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A hybrid fine-tuned optimizer for enhancing ECG data security in heart attack detection systems

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Abstract

Accurate analysis of ECG data is necessary for effective heart attack detection. The InRes-106 model, a hybrid fine-tuned optimizer that improves ECG data security and detection, is presented in this study. It blends deep learning models like ResNet50 and InceptionV3 with sophisticated image processing techniques like artifact removal and Histogram Equalization (HE). The study assesses five pre-trained models: VGG19, DenseNet201, MobileNetV2, and ResNet50 after pre-processing ECG images to enhance quality and remove artifacts before putting out the innovative InRes-106 model. With a

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remarkable 98.34% accuracy, this model establishes a new standard for heart attack detection and demonstrates improvements in cardiac care.

Subject Classification: *92B05, 92C20, 92C55.*

Keywords: *Data security, Coronary heart disease (CHD), Electrocardiogram (ECG), Heart attack detection.*

1. Introduction

Artifact removal and detailed picture augmentation are required for deep learning model optimization for ECG data security. The study uses sophisticated processing methods to enhance cardiac imaging datasets before model training [1]. This includes cleaning ECG images through background line removal and automated cropping to eliminate extraneous text. Histogram Equalization (HE) is then used to adjust brightness and contrast, improving image clarity [2]. The study assesses two approaches: first, it trains five deep learning models for COVID-19 detection on chest X-rays (InceptionV3, ResNet50, MobileNetV2, VGG19, DenseNet201). Secondly, it incorporates InceptionV3 and ResNet50 into InRes-106, a hybrid DCNN model, to improve detection performance and accuracy [3][4].

Using five classes Abnormal Heartbeat (AHB), Normal Heartbeat (NHB), High Myocardial Infarction (HMI), and Myocardial Infarction (MI) [5], and COVID-19—the dataset used consists of 1,932 paper-based ECG pictures [6][7]. The 3-channel EDAN SE-3 series electrocardiograph was used to take these pictures, which then underwent extensive pre-processing to remove artifacts and enhance contrast [8]. The goal of an ablation analysis is to improve image quality through Histogram Equalization (HE) and artifact removal by comparing InRes-106 with other deep learning models to improve ECG data security and heart attack diagnosis accuracy. In addition to the novel hybrid model InRes-106 [9], the evaluation of other pre-trained models offers important insights into refining deep learning techniques for medical image analysis. Improved diagnostic precision [10], fewer false positives and negatives, and better patient outcomes in critical cardiac care are all possible benefits of this work [11].

2. Related Work

IoT and machine learning have been the subject of much research over the last 10 years, especially for their potential use in the diagnosis and treatment of circulatory disorders such as coronary heart disease (CHD) [12]. This section summarizes important research that has been done to enhance the speed and accuracy of CHD detection. [13] has out one of the first research in this field, suggesting that heart problems might be remotely monitored and diagnosed using IoT [14]. Heart rate and blood pressure readings were obtained using wearable technology, and machine learning was used to analyze the data remotely to identify CHD. IoT's potential for remote monitoring was emphasized in the study, although transfer learning was not examined. Based on these results, [15][13] suggested diagnosing CHD using ECG data by fine-tuning the network with patient-specific readings by transfer learning using a pre-trained deep neural network. Compared to conventional models, this approach increased detection accuracy. In the same way, [16] created an Internet of Things system to track vital signs and recognize signals of cardiac disease using wearable electronics and deep learning. The study [17] indicated diagnosing coronary heart disease (CHD) with a hybrid transfer learning approach in conjunction with personal gadgets and mobile health apps [18]. Patient-specific data from personal monitors was used to fine-tune a strong artificial neural network that has been fine-tuned from a large database of generic health information. While the hybrid technique performed faster and more accurately than standard models, it was plagued by uneven data protocols and increased security risks. For IoT-based CHD detection, future research should improve data security and create common protocols.

3. Methodology

Artifact elimination and picture augmentation were necessary for deep learning model optimization. ECG pictures were cleaned, extraneous text and background lines were eliminated, and HE enhancement was used to adjust contrast and brightness. After testing five deep learning models, an InRes-106 hybrid architecture that included ResNet50 and InceptionV3 was examined. Performance was assessed by ablation research.

