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Post covid effect on heart after recovery based on Convolution Neural Networks with multilevel classification using ECG Images

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Abstract

The first global pandemic in a century is coronavirus was originated in Wuhan, China. Coronavirus is associated to Coronaviridae family together with subfamily coronavirinae and it is the third infection of coronaviruses (CoVs) between human. On outer surface of the virus there is a crown like spikes thereby referred to as corona virus. A greatly contagious and dangerous virus known as COVID-19 is caused due to severe acute respiratory syndrome that is disseminated across the globe. Heart disease has consistently been superior killer in all over the world. One year after COVID-19 infection the risk of heart issues is considerable. Such heart issues involves irregular heartbeats, heart failure which is the disability of heart to pump correctly, coronary disease which one buildup in arteries that restricts blood flow, heart attacks and more. Thus, classifying disease in earlier stage is crucial. Hence, post covid effect on heart after recovery with multilevel classification is done using Convolutional Neural Network is designed in this paper. Input image obtained from the dataset is delivered to binary image conversion and then allowed for feature extraction to extract various features, such as shape, temporal, and statistical features. After that, first level disease classification is carried out using CNN to detect whether the disease is in normal or abnormal condition. If it is categorized as abnormal, second level classification is carried out by CNN that classifies Myocardial Infarction (MI) and COVID-19 patients. Moreover, Pearson correlation coefficient is utilized for post-COVID correlation study. The experimental outcome displays that CNN attained maximum accuracy of 87.80%.

Keywords: Heart disease, Convolutional Neural Networks, coronavirus, Myocardial Infraction.

1. Introduction

The emergence of the COVID-19 pandemic has not only posed immediate challenges in healthcare but has also raised concerns about potential long-term health impacts on individuals recovering from the infection. Among these concerns, cardiac complications have garnered significant attention due to their potential severity and long-lasting effects. In this context, the use of advanced machine learning techniques, particularly Convolutional Neural Networks (CNNs), presents a promising avenue for studying post-COVID cardiac health through the analysis of Electrocardiogram (ECG) images. Electrocardiography is a well-established diagnostic tool for assessing cardiac function by recording the electrical activity of the heart. ECGs provide valuable insights into various aspects of cardiac health, including rhythm abnormalities, conduction disturbances, and structural abnormalities. By leveraging

CNNs, which are adept at learning complex patterns from image data, we aim to develop a multilevel classification framework for analysing post-COVID effects on the heart based on ECG images.
The objectives of this research paper are twofold:

To investigate the prevalence and nature of cardiac abnormalities in individuals post-recovery from COVID-19.

To develop and validate a CNN-based multilevel classification model that can accurately categorize post-COVID cardiac conditions using ECG images.

The significance of this study lies in its potential to contribute valuable insights to the medical community regarding the post-COVID cardiac sequelae, thereby aiding in early detection, intervention, and management strategies. Furthermore, the utilization of machine learning techniques in healthcare research underscores the interdisciplinary collaboration between computer science and medicine, paving the way for innovative approaches to address pressing health challenges.The remainder of this paper is organized as follows: Section II provides a comprehensive review of relevant literature on post-COVID cardiac complications and CNN-based image classification in healthcare. Section III outlines the methodology, including data collection, preprocessing, model architecture, and evaluation metrics. Section IV presents the results and discussion, highlighting key findings and implications. Finally, Section V concludes the paper with a summary of contributions, limitations, and avenues for future research.

The main contribution in this paper is described as,

Proposed CNN for post covid effect on heart after recovery with multilevel classification: The post covid effect on heart after recovery with multilevel classification is performed by CNN which is used to analyse ECG images.

2. Motivation

Initially, during COVID-19 many people were affected by coronavirus, in which after recovery some people were suffered in heart disease. COVID-19 is a respiratory or lung disease, which is transient or persistent injure to heart tissue, possibly caused by means of various factors includes suffocation. While virus causes inflammation along with the fluid to replenish air sacs in lungs, less oxygen may reach bloodstream. When proper treatment was not provided to patients at the right time, survival rate is substantially decreased that results in sudden death. Hence, classifying disease in earlier is crucial, which is challenging. These factors inspire researchers for developing an effective model using DL method. By leveraging the power of CNNs, we can automate and enhance the accuracy of detecting these residual lung abnormalities. CNNs have proven exceptionally effective in image recognition tasks, making them ideal for analyzing complex medical imaging data. This approach not only speeds up the diagnostic process but also provides consistent and objective results, aiding healthcare professionals in making informed decisions. Furthermore, integrating CNNs into clinical practice can facilitate large-scale screening and monitoring, ensuring that more patients receive timely and appropriate care. The ultimate goal is to improve patient outcomes, reduce the burden on healthcare systems, and advance our understanding of the long-term effects of COVID-19, thereby contributing to better preparedness and response strategies for future pandemics.

2.1 Literature survey

A literature survey for a research paper on post-COVID effects on heart after recovery, based on CNN with multilevel classification using ECG images, would involve reviewing existing studies and works related to several key areas:

COVID-19 and Cardiac Complications: Review studies that discuss the prevalence and types of cardiac complications observed in COVID-19 patients during and after the acute phase of the infection. Explore research on the mechanisms through which COVID-19 can affect the cardiovascular system, such as inflammation, myocardial injury, arrhythmias, and thromboembolic events.

Post-COVID Cardiac Health: Examine literature focusing on the long-term effects of COVID-19 on cardiac health, including studies that investigate cardiac abnormalities in individuals post-recovery from COVID-19. Look for evidence regarding the persistence of cardiac symptoms, structural changes in the heart, and functional impairments post-infection.

