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A Hybrid Detection Model for Meticulous Presaging of Heart Disease using Deep Learning: HDMPHD

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Abstract: Heart diseases that occur due to the blockage of coronary arteries, which causes heart attack, are also commonly known as myocardial infarction. Rapid detection and acute diagnosis of myocardial infarction avoid death. The electrocardiographic test or ECG signals are used to diagnosis myocardial infarction with the help of ST variations in the heart rhythm. ECG helps to detect whether the patient is normal and suffering from myocardial infarction. In blood, when the enzyme value increases, after a certain time pass occurs, heart attack. For ECG images, the manual reviewing process is a very difficult task. Due to advancements in technology, computer-aided tools and software are used to diagnosis myocardial infarction, because manual ECG requires more expertise .so that automatic detection of myocardial infarction on ECG could be done by different machine learning tools. This study detects the normal and myocardial infarction patients by selecting the feature with their feature weights by selecting from the model and by Random forest classifier selecting the index value using DenseNet-121, ResNet_50, and EfficientNet_b0 deep learning techniques .This proposed work used the real dataset from Medanta hospital (India) at the time of covid 19. The dataset is in the form of ECG images for Normal and myocardial infarction of normal and myocardial infarction detection. The accuracy achieved by the proposed model provides high performance on normal and myocardial infarction detection. The accuracy achieved by the proposed model for Efficientnet_b0 Random Forest to Select from Model Accuracy 84.244792, Precision 84.396532, Recall 84.227410, F-Measure 84.222295.

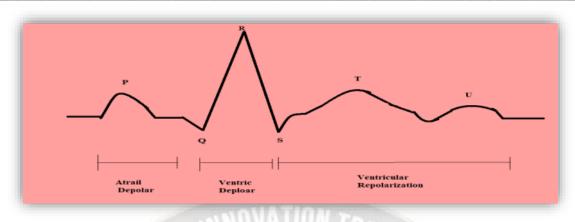
Keywords: COVID-19, deep learning, Dense_121 EfficientNet_bo, Myocardial infarction, Normal, ResNet_50.

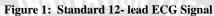
1. INTRODUCTION

Myocardial infarction is an HD brought about by the myocardial due to sufficient blood supply or even myocardial demises because of coronary artery blockage. As per measurements from the American Health Association, almost 720,000 Americans experience the suffering effects of myocardial localized necrosis every year [1]. In the beginning phase of this sickness, patients with myocardial infarction generally show symptoms like chest pain and chest uncomforted, however, a few patients have no symptoms related to heart disease shows [2,3], which makes it hard to treat at a time. Therefore, how to accomplish the early prediction and diagnosis of MI has a critical clinical

value and has turned into an exploration subject of numerous researchers. Electrocardiogram (ECG) is one of the standard measurement techniques to detect for normal and MI. [4]. In the field of ECG signal handling, numerous examination methods such as 12 lead ECG signals in which the normal and MI are analyzed by different waveforms [5]. As shown in Figure 1.1, in which the letters P, Q, R, S, T are used to represent the wave and peak valley of the ECG waveform. For a few instants, another peak is labeled with U. The upper peak is labeled with U and the heart chambers are denoted by P wave showing atria depolarization, the lower heart chamber is denoted by T wave and the QRS complex represents depolarization in ventricles [6] as shown in Figure 1.

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The remaining paper is organized as follows: In Section 2, a literature review is discussed, in Section 3 model is used in recent advancements in the proposed study domain. In Section 4Methods and Tools for Proposed methodology are obtained, for the different classification of image dataset Normal and MI .in Section 5, Results and Discussions. In Section 5, comparative work, in Section 6 conclusion results and findings conclude of the proposed work.