3.1 *Data collection*

A dataset of 1,932 paper-based ECG pictures, divided into five groups (COVID-19, MI, HMI, NHB, and AHB), was employed in the study. Using the 3-channel EDAN SE-3, it contains 859 NHB, 203 HMI, 74 MI, and 546

AHB pictures from 12-lead ECGs. Twelve leads containing P waves, QRS complexes, and T waves (I, II, III, aVF, aVR, aVL, V1, V2, V3, V4, V5, V6) are present in each image. The analysis is made more difficult by labels and background lines.

3.2 *Image Pre-processing*

Pre-processing of ECG pictures is essential to eliminate artifacts and noise that can impair model performance. To reduce artifacts and improve image quality, this work uses contour recognition, Non-Local Means (NLM), Gaussian blur, morphological opening, and cropping filtering to increase accuracy. By further refining the pictures, Histogram Equalization (HE) greatly improves the model's classification performance.

3.3 *Artifact removal*

The process is split into two stages: graph line removal and label removal. This is because the ECG pictures include unnecessary labels and graph lines.

a) Removal of Labels: ECG pictures with labels removed are automatically cropped to 2058 × 1210 pixels from 2213 × 1572 pixels. This technique can be used with other datasets that have comparable problems and maintain important details.
b) Graph line removal: ECG pictures are cropped and converted to binary via Otsu thresholding. After morphological opening and a (2, 2) kernel are used to eliminate the background lines, NLM filtering and Gaussian blur are used to reduce noise. After separating tiny contours, parameters are adjusted by trial and error.

3.4 *Image Enhancement*

Histogram Equalization (HE) is used to correct brightness and contrast in the pre-processed ECG pictures after artifact removal. By improving image contrast, smoothing pixel values, and remapping brightness values, this method recovers lost contrast.

3.5 *Assurance of image quality*

The algorithms utilized can have an impact on image quality, which is why MSE, SSIM, PSNR, and RMSE are computed for assessment. MSE scores above 0.5 indicate high-quality photos; the range is 0 to 1. Higher scores on the SSIM scale, which ranges from -1 to 1, suggest greater similarity. For 8-bit pictures, the PSNR should be between 30 and 50 dB; values less than 20 dB are regarded as subpar. Minimal variations between the original and processed images are indicated by lower RMSE values.

3.6 *Proposed Model*

In this study, two methods are assessed. Using five different deep learning models such as DenseNet201, MobileNetV2, VGG19, ResNet50, and InceptionV3 is the first method. To improve performance, the second method combines two models, InceptionV3 and ResNet50, into a single deep learning framework. The dataset has two sections: testing and training subsets before the model is prepared.

3.6.1 Dataset Split

Pre-processed 1,351 photos are used for training, 384 for validation, and 197 for testing, making up the training (70%), validation (20%), and testing (10%) sets of the dataset. These photos' IDs are accessible on GitHub.

3.6.2 First Approach

This method involves training and evaluating five previously trained models such as DenseNet201, MobileNetV2, VGG19, ResNet50, and InceptionV3 to see how well they perform in terms of accuracy.

3.6.3 Second Approach

The proposed InRes-106 model improves ECG data security for heart attack warning systems by fusing ResNet50 and InceptionV3 into a single DCNN architecture. It is highly accurate at detecting complicated visual patterns and has been fine-tuned for automated feature extraction. Activation functions, hyperparameters, loss functions, and other settings of the model are optimized through an ablation study employing the batch-sized Adam optimizer of 32, ReLU activation, classification cross-entropy loss, along with a 0.001 learning rate, and up to 160 epochs.

3.6.4 Base Model

The base model has 4 blocks, one average pooling layer along with one fully connected layer, and a 224 × 224 input size. After three convolutional layers (32 channels, 2 × 2 kernel), Block 1 incorporates max-pooling. It has 30 layers between the ResNet block and six convolutional layers in the Inception block, Block 2 combines InceptionV3 with ResNet50. Three ResNet layers and five Inception layers are added in Block 3, for a total of 45 layers. Block 4 features max-pooling and 28 ResNet layers. With an FC layer and average pooling at the end, the model generates five output channels for classification.