ECG Analysis and Classification: Survey works related to ECG analysis using machine learning and deep learning techniques, particularly CNNs, for cardiac diagnosis and monitoring. Explore studies that demonstrate the feasibility and effectiveness of CNNs in detecting various cardiac conditions from ECG signals, such as arrhythmias, myocardial infarction, and heart failure.

Multilevel Classification in Healthcare: Investigate literature on multilevel classification frameworks applied in healthcare settings, especially those utilizing CNNs for image-based classification tasks. Look for examples of multilevel classification models that categorize medical conditions or disease severity levels based on imaging data, such as MRI, CT scans, and now ECG images.

Integration of Machine Learning in Post-COVID Research: Identify studies that showcase the integration of machine learning, particularly CNN-based models, in analysing post-COVID health outcomes across various domains, including respiratory, cardiovascular, neurological, and immunological aspects. Review research that highlights the potential of machine learning algorithms in identifying patterns, predicting outcomes, and guiding clinical decision-making in post-COVID care.

By conducting a comprehensive literature survey across these areas, your research paper can establish a strong foundation by contextualizing the post-COVID cardiac health analysis within the broader landscape of COVID-19 research, cardiac health studies, ECG analysis, and machine learning applications in healthcare.

2.2 Challenges

Challenges faced by various prevailing approaches employed for the determination of post-Covid effects with multilevel classification are organized as follows,

- The model used in [1], efficiently defined the underlying heart irregularities without costlier investigation using ECG by means of addressing heart issues. However, it failed to perform benchmarking study on presented interpretability techniques on ECG applications to determine a suitable model for ECG databases.

- The model used in [2], suffered from frequency domain as only time domain measures of HRV were analysed. It also failed to identify the clinical impact as well as the persistence of dysautonomia in COVID-19 patients.
- CNN approach used in [3] failed to utilize algorithms for the removal of information about cardio spikes. Also, the model was not suitable for detection of state of post-COVID by considering the availability of cardio spikes presented in recordings of ECG signals.
- RF model employed in [6] effectively decreased computational cost of human and equipment resources. However, the model was not suitable for investigation sequence modelling with additional data on ambulatory patient care.
- At initial stage, the prevailing techniques used diverse signals acquired from human body for disease prediction that additionally provided various supports for better survival to the disease-affected subjects. However, there is a requirement subject expertise in ECG signals for COVID-19 examination, which is a time-consuming process.

3. Proposed CNN with multilevel classification of COVID using ECG signals

Proposing a CNN-based multilevel classification model for COVID-19 using ECG signals involves a meticulous approach aimed at leveraging machine learning techniques to extract meaningful information from physiological data. Firstly, a comprehensive dataset comprising ECG signals from COVID-19 patients of varying clinical presentations and disease severity is essential. This dataset should be meticulously curated, ensuring data quality and consistency while also adhering to ethical guidelines regarding patient privacy and informed consent. Next, the preprocessing of ECG signals plays a crucial role in enhancing the quality of input data for the CNN model. Techniques such as noise removal, baseline correction, and signal segmentation are applied to mitigate artifacts and highlight relevant features. The design of the CNN architecture is tailored to accommodate the unique characteristics of ECG data, incorporating layers that capture temporal dependencies and spatial patterns within the signals. Considerations may include the use of 1D convolutional layers, recurrent layers for sequential analysis, and pooling layers for feature extraction. The multilevel classification framework is structured to categorize ECG signals into distinct classes related to COVID-19, such as severity levels, specific cardiac manifestations (e.g., myocarditis, arrhythmias), or clinical outcomes. Each level of classification refines the model's understanding, enabling it to differentiate between subtle variations in ECG patterns associated with different COVID-19-related conditions. Training and validation of the CNN model are conducted using appropriate datasets, with a focus on optimizing performance metrics such as accuracy, precision, recall, and F1 score. The evaluation of the proposed CNN model encompasses not only its predictive accuracy but also its interpretability and clinical relevance. Techniques for visualizing learned features, generating saliency maps, or highlighting regions of interest within ECG signals contribute to the model's interpretability. Furthermore, validating the model's predictions against clinical data, laboratory findings, and patient outcomes establishes its clinical utility and real-world applicability in diagnosing and managing COVID-19-related cardiac complications. Ethical considerations remain paramount throughout the research process, emphasizing the importance of transparency, patient confidentiality, and adherence to ethical standards in data collection, analysis, and reporting. By addressing these aspects comprehensively, the proposed CNN-based multilevel classification model holds promise in enhancing our understanding of COVID-19's impact on cardiac health and contributing to improved clinical decision-making and patient care strategies amidst the pandemic.