2. LITERATURE REVIEW

Śmigiel, Sandra et.al [1] in this paper a researcher proposed a CNN model for identifying heart disease using ECG signals. The accuracy is achieved by the selection of the entropy-based features. The model allows computing on nonspecialized devices. Ribeiro, A.H. et.al [2] in this study researcher proposed a deep neural network model, based on analysis for the detection of automatic ECG. It used 12 lead ECGs in which determine 6 types of abnormalities. The results obtained as for F1score is above 80 %, specificity over 99% Rutger R et.al [3] In this study the authors proposed a 12 lead ECG models using DNN and decreased the healthcare burden. Bigler MR et.al [4] in this proposed work with the help of CNN predicted the myocardial ischemia for computed iECG ST segments .Analyzing the ROC different score for icECG segment is 0.903±0.043Mishra, S et.al [5] this paper presented a model for ECG records to demonstrated the heart-related abnormalities.ECG signals are classified for 5 different diseases such as RBBB, LBBB, STEMI, T-wave, and normal ECG.for data preprocessing shadow removal algorithm was used and calculated DL model accuracy 97% by the 3 layers dense factor. This is the threshold value that obtained the author in their work. For ECG achieved 94 % accuracy. Han C et.al [6], this study presents an AI-based model in which demonstrates the multiple leads based on acute myocardial infarction with asynchronous ECG lead

sets the developing algorithm on smart watches. This algorithm for smart watches easily detects cardiac disorders. The author computed this algorithm for measuring at least 3 leads and compared it with ECG analysis software and less accuracy was obtained after then taking 4 leads out of 12 lead set by the following AUROC 0.845, SD 0.011; 2-lead set: AUROC 0.813, SD 0.018; single-lead sets: AUROC 0.768, SD 0.001.Dongdong Zhang et.al [7] in this study authors proposed a noninvasive approach for ECG in cardiovascular disease diagnosis. In this proposed work, DNN model for 12 lead ECG recordings which is for the classification of cardiac arrhythmias. The public dataset 12lead ECG was used. This proposed model achieves an accuracy F1score of 0.813, this model is trained on a single lead as well as 12 leads simultaneously. B Pyakillya et.al [8] in this study using 1D CNN with FCN layers, ECG classification results computed and best resulted in accuracy achieved about 86%..Baek, YS et.al [9] in this study proposed a DNN model for NSR to detect AF on 12 lead ECGs. An analysis is based on 2,412 raw digital data, training, testing, and validation were operated on AF and QRS with a ratio of 7:1:2.the following ROC values obtained 0.79 and 0.75; recall, 82% and 77%; specificity, 78% and 72%; F1 score, 75% and 74%; and overall accuracy, 72.8% and 71.2% Li D et.al [10] proposed a neural network for 12 lead ECG. Nine types of arrhythmias were demonstrated which have a GRU and inception physionet dataset used and obtained accuracy 0.928, sensitivity 0.901, and specificity 0.984 respectively. Alghamdi A et.al [11] in this study researcher a transfer learning technique using the VGG-Net which is used the parameters of fine-tuning and fixed feature extractor for obtaining the networks such as VGG-MI1 and VGG-MI2. This network model is used to select the ECG images as feature descriptors to improve the informative features. This study has used the dataset of PTB to diagnose the ECG database. It achieves accuracy, sensitivity, and specificity 99.02%, 98.76%, and 99.17%, for

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model VGG-MI1 and VGG-MI2, an accuracy of 99.22%, a sensitivity of 99.15%, and a specificity of 99.49%. Ali Haider et.al [12] proposed an approach using deep learning for single shoot detection in MobileNet v2. It is used to detect cardiovascular disease. It processes the data for processing the ECG images to find cardiac abnormalities. It computed the accuracy on 12 lead ECG-based images as 98% on show four major cardiac abnormalities. Mathur et.al [14] proposed an approach using the capsule neural network for myocardial infarction. It used medical datasets with the invention of wearable devices. Machine learning techniques such as SVM and DT are used to detect MI by the capsule neural network.

3. PROPOSED DEEP LEARNING MODELS USED

In the current proposed work, deep learning models are used to develop a hybrid model. These models are ResNet_50, densetNet_121, Efficient Net_b0 [2].