3.6.5 Ablation Study

The performance of the CNN model differs for each dataset and can be enhanced by modifying its hyperparameters. Ablation experiments investigate various configurations that could affect performance in a favorable, negative, or neutral way. Ten instances are used in this study to adjust a variety of factors, including filter sizes and learning rates, to improve accuracy and control computing costs.

3.6.6 Proposed Model Architecture

The activation functions, and the residual scaling factor (RSF) among ResNet50 and InceptionV3 blocks, filter sizes, average pooling layers, loss functions, flatten layers, learning rate, optimizer, and batch size were among the parameters that were adjusted in ten ablation studies to optimize the InRes-106 model. To stabilize training, the RSF was set between 0.1 and 0.3. Comparing activation functions, Parametric ReLU (PReLU) testing was conducted in addition to ReLU testing. PReLU has the potential to outperform ordinary ReLU by providing a trainable multiplier for negative inputs. The following is the formula for the PReLU function.

$$A_i = \begin{Bmatrix} B_i, & \text{if } B_i \geq 0 \\ K_i B_i, & \text{if } B_i < 0 \end{Bmatrix} \tag{1}$$

Here, *Ki* represents a learnable scaling parameter, while the other variables are trainable parameters. The starting value is 0.1 and is made trainable, allowing it to be modernized throughout the training iterations. The below Figure 1 shows the suggested architecture for the model.

A consistent structure consisting of 106 layers and 4 blocks is shared by the base model and the suggested model for improving ECG data security. Each layer is comprised of three blocks: one ResNet, one trainable RSF parameter, and one Inception block. An Inception block, a map of features, an RSF value, a ResNet block a PReLU initiation stage (which substitutes ReLU for PReLU), and another feature map make up each

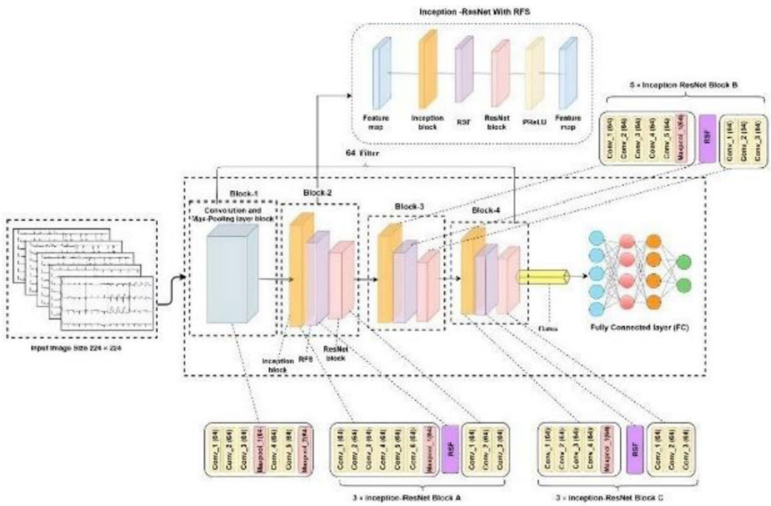


Figure 1

Proposed model architecture

block. A flattened layer linked to the fully connected (FC) layer takes the place of the average pooling layer, and 64 filters are used in all convolutional layers.

4. Results

4.1 *Evaluation metrics*

The classification models in this study were assessed using a range of measures, such as the F1-score, accuracy, recall, mean absolute error (MAE), root mean square error (RMSE), specificity, and false positive and negative rates (FPR and FNR, respectively). The values of false negative (FN), false positive (FP), true positive (TP), and true negative (TN) were used to generate the performance measures using the corresponding equations. The total number of observations is represented by n in the MAE and RMSE calculations, and the predicted value of y is indicated by yP.

