial. The number of datasets achieved from dividing 1min signal to 2 seconds for each of the 6 locations are given in Table III.

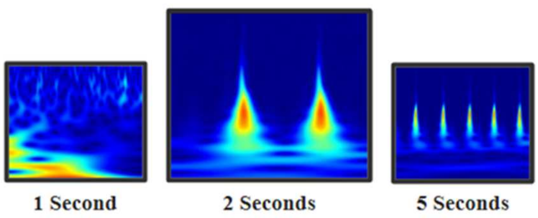

Fig 3. Segregated scalograms

TABLE II. Dataset

Parameter	Value
Number of Datasets (Detection/Localization)	4000/600
Signal Duration	1 min / 2 seconds
Epochs	5
Initial Learning Rate	0.0001
Train: Validation: Test ratios	80: 10: 10
Batch Size	12

TABLE III. Dataset of 6 Locations of MI

Name	Frequency	Samples
Inferior Lateral (IL)	56	1680
Anterior (A)	47	1410
Anterior Septal (AS)	77	2310
Inferior (I)	89	2670
Anterior Lateral (AL)	43	1290
Healthy (H)	80	2400

A. ANN Method for MI Detection

Myocardial infarction (MI) is a life-threatening medical emergency that requires prompt diagnosis and treatment. Artificial Neural Networks (ANNs) are one of the machine learning approaches that can be used for MI detection.

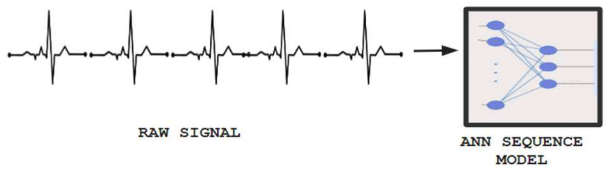

Fig 4. ANN method

To detect MI using ANNs as shown in Fig.4, the first step is to collect a dataset of electrocardiogram (ECG) 23 recordings from patients with and without MI and label them accordingly. The database is taken from PTB Database, and it is sorted. The ANN consists of an input layer that takes in the signal values, hidden layers that process the data, and an output layer that produces a binary classification result (MI or no MI). The ANN model is then trained using the data in about13 Epochs. It was found to stop since there was no more improvement in accuracy. Once the ANN is trained, it can be evaluated using a separate 10% of the ECG dataset which was divided for testing. The performance of the ANN model can be measured using metrics such as accuracy, sensitivity, and specificity. If the performance is satisfactory, the trained ANN model can be deployed to a production environment where it can be used to detect MI in real-time ECG recordings. Once the ANN is trained, it can be evaluated using a separate 10% of the ECG dataset which was divided for testing.

B. CNN Method for MI Detection

A Convolutional Neural Network (CNN) is a type of deep learning model employed for a wide range of tasks, including image classification, object detection, and various computer vision applications.The architecture of a CNN is designed to process and classify images by using layers of convolution, pooling, and fully connected layers. Here, AlexNet, GoogLeNet, and ResNet are compared and used to Detect MI. As depicted in Figure 5, the signals are transformed into scalogram images with dimensions of 227x227 using Continuous Wavelet Transform (CWT). This method is considered efficient when compared to other transforms because it retains both the frequency and time components of the signal, making it a prevalent choice for real-world applications.

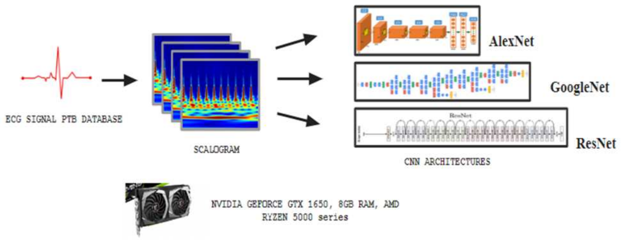

Fig 5. CNN method

The raw ECG data are collected from the database, in any conventional method the usual procedure will be to pre-process the data. But this involves tasks such as data cleaning, normalization, and data augmentation which consumes a lot of time. To avoid these complex steps, we use scalogram images as an alternative so we will get the Time-frequency component segregated as one image effortlessly. These images serve as the input for the CNN model we propose.
The CNN architecture is crucial for the classification of Images. Here, we use existing CNN architectures such as Alexnet, GoogleNet, and Resnet as a starting point and customize them according to our needs which is only to have 2 classifications at the end. This is Transfer learning, a powerful technique in deep learning where a model trained on one task is used to improve the performance of a model on a related but different task. This strategy facilitates quicker and more effective training of models, particularly when dealing with restricted datasets. Once the Convolutional Neural Network (CNN) has been constructed, the next step is to train it on the pre-processed data. The data is typically split into training, validation, and testing sets, and we utilize suitable metrics to assess the model's performance. These architectures consist of many layers such as AlexNet of 25, but GoogleNet and ResNet take a toll on computing power and demand more with 144 and 177 layers. For this method of classification, we have used the NVIDIA GEFORCE GTX 1650, 8GB RAM, RYZEN 5000 series.