3.1 RESNET_50

The residual networks solved the vanishing gradient issued by two tricks such as batch normalization and short skip connection. It is an image model. This model calculates the residual difference by the given equation [11]:

$$H'(x) = F(x) + x....(1)$$

$$H'(x) = F(x) + x...(2)$$

$$H(x) - x = F(x)...(3)$$

$$H(x) - x = F(x)...(4)$$

The ResNet is 50 layers deep. It has 152 layer models for ImageNet and produces 3.57% top 5 errors. It trains 20 layers for that the training error was low but the test error was high, and this generates overfitting problems [12]. This is for known problems .For the unknown problems, the training error was high and the test error was high. It means the deeper networks with more layers are very difficult to train [8]. As shown in Figure 2, their feature weight summary

| Layer (type) | Output Shape | Param # | Connected to |
|-------------------------------|----------------------|---------|------------------|
| input_10 (InputLayer) | [(None, 224, 224, 3) | 0 | |
| conv1_pad (ZeroPadding2D) | (None, 230, 230, 3) | 0 | input_10[0][0] |
| conv1_conv (Conv2D) | (None, 112, 112, 64) | 9472 | conv1_pad[0][0] |
| conv1_bn (BatchNormalization) | (None, 112, 112, 64) | 256 | conv1_conv[0][0] |
| conv1_relu (Activation) | (None, 112, 112, 64) | 0 | conv1_bn[0][0] |
| pool1_pad (ZeroPadding2D) | (None, 114, 114, 64) | 0 | conv1_relu[0][0] |
| pool1_pool (MaxPooling2D) | (None, 56, 56, 64) | 0 | pool1_pad[0][0] |
| conv2_block1_1_conv (Conv2D) | (None, 56, 56, 64) | 4160 | pool1_pool[0][0] |
| | | | |

Figure 2: ResNet _50 weight Results

3.2 DENSENET_121

DenseNet is an idea of extremity. The core idea of DenseNet is reusing the feature. The main difference is that it requires fewer parameters required [10]. In DenseNet, there is no need to learn redundant feature maps. DenseNet concatenates the incoming feature maps. The problem in DenseNet due to the concatenate may result in an explosion [12].The equation used for DenseNet is:

xl = Hl([x0, x1, x2 xl - 1]).....(5)

DenseNets are divided into Dense Blocks in which feature map dimensions remain constant within a block. The number of filters changes in between them. In filters, various layers are developed, called transition layers [11] as shown in Figure 3.

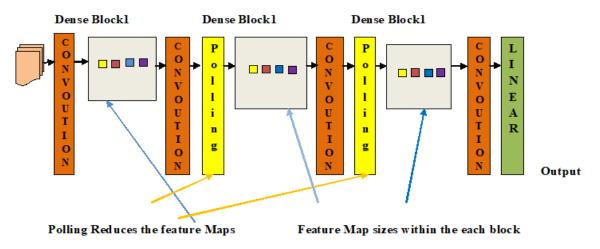


Figure 3:DenseNet 121 Architecture

3.3 EFFICIENT NET_B0

It is a CNN. For Efficient Net, all dimensions with depth/width/resolution are scaled using a compound coefficient. The major idea behind the efficient net is to efficiently scale up the size of CNN.In efficient Net, design a Convnet based on the width, depth, and image input resolution of layers or to combine the different layers combinations [2]. It is the most prominent CNN that is used to classify the images. With the help of an efficient net

containing hundreds and thousands of images could be labeled. It has 237 layers. It works on the idea of compound scaling dimensions such as width, depth resolution. Efficient Net based on the baseline network that optimizes the accuracy and efficiency measured by the FLOPS basis (floating-point operations per second) [10]. It uses MBConvto scale up the baseline network efficiently obtain the family of deep learning models called Efficient Net, as shown in Figure 4.