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

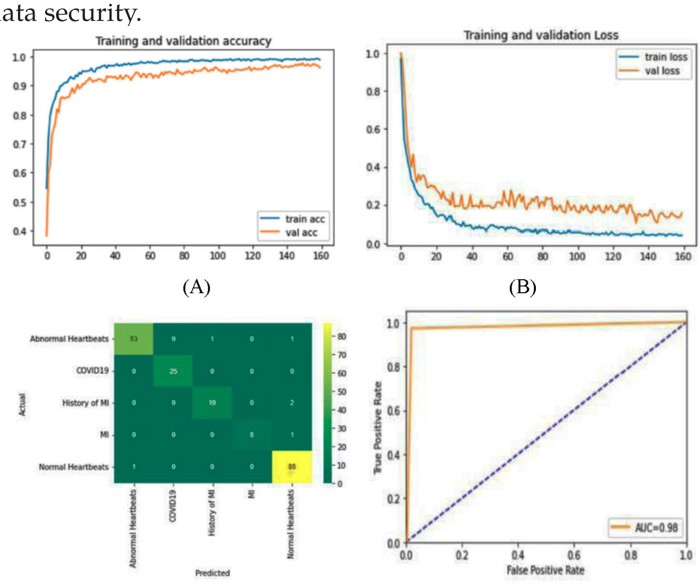
$$Specificity = \frac{TN}{TN+FN} \tag{3}$$

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

$$F1\ score = 2\frac{Precision \times recall}{Precision \times recall} \tag{5}$$

4.2 *The Deep Learning Models' Outcomes and Analysis*

Performance metrics with the use of Adam optimizer, with a 0. 001 learning rate are given for five deep learning models in Table 1. Out of all the tests that have been done, it had the highest testing accuracy of 90. The F-score of the proposed approach was 90% while the accuracy was 56%, the test set accuracy of 77% and the validation accuracy of 88. 45%, InceptionV3 was in the lead. With a testing with 89.63% accuracy and 89.32% F1-score, ResNet50 came in second. DenseNet201, VGG19, and MobileNetV2 all did marginally worse. These findings led to the application of the InRes-106 DCNN model to improve the detection of ECG data security.



(A) (B)

(C) (D)

Figure 2

Illustrates the effectiveness of the proposed InRes-106 model:(A) Training and validation accuracy and (B) loss curves using the Adam optimizer with compression proportional to a 0. 0007 learning rate across 160 epochs; (C) Confusion matrix and (D) The ROC curve displaying the best outcomes during the ablation research

Table 1

Analysis of the models for deep learning performance outcomes using the already-processed data set.

Models	Precision	F1- score	Specificity	Recall
InceptionV3	90.86	90.54	90.68	90.18
ResNet50	89.7	89.32	89.19	89.31
DenseNet201	85.23	82.90	93.59	81.67
VGG19	81.23	80.37	87.63	79.12
MobileNetV2	78.72	78.23	78.94	77.89

4.3 *Findings and Evaluation of the Optimal Model*

4.3.1 Optimization Model's Performance Assessment Matrix

Classification accuracy increased from 95.59% to 98.34% after ten ablation trials through parameter optimization, including filter number, size, pooling layers, and learning rates. The InRes-106 model yielded the following results: 96.91% sensitivity, 98.01% specificity, 98.34% accuracy, 97.74% precision, 96.14% F1-score, 0.98% FPR, 5.74% FNR, and 2.26% FDR. These findings show that InRes-106 outperforms other deep learning models in terms of performance as shown in Table 2.

Table 2

Effectiveness assessment matrix of the optimal setup for the suggested model.

Evaluation of the Optimal Configuration's Performance							
Accuracy	**Precision**	**Specificity**	**Sensitivity**	**FPR**	**FNR**	**FDR**	**F1-Score**
98.34	97.74	98.01	96.91	0.98	5.74	2.26	96.14

4.3.2 The Optimum Model's Statistical Analysis

The preprocessed dataset's statistical analysis, which includes the Wilcoxon signed-rank test, MAE, RMSE, SD, and KC, is displayed in Table 3. With a KC score of 97.604%, Cohen demonstrates almost perfect agreement. The higher performance of InRes-106 is confirmed by the Wilcoxon signed-rank test, which reveals substantial differences ($p < 0.005$) between InRes-106 and other models. Comparisons with InceptionV3 and ResNet50 yield p-values of 0.004.