C. *ANN Method for MI Localization*

Myocardial infarction localization is a task in medical image analysis that involves identifying and localizing the region of the heart affected by a myocardial infarction (MI), also known as a heart attack. To identify the region of the heart affected by myocardial infarction, a region proposal algorithm can be used. This involves selecting a set of candidate regions in the image that are likely to contain the infarction.
ANN method to classify the location as shown in Fig.6 is done by taking the signals of all 12 leads, since multi-leads are required to locate the 6 parts in heart and to find which part caused the MI. So, this ANN method is another simpler method compared to our parallel CNN model. The accuracy is so low, since the signals aren't pre-processed and there can be ambiguity in concatenating all the 12 leads together.

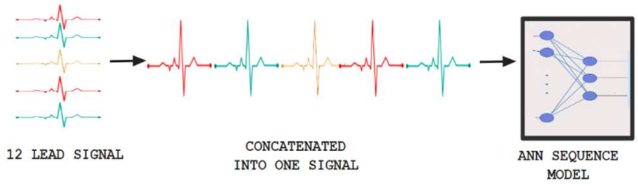

Fig 6. ANN method for MI localization

D. *Collage Method for MI Localization*

The collage method shown in Fig.7 is a technique for localizing MI that involves analysing multiple electrocardiogram (ECG) leads to identify the location of the infarcted region. This method is commonly used in clinical practice for the diagnosis and management of MI. To begin, ECG recordings are collected from multiple leads, such as standard 12-lead ECG, and converted to scalograms.

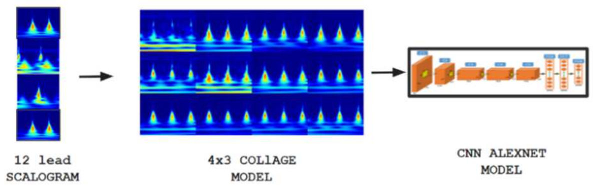

Fig 7. Collage method for MI localization

The next step is to create a "collage" of the ECG leads, which involves overlaying the ECG scalograms from different leads onto a single image. The size of a single scalogram is 227 x 227 and there are 12 leads, so 12 scalogram images for a subject. The arrangement of collage is 4x3 which give 4 columns of scalogram and 3 rows of scalogram giving final size of a collage image of 908 x 681 which is fed into CNN model. Here we used AlexNet model based on the conclusion from the comparison done in CNN method for MI detection. The collage model can be much simpler and easy to understand.

E. *Parallel CNN Method for MI Localization*

Our proposed model in Fig.8 is to have CNN which can simultaneously train and test 12 different inputs and concatenate the extracted feature which is fed to a fully connected layer and classify them for 6 different locations in the heart.
Before classifying, the datasets are prepared by an automatic sorting algorithm, where the 1min signal is taken for each 12 leads, then segregated into 2 seconds without any overlapping, then converted into scalograms which is automatically stored into the folders.

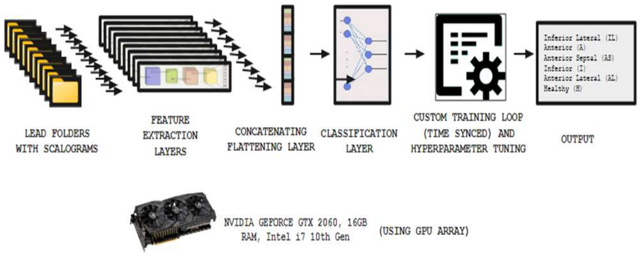

Fig 8. Parallel CNN method

There are 12 experts, each expert handles one of the 12 leads where it extracts the feature from one lead then the features are concatenated. In order to update the weights and filters parallelly, the proposal of custom training loop has allowed us to manually tune the training loop, so that whenever it randomizes the datasets after an epoch, it randomizes everything at the same kind of randomization to maintain the synchronicity. The hyperparameter set to be evaluated next is chosen using Bayesian optimization, which in turn takes into account earlier assessments. By selectively choosing parameter combinations, this method is capable of focusing on the areas of the parameter that are likely to produce the best validation scores. As a result, it typically requires fewer iterations to arrive at the optimal set of hyperparameters, as it disregards regions of the parameter space that are deemed unlikely to improve the model's performance. This can significantly reduce the number of times the model needs to be trained and validated since only those settings that are expected to lead to higher validation scores are considered for evaluation.