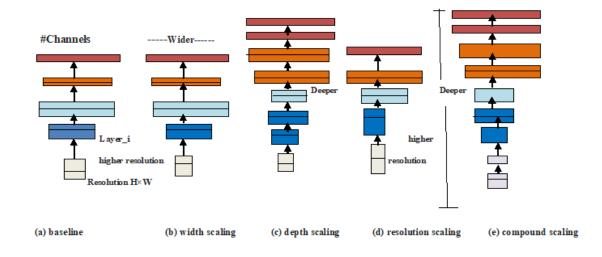
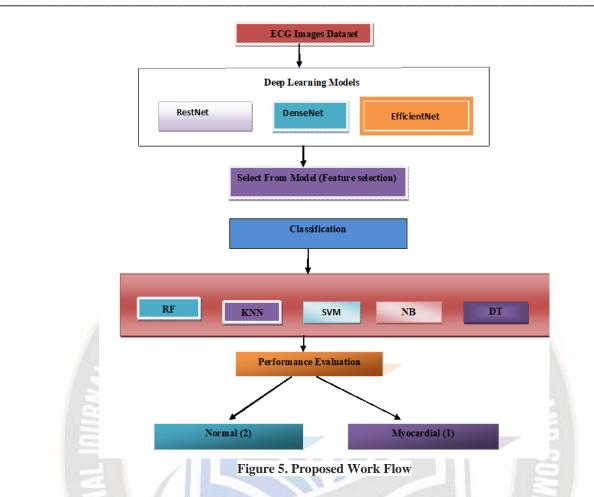


Figure 4: EfficientNet_b0 Framework

4. METHODS AND TOOLS

The proposed work dataset has collected from Medanta hospital at the time of covid 19. The dataset is for normal and myocardial infarction .This proposed implementation is worked on a real dataset. In normal and MI we have 960 samples of images. The research workflow as flow: As Shown in Figure 5 .Step 1: Dataset label id represents the normal and myocardial infarction, if there is no disease; value label for normal is 2 and for MI is labeled as 1.

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4.1 FEATURE SELECTION

In this study, the feature selection method is used with a deep learning model to select the relevant features from the dataset. Select from the model is used for selecting the features which are based on feature importance. Features, mean columns and 105 selected columns are those that have significant values for all 960 images that can lead to better accuracy. Feature selection using Random forest comes under the category of embedded methods. Random Forest is a machine learning algorithm that gives better predictive performance analysis. Feature importance is shown by a random forest classifier to identify features that have an importance of more than 0.002 (threshold value) with the use of Gini Criterion and correlation to select from model. The number of features before transformation is 2000 which is extracted by deep learning Model DenseNet, ResNet, Efficient Net, then after that the transformation of features is selected 105.The Gini index is computed by the following formula.

Gini Index = $1 - \sum_{i=1}^{C} (pi) = \dots \dots \dots \dots \dots (6)$

The Gini index is computed by subtracting the sum of squared probabilities for one class. Favorably used for larger partitions.

Different types of performance metrics are used to evaluate the results, which are as follows:-

ACCURACY

It measures on the basis of correct predictions and the total number of predictions.

$$Accuracy = \frac{Accurate_Predictions}{Number_no_Predictions}$$
(7)

PRECISION

Precision is referred to as the prediction value is positive. It is computed as:

$$Precision = \frac{True_pos}{True_pos+False_pos}.....(8)$$

RECALL

True positive rate is calculated as recall by the following formula:

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$$\operatorname{Recall} = \frac{\operatorname{True_Pos}}{\operatorname{True_Pos+False_Neg}}....(9)$$

F-MEASURE

It is calculated based on precision and recalled the weighted harmonic mean by the given formula:

4.2 DATASET

The given sample dataset is used for the hybrid approach. This sample dataset for a normal and myocardial dataset in the form of image signals used for individual patients. The total dataset has 960 samples of ECG signals for Normal and Myocardial.