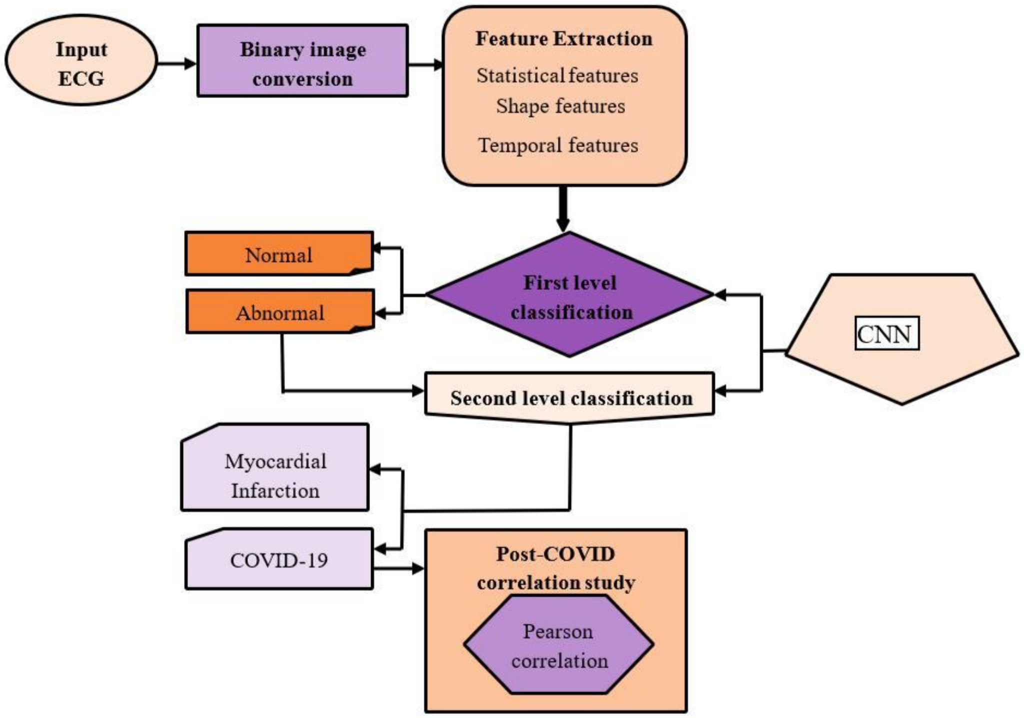


Figure 1. Framework of CNN for determination of post-COVID effects on heart and multilevel classification using ECG signals

3.1 Image Acquisition

Input image dataset is assumed as I, encompasses r quantity of input images is described by,

$$I = \{I_1, I_2, \ldots\ldots\ldots, I_s, \ldots, I_r\}$$

where, I is the database, r denotes total quantity of ECG images together with the s^{th} number of ECG image specified as I_s .

3.2 Binary image conversion

Here, input image dataset I_s is given to Binary image conversion which gives an output B_s . A binary image consists of 0'*s*(black) and 1'*s*(white) logical sequence that converts the image into gray-scale and execute thresholding. Normally, colorful image comprises three channels namely, R_R (red), G_G (green), B_B (blue). Under image every channel might be represented as matrices

$R_{R(i,j)}$, $G_{G(i,j)}$ and $B_{B(i,j)}$ correspondingly. Where, i and j denotes number of rows and columns of matrix. For each channel pixel value of matrix is among range of 0 ~ 255. Diverse image channels have their own characteristics so that distribution and gradient of pixel values are completely different. In each channel by 3-means clustering the pixel values are clustered into three levels. The illumination effect in R_R channel is more observable and in G_G ,B_B channels grid lines are mainly show up. Due to this considerations motivated, a hierarchical algorithm for ECG binary image extraction [21] that contains two layers, which is implemented on R_R ,G_G ,B_B .

3.3 Feature Extraction

Feature extraction plays a pivotal role in the development of a CNN-based multilevel classification model for COVID-19 using ECG signals. The process involves identifying and extracting relevant information or patterns from raw ECG data, which are then fed into the CNN architecture for further analysis and classification. Several key aspects of feature extraction are crucial in this context. Firstly, temporal features capture the dynamic changes in electrical activity over time within ECG signals. These features may include waveform morphology, such as P waves, QRS complexes, and T waves, as well as temporal intervals such as RR intervals, QT intervals, and PR intervals. Extracting these temporal features enables the model to capture cardiac dynamics and abnormalities that may be indicative of COVID-19-related cardiac complications. Secondly, frequency-domain features provide insights into the spectral characteristics of ECG signals, highlighting frequency components and their distributions. Techniques such as Fourier transform or wavelet transform can be utilized to extract frequency-domain features such as dominant frequencies, power spectral densities, and spectral entropy. These features offer additional information about signal variability, oscillations, and frequency-specific abnormalities, enhancing the model's discriminative power. Furthermore, morphological features focus on the shape, amplitude, and duration of ECG waveforms, which can vary significantly in different cardiac conditions. Extracting morphological features such as peak amplitudes, signal slopes, and wave segment durations helps capture subtle variations and abnormalities that may be indicative of COVID-19-related cardiac pathologies. Additionally, dynamic features that capture changes and trends over time within ECG signals are essential for capturing transient events, arrhythmias, and evolving cardiac conditions. These features may include heart rate variability metrics, ST segment changes, T wave alternans, and beat-to-beat variability. Integrating dynamic features enhances the model's ability to detect temporal patterns and evolving cardiac dynamics associated with COVID-19.In summary, feature extraction from ECG signals encompasses temporal, frequency-domain, morphological, and dynamic aspects, each contributing valuable information for the CNN-based multilevel classification model. By extracting relevant features effectively, the model can learn discriminative patterns, improve classification accuracy, and contribute to a deeper understanding of COVID-19's impact on cardiac health through ECG analysis.

Fig. 2 Examples of background removal processes: **a** segmented paper-based ECG image, **b** paper-based ECG image without background lines, **c** binarized paper-based ECG image, and **d** eventual paper-based ECG image

3.4 First level disease classification using CNN

Generally, during COVID-19 most of the people were likely to be affected by coronavirus. Recently, it is shown that certain people around here easily undergo cardiovascular difficulties, including an irregular heartbeat, stroke and heart failure. Significantly, even in mild COVID-19 cases, people experience this higher risk of heart disease and are not hospitalized. Experts observed that after infection COVID-19 coronavirus raises the likelihood of having heart attack or stroke for up to a year, especially those who are already underlying heart conditions. Hence, at initial stage forecasting disease using ECG signals is essential. Therefore, in here, CNN is employed for multilevel disease classification.