For these extensive computations, we have used the NVIDIA GEFORCE 2060rtx 8GB GPU Memory RTX series. According to the datasets and our model, we fine-tune our model. Fine-tuning involves tweaking the CNN architecture to improve its performance. This is done by adjusting hyperparameters, changing the optimizer, or adding regularization techniques This allows us to compare the and identify any discrepancies or abnormalities that may indicate the location of the infarcted region. The location of the infarcted region can be determined based on the location of the ECG abnormalities.

F. Parallel CNN Method on External Datasets

To validate the accuracy and generalizability of the parallel CNN method for MI localization, it is important to test the method on external datasets that were not used for training the CNNs. This process is known as external validation and is necessary to determine whether the method can accurately detect MI in a variety of settings and populations. During external validation, the ECG recordings from the external datasets are pre-processed in the same way as the training dataset. The pre-processed ECG signals are tested by feeding into the parallel CNNs to generate probability maps, which are combined to produce a final probability map indicating the likelihood of MI at each location in the heart. The accuracy of the parallel CNN method is evaluated by comparing the locations of the infarcted regions predicted by the method with the actual locations of the infarcts as determined by other diagnostic tests such as echocardiography or cardiac MRI. Here there are 6 external databases, where their properties are given in Table IV.

It is important to note that the accuracy of the method may vary depending on factors such as the quality of the ECG recordings, the size and diversity of the external datasets, and the architecture of the CNNs. Therefore, external validation should be performed on multiple datasets and the results should be carefully analysed and interpreted in conjunction with other diagnostic tools and clinical judgment.

TABLE IV. EXTERNAL DATASET

NAME	LABEL	SUBJECTS	FREQUENCY
Shaoxing and Ningbo Hospital ECG Database	JS	45,152	500hz
PTB-XL electrocardiography Database	HR	18885	500hz
PTB Diagnostic ECG Database	S	545	1000hz
China Physiological Signal Challenge in 2018	A	664	500hz
Georgia 12-Lead ECG Challenge Database	E	525	500hz

IV. RESULTS AND DISCUSSION

A. Detection Methods

In detection methods, we have trained both ANN and CNN models to compare the effectiveness over the efforts and time consumed to preprocess the datasets. After running ANN, accuracy is 97.25% and its confusion matrix is shown in Fig.9. ANN model's accuracy was exceeded by CNN model. In the CNN model where we compared three architectures; AlexNet, GoogLeNet, and ResNet with different Optimizers, Epochs. The results are shown in Tables V, VI and VII.

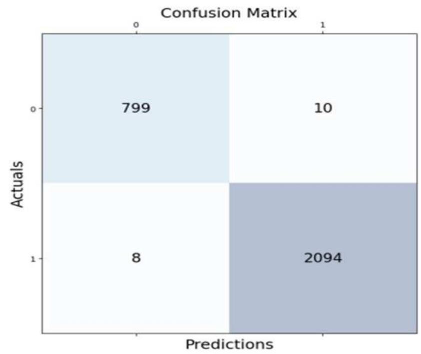

Fig 9. Confusion matrix for ANN model

The duration for ResNet is too high and requires more computational power, the architecture has not been further used in the experiments. AlexNet performance is better among the three with its accuracy of 99.66% and takes lesser duration to obtain it. GoogLeNet with 100% is not preferred due to the overfitting conditions. Overall, the performance of CNN method is better than ANN.

TABLE V. ALEXNET RESULTS

Architecture	Optimizer	Epoch	Validation	Testing	Duratior
AlexNet 25	SGDM	20	99.66%	99.32%	1.9hrs
		10	97.97%	98.78%	1hr
		5	95.93%	95.93%	29mins
	ADAM	20	98.98%	99.59%	2.3hrs
		10	96.95%	96.88%	1.1hrs
		5	97.63%	98.51%	34mins
	RMSProp	20	96.61%	97.15%	2.2hrs
		10	99.32%	98.24%	1hr
		5	95.25%%	97.29%%	32mins

TABLE VI. GOOGLENET RESULTS

Architecture	Optimizer	Epoch	Validation	Testing	Duration
GoogleNet 144 layer	SGDM	20	98.31%	99.32%	2.7hrs
		10	98.98%	98.64%	1.3hrs
		5	96.61%	96.21%%	38mins
	ADAM	20	99.32%	99.86%	2.7hrs
		10	100%	99.86%	1.3hrs
		5	98.31%	97.97%	39mins
	RMSProp	20	99.32%	99.86%	2.7hrs
		10	98.31%	99.19%	1.3hrs
		5	98.98%	99.19%	39mins