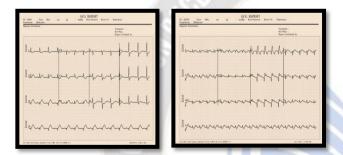


Figure 6: Sample Dataset for MI

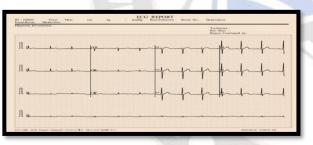


Figure 7: Sample Dataset for Normal

5. RESULTS AND DISCUSSIONS

In this study, the collected dataset contains 960 samples of Normal and Myocardial Infarction ECG records. It is the real data collected at the time of covid-19. We split the ECG image dataset into training and testing sets. Training gives the actual results and the testing set validates the data as shown by table 1 to table 4.

| Table 1: ResNet | _50 Results |
|-----------------|-------------|
|-----------------|-------------|

| Proposed | Accuracy | Precision | Recall | F- |
|------------|----------|-----------|--------|---------|
| Classifier | | | | measure |

| RF | 76.432292 | 77.318049 | 76.384857 | 76.217418 |
|-----|-----------|-----------|-----------|-----------|
| CNN | 66.276042 | 67.613101 | 66.346336 | 65.682521 |
| SVM | 56.510417 | 64.796407 | 56.703198 | 49.733098 |
| NB | 64.713542 | 67.451856 | 64.608822 | 63.174592 |
| DT | 71.875000 | 72.111029 | 71.847110 | 71.782380 |

In Table 1, when the dataset is trained using the DL model, the ResNet_50 gives the results as in terms of accuracy is 76.432292.

| Table 2:DenseNet | _121 | Results |
|------------------|------|---------|
|------------------|------|---------|

| Proposed | Accuracy | Precision | Recall | F- |
|------------|-----------|-----------|-----------|-----------|
| Classifier | 0 | | | measure |
| RF | 62.239583 | 65.944792 | 62.363345 | 60.044777 |
| KNN | 57.552083 | 60.316882 | 57.683856 | 54.722222 |
| SVM | 52.343750 | 53.039452 | 52.457749 | 50.008181 |
| NB | 52.734375 | 64.677760 | 52.967067 | 41.128050 |
| DT | 66.796875 | 68.349253 | 66.871253 | 66.139615 |

In Table 2, when the dataset is trained using the DL model, the DenseNet_121 gives the results as in terms of accuracy is 62.239583.

Table 3: Efficient Net_b0 Results

| Proposed | Accuracy | Precision | Recall | F- |
|------------|-----------|-----------|-----------|-----------|
| Classifier | | | | measure |
| RF | 82.031250 | 82.032013 | 82.029406 | 82.030153 |
| KNN | 60.286458 | 60.822953 | 60.341671 | 59.861751 |
| SVM | 61.588542 | 61.865186 | 61.546130 | 61.311409 |
| NB | 68.750000 | 70.281018 | 68.677264 | 68.095492 |
| DT | 81.770833 | 81.767626 | 81.767626 | 81.768855 |

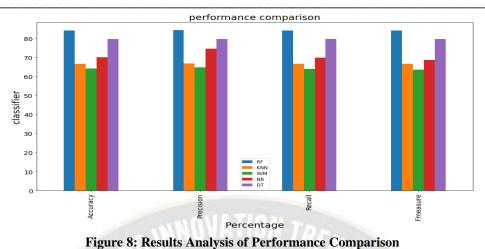
In Table 3, when the dataset is trained using the DL model, the Efficient Net_b0 gives the results in terms of accuracy is 82.031250.

| Table 4: | Hybrid | EfficientNet_ | _b0 with | Feature | selection |
|----------|--------|---------------|----------|---------|-----------|
|----------|--------|---------------|----------|---------|-----------|

| Proposed | Accuracy | Precision | Recall | F- |
|------------|-----------|-----------|-----------|-----------|
| Classifier | | | | measure |
| RF | 84.244792 | 84.396532 | 84.227410 | 84.222295 |
| KNN | 66.796875 | 66.885399 | 66.814285 | 66.767069 |
| SVM | 64.192708 | 64.934604 | 64.132735 | 63.682823 |
| NB | 70.182292 | 74.750140 | 70.069582 | 68.664957 |
| DT | 79.687500 | 79.690680 | 79.684236 | 79.685296 |