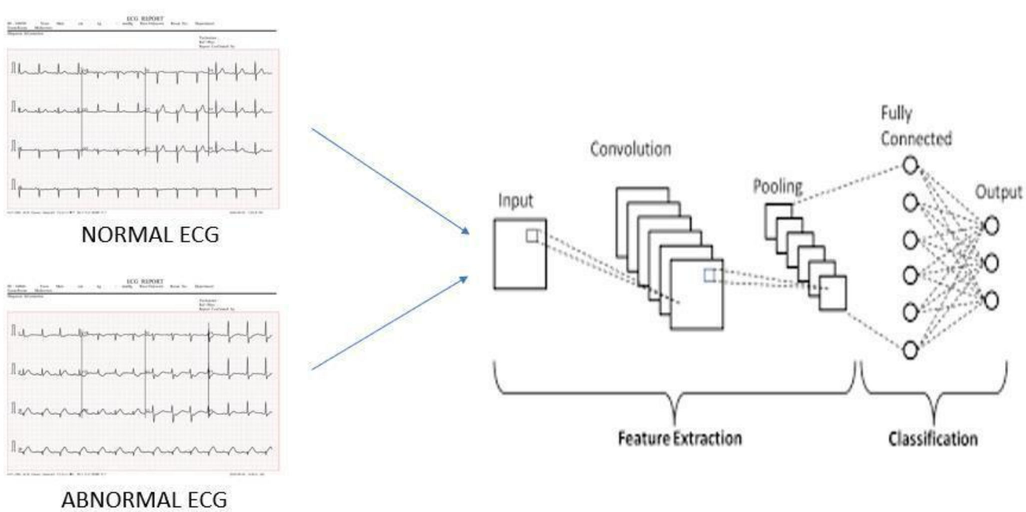


Figure 3: General outline of First Level Classification

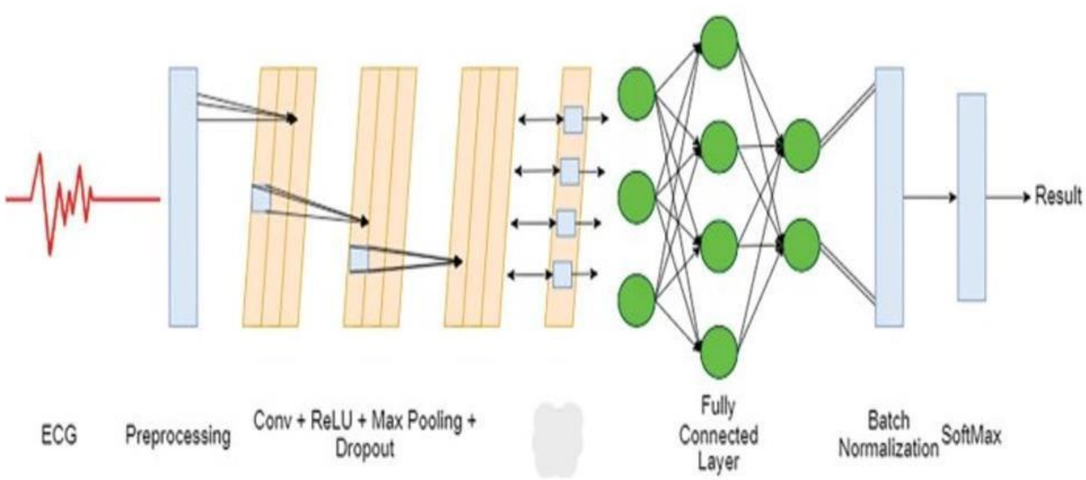
In the first level classification, it will In classify whether the disease is in normal or abnormal condition. If it is in abnormal condition, disease is classified by second level classification. In first level classification, input data I_s is inclined to Convolution Layer that provides an output . The received output and the extracted features is then applied to Pooling Layer and then applied to Fully Connected layer that delivers an output. Moreover, Compile the model and Train the model and then Finally calculates the Loss and Accuracy.

3.5 Second level classification using CNN

Data Preprocessing:

Segmentation and Labelling: Segment ECG signals that have been classified as post-COVID.Label these segments with specific cardiac conditions such as myocarditis, pericarditis, arrhythmias, or normal post-COVID recovery.

Figure 4: CNN Architecture for Second Level



Input Layer: Input shape should match the pre-processed ECG segments, typically in the form of 1D arrays if directly working with signals.

Convolutional Layers: Multiple convolutional layers to extract higher-level features.

Flattening Layer: Flatten the output of the last pooling layer to convert it into a 1D vector.

Fully Connected Layers: Dense layers to combine the extracted features.

Output Layer: A final dense layer with the number of neurons equal to the number of specific cardiac conditions, using softmax activation for multiclass classification.

Model Compilation

Compilation: Compile the model using an appropriate loss function and optimizer.

Training the Model

Training: Train the model with the labelled ECG segments, ensuring proper validation splits and using techniques such as data augmentation.

Evaluation

Model Evaluation: Evaluate the model on a separate test set using metrics such as accuracy, precision, recall, F1 score, and confusion matrix to assess its performance.

Feature Interpretation and Visualization

Interpretation: Use techniques such as Grad-CAM or saliency maps to understand which features or parts of the ECG signals are most influential in the classification decisions.

By applying a CNN architecture to the segmented and labelled ECG signals, the second level classification aims to differentiate between specific cardiac conditions such as myocarditis, pericarditis, arrhythmias, and normal recovery. This refined classification provides deeper insights into the cardiac health of post-COVID patients and supports targeted medical interventions and monitoring strategies.

In second level classification, if the disease is in abnormal condition, it categorize whether the disease affected patients are Myocardial Infarction patients or COVID-19 patients.