Table 3

Analysis of statistical data of the ideal setup of the suggested model.

Evaluation of the Best Suggested Models Statistical Results				
SD	**MCC**	**KC**	**MAE**	**RMSE**
0.956	95.40	97.604	2.89	11.62

4.3.3 Evaluation of the Optimum Models Performance

Accuracy curves for training and validation, loss curves, ROC curves, and confusion matrix are examples of evaluation metrics. Figures 2A and 2B's learning and loss curves demonstrate smooth convergence devoid of overfitting. The confusion matrix in Figure 2C shows balanced performance in all five classes, and the ROC curve in Figure 2D, with an AUC of 98.37%, shows good class discrimination.

4.3.2 K-Fold Cross Validation

The K-fold cross-validation was utilized to evaluate the model efficacy using the ECG dataset. Testing accuracies were 99.33% to 99.45% at varying folds; the maximum accuracy of 99.45% was obtained using seven-fold cross-validation. This demonstrates the stability and reliability of the model's operation as shown in Figure 3.

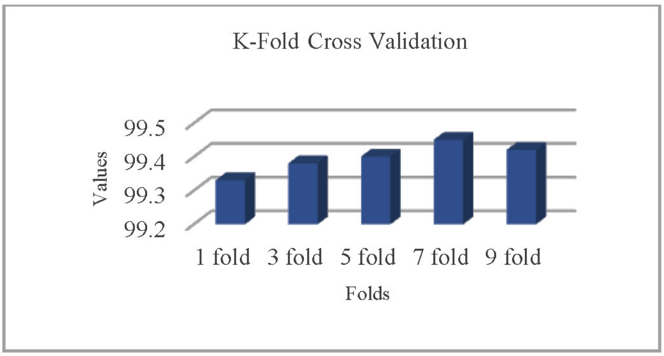


Figure 3

Results of K-fold cross-validation.

4.3 *Comparative Analysis*

Table 4 shows the comparative study of the suggested model results with other existing studies.

Table 4
Comparative study of the proposed model results with the other existing study.

Reference	Model	Accuracy
Irmak [19]	CNN model Encouraged in VGG-16 model	Binary class: COVID-19 vs. MI: 96.74% Binary class: COVID-19 vs. AHB: 93.20% Multi-class: COVID-19 vs. ABH vs. MI: 86.55%
Proposed work	InRes-106	98.34%
T. Anwar and S. Zakir [20]	EfficientNet B3	The percentages were 81.8% before and 76.40% post-application of augmentation procedures.

Using a VGG-16-based CNN, Irmak (2022) obtained an accuracy of 93.20% for COVID-19 vs. AHB, 96.74% for COVID-19 vs. MI, and 86.55% for multi-class classification. With EfficientNet B3, Anwar and Zakir [20] reported 81.8% accuracy before augmentation and 76.40% accuracy after. The accuracy of 98.34% was much greater for the proposed InRes-106 model in comparison.

5. Discussion

Metrics including the F1-score, RMSE, FPR, FNR, accuracy, recall, and specificity were used to assess the models. With a testing accuracy of 90.56%, InceptionV3 outperformed DenseNet201, ResNet50, MobileNetV2, and VGG19. The better ECG data security of the InRes-106 hybrid DCNN, which demonstrated 98.34% accuracy and high sensitivity (96.91%), specificity (98.01%), and precision (97.74%), led to its selection. With an AUC of 98.37% and strong K-fold cross-validation accuracies (99.33%–99.45%), it fared well in ablation investigations. When it comes to heart attack detection, InRes-106 provides better ECG image categorization and data security than other models.

6. Conclusion

The InRes-106 model greatly enhances ECG image categorization and heart attack detection by fusing InceptionV3 with ResNet50. Image artifacts and quality concerns are successfully handled by its hybrid design and extensive pre-processing. It demonstrates improved sensitivity, specificity, and accuracy over earlier techniques, establishing a new standard for deep learning in the security of ECG data and advancing medical picture analysis.

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