In Table 4, when the dataset is trained using the DL model, the Hybrid EfficientNet with feature selection gives the results in terms of accuracy is 84.244792.Shown in Figure 7-10

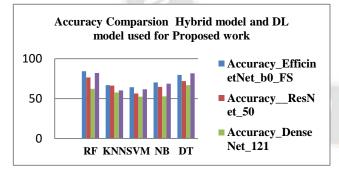
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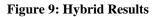


The graph shows the results for Random Forest giving better outcomes as their performance metrics.

| Propos ed Classifi er | Accuracy - EfficinetN et_b0_FS | Accurac yRes Net_50 | Accuracy - DenseNet _121 | Accuracy_ EfficinetNet _b0 |
|--------------------------------|---|-----------------------------|-----------------------------------|----------------------------------|
| RF | 84. <mark>2</mark> 44792 | 76.4322 92 | 62.239583 | 82.031250 |
| KNN | 66 <mark>.</mark> 796875 | 66.2760 42 | 57.55 <mark>2083</mark> | 60.286458 |
| SVM | 64 <mark>.</mark> 192708 | 56.5104 1 <mark>7</mark> | 52.343750 | 61.588542 |
| NB | 70.182292 | 64.7135 42 | 52.734375 | 68.750000 |
| DT | 79.687500 | 71.8750 00 | 66.796875 | 81.770833 |

Table 5: Average Accuracy Results





As shown in Table 5, the best resultant value is showing. Different index values with their label id, results are shown in graphical form. According to the label id, actual represents normal and prediction shows myocardial infarction. Accuracy of the results check by below-given results. Label: Actual: 1 Pred: 2, shows that the patient is suffering from MI but disease prediction is normal.



Label: Actual: 1 Pred: 1, Shows that the patient is suffering from MI, the disease prediction is also MI.



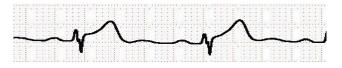
Label: Actual: 2 Pred: 2, Shows that patients are Normal, disease prediction is Normal.



Label: Actual: 2 Pred: 1, Shows that the patient is normal but the disease prediction is MI. Figure 13: Weight Summary Results EfficientNet_b0



Label: Actual: 2 Pred: 2, Shows that patients are Normal, disease prediction is Normal.



Label: Actual: 2 Pred: 2 Shows that patients are normal, disease prediction is Normal.

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Label: Actual: 2 Pred: 1 Shows that the patient is Normal but disease prediction is MI.



Label: Actual: 2 Pred: 2 Shows that patients are Normal, disease prediction is Normal.

| | | A |
|--|--|---|
| | | |

Implementing the results using Deep learning model ResNet_50, DenseNet_121, EfficientNet_b0 after applying the algorithm selected from model Feature selection method with random forest. The Efficient Net gives the best accuracy in the image dataset (Normal and MI) according to their width, depth, and image input resolution of layers. Selecting the index value according to the featured ECG image easily predicts who are affected by myocardial infarction and others are normal as shown by the results outcomes.

5. COMPARISON ANALYSIS

In the below table, the Work showed done by existing researchers using Different models and methods. With the help of previous studies we shown by work accuracy and model approaches as shown by table 6.

| Table 6: Comparative Work An | nalysis |
|-------------------------------------|---------|
|-------------------------------------|---------|

| AUTHOR | SOURCE DATA | CLASSIFIER | ACCURACY |
|---|-----------------------|-----------------------------|---|
| Smigiel, Sandra et.al [1] (2021) | ECG Images Dataset | NN Model | Entropy- Based Features |
| Ribeiro, A.H. et.al [2] (2020) | ECG Images Dataset | eep Neural Network Model | F1score= 80 %, Specificity Over 99% |
| Bigler MR et.al [4] (2021) | ECG Images Dataset | NN Model | ROC Obtained Score 0.903±0.043 |