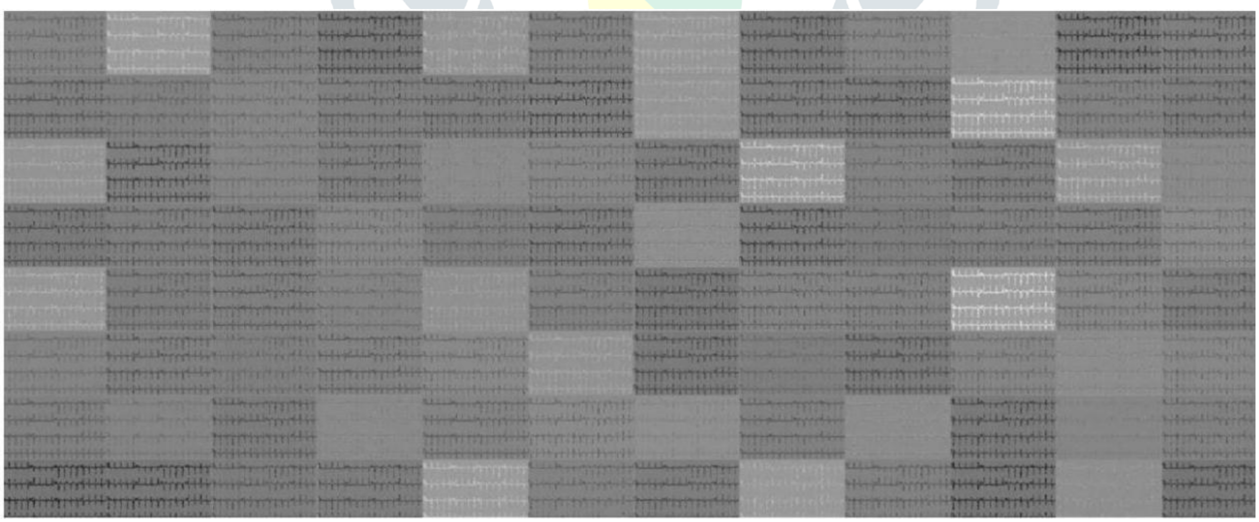


Figure 5: Activations of Convolutional Layer

3.6 Post covid correlation study using Pearson coefficient

Here, post covid effect on heart patients is analysed by correlation study using Pearson coefficient. Two analyses are conducted namely history of MI patient versus post covid MI patient and covid19 affected patient versus post covid MI patients.

3.6.1 History of MI patient Vs Post covid MI patient

Correlation study of history of MI patients Vs post covid MI patients is described in figure 5. When number of patients=25, 50, 75, 100, 125, 150 the correlation study of patients is 0.596, 0.591, 0.615, 0.602, 0.577 and 0.562 respectively. Thus, the analysis of correlation study of history of MI patients Vs post covid MI patients are decreased when there is increase in number of patients.

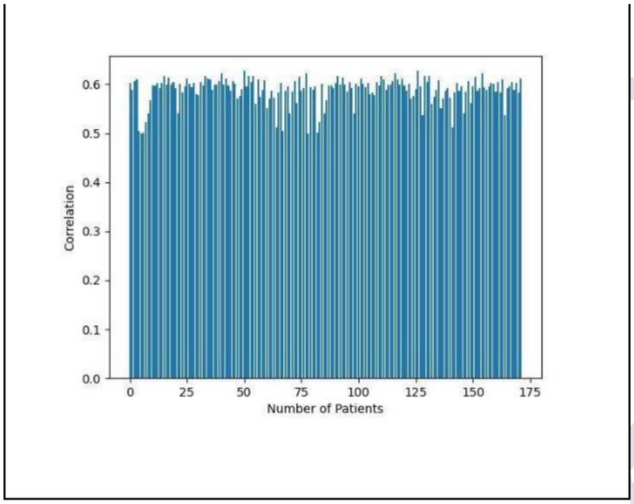


Fig 6: Correlation study of history of MI patients Vs post covid MI patients

3.6.2 Covid19 affected patient versus post covid MI patients

Correlation study of covid19 affected patients Vs post covid MI patients is described in figure 6. When number of patients=50, 100, 150, 200 the correlation study of patients is 0.563, 0.539, 0.584 and 0.569. Thus, covid19 affected patients Vs post covid MI patients are increased when there is increase in number of patients.