TABLE VII. RESNET RESULTS

Architecture	Optimizer	Epoch	Validation	Testing	Duration
ResNet 177 layers	SGDM	10	96.27%	97.70%	4.2hrs
		5	97.31%	98.97%	2.4hrs
	ADAM	10	98.27%	98.70%	4.3hrs
		5	97.31%	98.97%	2.6hrs
	RMSProp	10	98.27%	96.70%	4.1hrs
		5	98.97%	96.21%%	2.3hrs

Googlenet, Alexnet and Resnet performance vary because each have different layers and number of neurons vary in each layer, these architectures are optimizable for different applications and here we have concluded that GioogleNet and AlexNet are quick and provides enough accuracy compared to ResNet which requires more powerful CPU and time.

B. *Localization Methods*

Our proposed work detects MI and its occurrence in 5 different locations of the Heart as in Table VIII.

After tuning the hyper parameters, which are Initial Learning Rate, Batch Size and Dropout Rate: 0.00015,12 and 0% respectively, with a high accuracy rate of 98.78% is achieved. This model is fast in learning because it saturates at 3rd epoch to the highest accuracy rate over 98.78%. Fig 10 depicts the accuracy of each expert.

TABLE VIII. RESULTS OF LOCALIZATION METHODS

Iteration	Initial Learning Rate	Batch Size	Dropout Rate	Accuracy
29	0.00015	12	0%	98.78%
16	0.0003	12	0%	86.70%
20	0.00143	14	0%	90.00%
26	0.00295	10	15%	61.67%
6	0.519	13	49%	18.33%

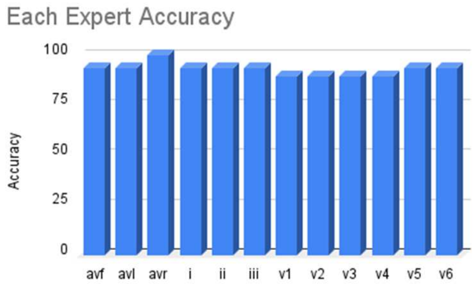

Fig 10. Accuracy of each expert

Here is the accuracy for Different locations of the Heart:

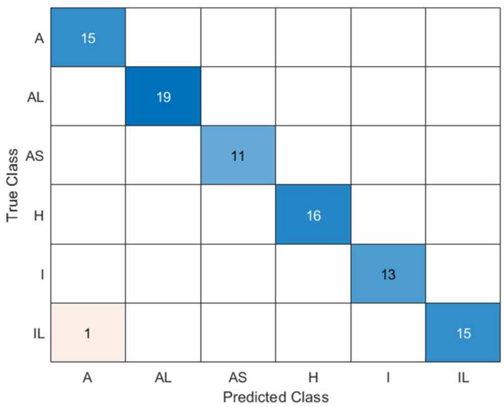

Fig 11. Accuracy for Different locations of the Heart

The proposed method is better than ANN because having a 2D representation of signals consists of more information on both time and frequency which is so effective in categorizing parallelly.

C. *External Datasets Comparison*

Using the real time dataset, that is apart from PTB database, the proposed model gives a good accuracy of 83.3%. The presented table demonstrates the applicability of this model for real-time electrocardiogram (ECG) analysis, where it gives more accuracy further with more epoch and hyper parameter tuning as shown in Table IX.

Further this model has also been compared with ANN model and collage model for MI localization but the outcomes are not what was anticipated. In ANN model, the accuracy can be achieved is 20.18% because of noise in value. Whereas in the collage model, it is slow in learning. Here it saturates to the accuracy of 95.35% at 20th epoch but in the proposed model it can attain 98.78% at 3rd epoch itself.

V. CONCLUSION AND FUTURE SCOPE

The proposed model which has been trained with only 600 datasets per class has been able to achieve greater accuracy. The key findings are this model performs better with AlexNet and GoogleNet architectures. It has higher accuracy by using scalogram method than ANN since the signals frequency and time representation are more detailed. Combination of various datasets gives different accuracy.

As a future scope, this can be improved by training the model with multiple databases to improve the accuracy for the real world. This can be tested with real ECG signals taken from patients rather than on database banks. Increasing the number of classifications can indeed add on the benefit more and its applications. Time complexity analysis of model can be done for future enhancement.

There are few limitations to overcome, like the need of more GPU memory to train entire datasets to achieve more accuracy. Memory with 2060rtx 8GB GPU Memory, 3060rtx 12GB GPU Memory, A2000rtx 24GB GPU Memory were not sufficient. By using cloud method, it is hard to get a slot frequently via Cloud GPU memory and by using Google Collab, it is limited in time.

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