| | Mishra, S et.al [5] (2021) | ECG Images Dataset | L Model | Accuracy 97% By the 3 Layer Dense |
|----|------------------------------------|---------------------------|--|---|
| | | | | Factor, ECG Achieved 94 % |
| | Han C | ECC Image | I-Based Model | Accuracy AUROC 0.845, |
| 0 | et.al [6] (2021) | ECG Images Dataset | r-Based Model | SD 0.011; 2-Lead Sets: AUROC 0.813, SD 0.018; Single-Lead Sets: AUROC 0.768, |
| | | | - | SD 0.001. |
| | Dongdong Zhang et.al [7] | ECG Images Dataset ECG | NN Model For 12 Lead ECG ecordings | Accuracy F1score Of 0.813 |
| | (2021) | | | |
| | B Pyakillya et.al [8] (2017) | ECG Images Dataset | NN | Accuracy 86%. |
| | Baek, YS | ECG Images | NN Model For | ROC Value |
| | et.al [9] | Dataset | SR | Obtained 0.79 |
| | (2021) | | | and 0.75; Recall, |
| 1 | | | | 82% and 77%; |
| | | 500 | | Specificity, |
| | | | | 78% and 72%; |
| | | | 3 | F1 Score, |
| 2 | | | | 75% and |
| | 1 100 | | | 74%; and |
| | | | | Overall |
| 9 | 1 | | | Accuracy, |
| 1. | | | | 72.8% |
| | | 12 | | and 71.2% |
| | Li D | ECG Images | eural Network | Accuracy 0.928, |
| | et.al | Dataset | 1.1 | Sensitivity 0.901 |
| | [10] (2020) | | | Specificity 0.984 |
| | Alghamdi | ECG Images | ransfer Learning | Accuracy, |
| | , A et.al | Dataset | Technique | sensitivity, |
| - | [11] (2020) | 1 | Using | And Specificity |
| | | | ne VGG-Net | 99.02%, 98.76%, |
| | | | | And 99.17%, |
| | | | | For Model |
| | | | | VGG-MI1 |
| | Ali Haider | ECG Images | NN Mobilenet | Accuracy |
| | et.al [12] | Dataset | 2. | On 12 Lead |
| | (2019) | | | ECG Based |
| | | | | Images As |
| | | | | 98 % |
| | | I | 1 | L] |

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| Mathur | ECG Images | VM And DT | Capsule |
|------------|------------|--------------|------------------|
| et.al [14] | Dataset | | Neural |
| (2021) | | | Network |
| | | | For |
| | | | Myocardial |
| | | | Infarction |
| Our Work | Real ECG | eep Learning | Efficientne |
| | Images | lodels , | t_ |
| | Dataset | F,SVM,KNN, | b0 |
| | | NB,DT | Random |
| | | | Forest |
| | | | With Select |
| | | | From |
| | | 100 | Model |
| | | 1 A 100 | Accuracy |
| | | 138 1 | 84.244792, |
| | 1100 | SY 1 | Precision |
| | 6 | 1 (A) | 84.396532, |
| | | | Recall |
| | 5 | 11- | 84.227410, |
| | 1 | | F-Measure |
| | 12 | 100 | 84.222295. |

6. CONCLUSION

This paper proposed a hybrid method for heart disease based on the deep learning model combined with select-from-from-model embedded feature selection method. The Efficient Net_b0 method of DL according to width, height, and resolution of the dataset, data are standardized to obtain the best results. To the performance of a network is enhanced, the weights are considered as input and output for the ECG image dataset. Efficient net_b0 with Random forest feature selection (selected from a model) embedded method shows the high accuracy prediction for the hybrid model of heart disease. The experimental proposed model obtains accuracy 84.244792, Precision 84.396532, Recall 84.227410, F-measure 84.222295. Therefore that according to this proposed study. This hybrid approach proves that the deep learning model gives a higher rate of classification accuracy and they are feasible, reliable for predicting normal and myocardial infarction. The testing and training are implemented using each model of deep learning.. The best method is EfficientNet_b0 in terms of accuracy rate .In future this continues this hybrid approach to adjust the parameters of deep learning and provide each value as a column name labeled value as well as other different deep learning optimization techniques could be used for better performance outcomes.

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