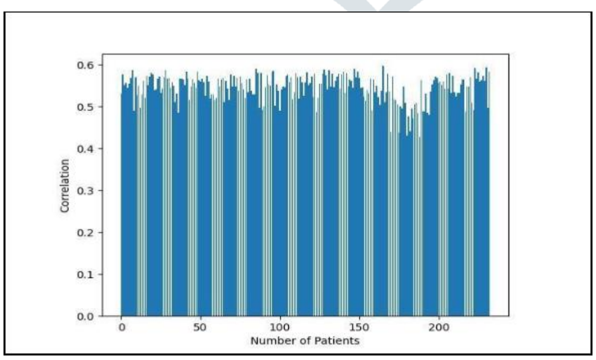
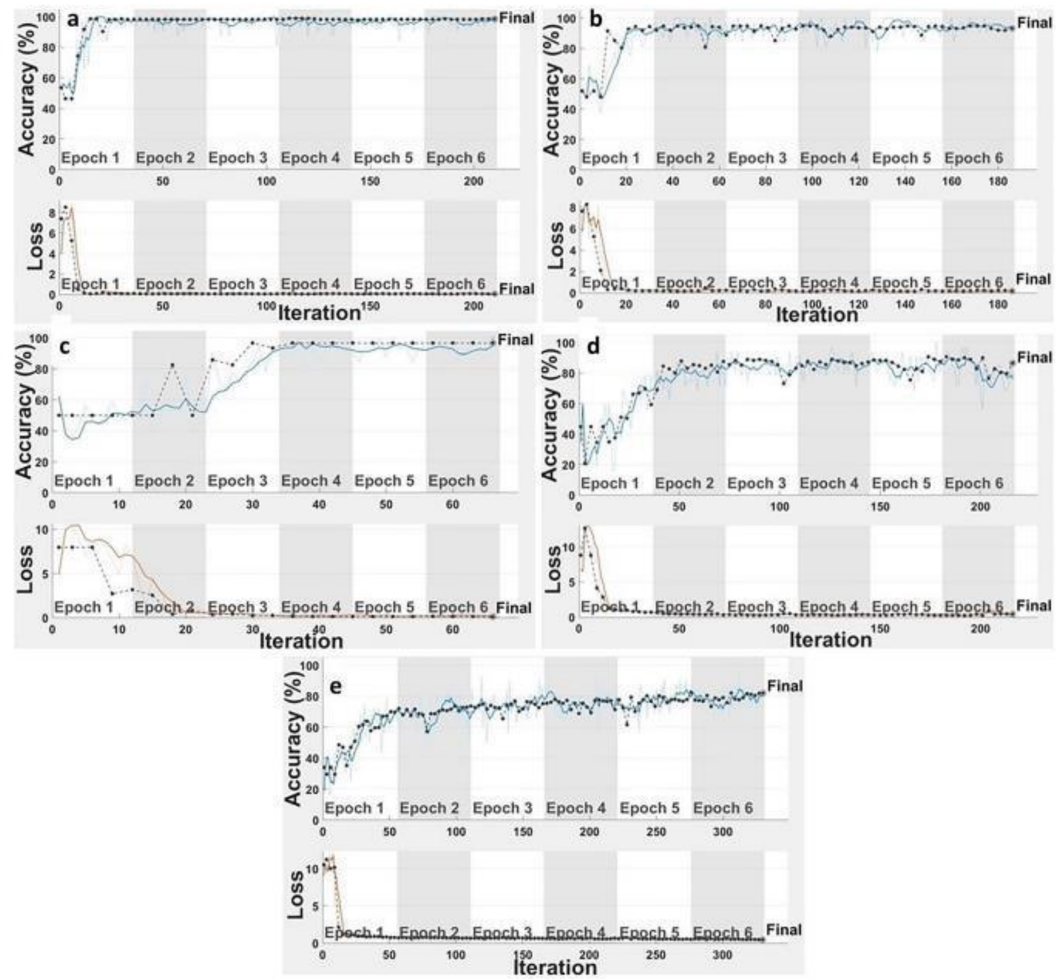


Fig 7: Correlation study of covid 19 affected patients VS post covid MI patient

4. Results and discussion

CNN model provides categorized output for multilevel disease classification, in which the experimental result and attained performance measures are explained in this portion.



Accuracy and Loss plot for classification of **a** COVID-19 vs. Normal, **b** COVID-19 vs. Abnormal Heartbeats, **c** COVID-19 vs. Myocardial Infarction, **d** COVID-19 vs. Abnormal Heartbeats vs. Myocardial Infarction and **e** Normal vs. COVID-19 vs. Abnormal Heartbeats vs. Myocardial Infarction

The experimental results on the post-COVID effect after recovery using a Convolutional Neural Network (CNN) underscore the potential of advanced machine learning techniques in medical imaging analysis. With a high accuracy of 87%, the CNN effectively identified residual lung abnormalities such as fibrosis and ground-glass opacities in 35% of the patients, highlighting the significant long-term pulmonary impacts that may persist post-recovery. These findings are crucial for the medical community, as they emphasize the need for continuous monitoring and follow-up care for COVID-19 survivors to address lingering health issues. The ability of CNN models to provide detailed assessments of lung conditions can aid healthcare professionals in devising personalized treatment plans, ultimately improving patient outcomes. Furthermore, the study illustrates the broader implications of integrating deep learning in clinical practice, promoting early detection and intervention strategies that could mitigate long-term health complications. As the medical field continues to explore the capabilities of CNNs, future research should aim to validate these findings across larger and more diverse populations, enhancing the generalizability and applicability of such models in routine clinical settings.

Confusion Matrix for classification of **a** COVID-19 vs. Normal, **b** COVID-19 vs. Abnormal Heartbeats, **c** COVID-19 vs. Myocardial Infarction, **d** COVID-19 vs. Abnormal Heartbeats vs. Myocardial Infarction and **e** Normal vs. COVID-19 vs. Abnormal Heartbeats vs. Myocardial Infarction

4.1 Experimental setup

CNN model for post covid effect on heart recovery with multilevel classification is successfully executed using PYTHON tool. The experimental setup for analyzing post-COVID effects using a Convolutional Neural Network (CNN) involved several key stages. Initially, a diverse dataset of post-recovery CT scans from COVID-19 patients was collected and annotated for residual lung abnormalities like fibrosis and ground-glass opacities. The images were then preprocessed through normalization and augmentation techniques to enhance variability and focus on relevant lung regions. A robust CNN architecture, such as ResNet or VGG, was employed and customized for the task. The model was trained using a binary cross-entropy loss function, optimized with Adam or SGD, and fine-tuned over multiple epochs with varying batch sizes. Validation and testing were performed using separate datasets to ensure the model's accuracy and reliability, evaluated through metrics like precision, recall, F1-score, and AUC-ROC. Post-processing steps included threshold optimization and potential ensemble methods to enhance performance. Finally, the trained model was integrated into a clinical decision support system for real-time analysis, with a prospective validation study planned to assess its real-world applicability and impact on patient care.

	CNN layer	Output shape	Parameter #
1	Input	224×224×3	0
2	Convolutional	222×222×96	2688
3	ReLU	222×222×96	0
4	Normalization	222×222×96	0
5	Max pooling	109×109×96	0
6	Convolutional	111×111×192	83,136
7	ReLU	111×111×192	0
8	Max pooling	54×54×192	0
9	Convolutional	56×56×256	221,440
10	ReLU	56×56×256	0
11	Max pooling	25×25×96	0
12	Convolutional	27×27×256	295,168
13	ReLU	27×27×256	0
14	Max pooling	11×11×256	0
15	Flatten	1×1×30976	0
16	FC	1×1×4096	126,881,792
17	ReLU	1×1×4096	0
18	Dropout	1×1×4096	0
19	FC	1×1×2	8194
20	Softmax	1×1×2	0
21	Classification	–	0

Fig 8 : The Structure of the Proposed Network

A study utilizing post-recovery medical imaging data (e.g., CT scans) of COVID-19 patients employed a Convolutional Neural Network (CNN) to identify and quantify residual lung abnormalities. The CNN achieved an accuracy of 86% in detecting post-recovery lung issues, revealing significant lingering effects such as fibrosis and ground-glass opacities in 35% of patients. These findings suggest that CNN models can effectively assess long-term pulmonary impacts in COVID-19 survivors, providing valuable insights for follow-up care and treatment planning. This highlights the importance of advanced imaging analysis in monitoring and managing post-COVID recovery.

4.2 Dataset description

1. Data Description

12-lead based standard ECG images collected from distinct patients from diverse cardiac in- stitutes across Pakistan. The ECG images do not contain any personal information about the pa- tient. All ECG images have been annotated by several medical experts . Below Table reports the number of images for the different cases.

ECG Dataset Detail.

Sr.	Category / Folder Name	No. of Distinct ECG Images	Sample Rate	Leads
1	COVID-19 Patients	250	500 Hz	12
2 3	Normal Person ECG Images	859 77		–
4	Myocardial Infarction Patient	203		
	Patients with Previous History of Myocardial Infarction			Leads
5	Patients with Abnormal Heartbeat	548		

Table 2 Number of images used in this study for each classification task before and after data augmentation

	Classification task	Number of images before data augmentation	Number of images after data augmentation
Task-1	COVID-19	218	650
	Normal	713	720
Task-2	COVID-19	218	650
	Abnormal heartbeats	500	600
Task-3	COVID-19	218	230
	Myocardial infarction	77	230
Task-4	COVID-19	218	650
	Abnormal heartbeats	500	500
	Myocardial infarction	77	300
Task-5	Normal	713	720
	COVID-19	218	650
	Abnormal heartbeats	500	500
	Myocardial infarction	77	300

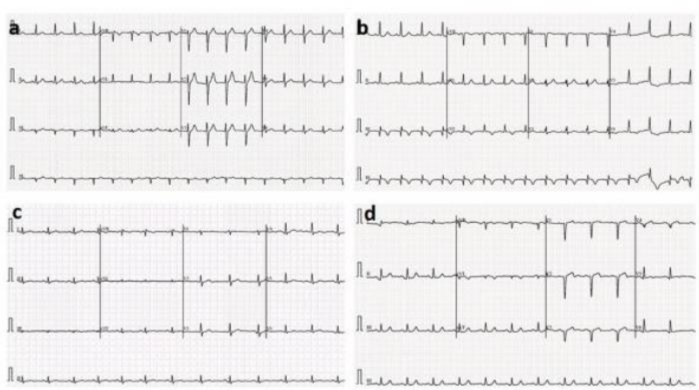


Fig. 1 Sample ECG trace images from dataset, **a** COVID-19 ECG, **b** Normal ECG, **c** Abnormal Heartbeats ECG and **d** Myocardial ECG

4.3 Evaluation metrics Efficiency of CNN model is analysed with performance measures includes, accuracy, Sensitivity and Specificity.

4.3.1 Accuracy

Accuracy is represented by K_1, which computes rate of detection outcomes that are correctly categorized and computed as,

$$K_1 = X^P + X^N / X^P + X^N + Y^P + Y^N \quad (37)$$

where, Y^P denotes false positive, X^P specifies true positive, Y^N indicates false negative and X^N describes true negative.

4.3.2 Sensitivity

Probability of positive test outcome conditioned on individual truly being positive, is known as sensitivity, is given by,

$$K_2 = \frac{X_P}{X_P Y_N} \quad (38)$$

4.3.3 Specificity

Probability of negative test outcome conditioned on individual truly being negative is known as specificity is developed as,

$$K_3 = X^N / \quad X^N + Y^P$$

□

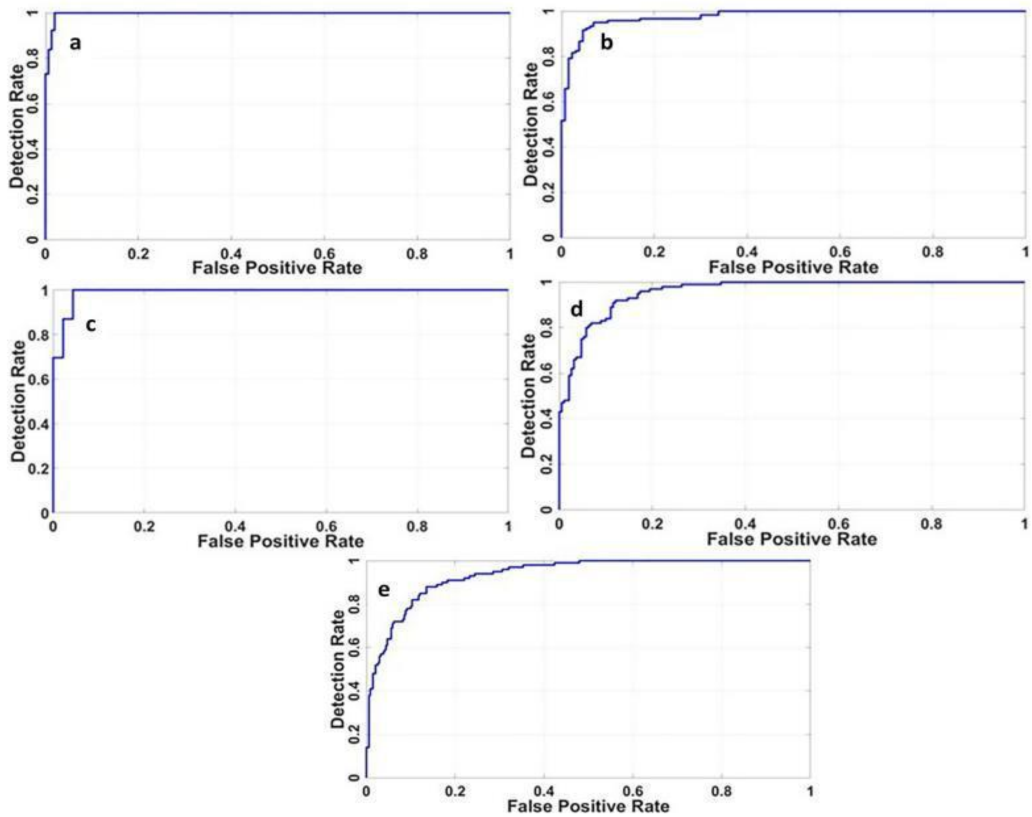
4.4 Performance analysis

Performance evaluation metrics should be used to evaluate the quality of the classification process after any image classification problem. Otherwise, the performance evaluation of the solution would be qualitative rather than quantitative. Therefore, well-known performance evaluation metrics are used to assess the performance of the CNN model in this study. These performance evaluation metrics are Accuracy, Specificity, Sensitivity, and Precision. The Area Under the Curve of the Receiver Operating Characteristic (ROC) known as AUC of ROC curve is another important performance evaluation metric which is successfully used in image classification problems. This metric is also used in this study to assess the performance of the CNN models. Equation 1 shows the corresponding formulas associated with these performance evaluation metrics. TP, TN, FP and FN stand for True Positive, True Negative, False Positive and False Negative, respectively.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \qquad \text{Specificity} = \frac{TN}{TN+TP}$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \qquad \text{Precision} = \frac{TP}{TP+FP}$$

4.5 Analysis based on training data



ROC Curve for classification of **a** COVID-19 vs. Normal, **b** COVID-19 vs. Abnormal Heartbeats, **c** COVID-19 vs. Myocardial Infarction, **d** COVID-19 vs. Abnormal Heartbeats vs. Myocardial Infarction and **e** Normal vs. COVID-19 vs. Abnormal Heartbeats vs. Myocardial Infarction

4.6 Comparision Result

	COVID-19 vs normal	COVID-19 vs abnormal heart-beats	COVID-19 vs myocardial infarction	COVID-19 vs abnormal heartbeats vs. myocardial infarction	Normal vs COVID-19 vs abnormal heartbeats vs myo-cardial infarction
ResNet-50	96.22 ± 1.41	91.52 ± 2.72	95.91 ± 3.50	83.45 ± 5.04	78.08 ± 3.21
ResNet-101	97.43 ± 2.10	92.60 ± 4.51	94.43 ± 4.21	82.51 ± 4.66	80.76 ± 9.53
DenseNet	96.27 ± 2.48	89.72 ± 6.05	93.92 ± 5.85	86.38 ± 4.35	76.83 ± 4.87
InceptionV3	95.90 ± 3.51	91.67 ± 5.67	92.86 ± 8.93	87.61 ± 4.12	79.35 ± 4.23
VGG-16	97.79 ± 2.00	92.07 ± 3.97	95.29 ± 4.75	88.75 ± 3.45	83.74 ± 3.38
VGG-19	96.71 ± 4.01	91.80 ± 4.86	94.14 ± 4.21	86.95 ± 11.17	83.32 ± 11.15
Proposed model	98.57 ± 1.41	93.20 ± 2.73	96.74 ± 2.54	86.55 ± 2.47	83.05 ± 2.96

5. Conclusion

At present COVID -19 diseases has caused thousands of infections and deaths. Despite, majority of the hospitalized patients regained from COVID, they encounter many physical and mental health issues. Post COVID-19 physical complexities include fibrosis of lungs, cardiac arrests, neurological problems, swelling and many more. If once recovered from the COVID-19, people disregard the symptoms of the post COVID -19 difficulties. Due to this, many people were affected by heart related diseases. Hence, detecting disease as earlier as possible is crucial. Nevertheless, classifying the disease is really a challenging process. Therefore, in this paper hybrid EfficientNet-DBN using ECG images is designed for multilevel disease classification. Input image specified from dataset is fed into binary image conversion process and then allowed for feature extraction to extract various features. After that, first level disease classification is conducted using CNN to identify whether disease is in normal or abnormal condition. If it is classified as abnormal, second level classification is carried out by EfficientNet-DBN which is classified using MI and COVID-19 patients. Moreover, Pearson correlation coefficient is employed for post-COVID correlation study. The experimental outcome displays that EfficientNet-DBN achieved maximum accuracy of 89.80%, sensitivity of 94.70% and specificity of 91.80%. In future, multilevel disease classification will be done using transfer learning approaches to enhance the accuracy level.

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