

# Early Detection of Cardiac Abnormalities in COVID-19 Patients by Autoencoder Based Analysis of ECG Patterns

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## Abstract

Heart diseases have been greatly affected by COVID-19 and many people have suffered from heart problems. Since COVID-19 affects the cardiovascular system and can cause serious complications, it is important to diagnose cardiovascular abnormalities in patients as soon as possible. This research study presents a method to identify abnormalities in electrocardiogram imaging in COVID-19 patients using a deep learning model-based autoencoder. Autoencoders learn compressed representations of electrocardiogram patterns, ready for unsupervised feature extraction. The model distinguishes abnormal patterns from a normal baseline by reconstructing electrocardiogram (ECG) images and using new techniques to identify abnormalities. While testing and training on electrocardiogram images from COVID-19 patients, the model was shown to be effective in diagnosing heart disease with high accuracy (91.11%). This technology can facilitate immediate diagnosis of electrocardiogram abnormality in COVID-19 patients and help doctors conduct risk assessment and early diagnosis.

**Keywords:** Autoencoder, Classification, COVID-19, Deep learning, Machine learning, Unsupervised learning

## 1. Introduction

The main cause of death after Covid-19 worldwide is Heart attack, often known as Heart disease. Since the start of the Covid-19 pandemic, the number has risen which affects people [1]. Heart failure is a typical clinical condition experienced in different medical services settings with huge financial effect [2]. Researchers and subject-matter experts worked diligently to find precise and trustworthy methods for the identification and diagnosis of Heart disease after COVID-19 in patients. Machine learning (ML) and Profound learning (Deep learning) approaches are growing and developing all the time, providing effective solution with various types of data [3]. All over the world, from recent survey cardiovascular diseases are nearly everyone's cause of death. The human health can be impacted by any untreated disease which effect major organs of body. If we treat chronic diseases in timely manner then we can avoid all major problems coming in future. In recent years, deep learning has become a powerful tool for image analysis, including medical image processing. Autoencoders have shown great potential in search of absent pattern by learning compressed representations of data and identifying cases that differ from patterns. The aim of this study is to use

the autoencoder method to detect abnormalities in electrocardiographic images of COVID-19 patients. An electrocardiogram (ECG) is a diagnostic test that records the electrical activity of the heart over time. It helps to recognize heart diseases such as arrhythmia, heart attacks, and other heart abnormalities. The electrocardiogram (ECG) is measured using electrodes placed in the skin and captures electrical signals generated by the heart. These electrodes are attached to the chest, arms and legs in certain areas. The signal is transferred to the electrocardiogram (ECG) machine, which creates a diagram showing electrical activity of the heart. The main contributions of this study are as follows: (1) Developing a deep learning-based autoencoder model to detect electrocardiogram (ECG) abnormalities specifically in COVID-19 patients, (2) Evaluating the model's performance using electrocardiogram data from COVID-19 patients demonstrates the model's ability to detect heart disease, (3) Analysis clinical use of the model. The goal of scientific statement is to use DL to empower accuracy medication [4]. A neural network that performs principal component analysis is called autoencoder.

The encoder which reduces the input dimensionality and the decoder which restores the input dimensionality are two sub-networks of autoencoder. These networks are trained together to minimize the differences. It is observed that better precision and accuracy in early detection can be accomplished with this model. This paper is organized into multiple sections. Section II defines the literature review. The proposed methodology is covered in section III. Section IV focuses on findings or results while section V provides conclusion and future scope.

## 2.Literature Review

Corona Virus Disease - 2019, conveniently abbreviated as COVID-19 had grasped the world in its tentacles, leaving behind its impact on health of human beings and many other living beings on earth. The challenges raised by the disease can still be felt on world's order, its economy and human health in particular. Previous research has extensively studied various factors influencing heart attack risks, often leveraging machine learning to enhance prediction accuracy. Several studies have focused on primary data from real-world COVID-19 cases to understand the interplay between COVID-19 and heart attack risk. In this section, we review notable studies that have employed machine learning algorithms to analyze cardiovascular risk factors, including patient demographics and clinical attributes.

### 2.1 Covid-19 and its Long-Term Cardiovascular Effects

As a result of cardiovascular problems in the acute phase of infection and increasing data describing symptoms and functional deterioration in patients after the COVID-19 virus, more attention is being paid to the long-term cardiovascular complications of COVID-19. It is unclear to what extent these problems are secondary to specific pathological processes rather than direct consequences of infectious problems. All the complications investigated like atrial fibrillation and heart failure represent the greatest burden, occurring in more than 10 in 1000 people 30 days after exposure to the virus.

### 2.2 Role of Medical Imaginary, AI and Machine learning to identify unexpected pattern in Covid-19

Medical diagnosis is one of the important areas where artificial intelligence is used in medicine and treatment. The information obtained using various methods such as computerized tomography (CT), magnetic resonance imaging (MRI), and X-rays is highly quantifiable. Author has attempted to use artificial intelligence and machine learning to assess the effect of COVID-19 on human health and the possibility of death owing to the exposure to COVID.

The research work discusses the examination and effect of post-treatment care issues on the patients who have faced heart related complications as an outcome of COVID-19 [5]. This study examines various facets, including clinical practices, post-treatment care, challenges and solutions, patient outcomes, and recommendations for best practices to improve the administration of COVID-19 patients with heart problems in future healthcare settings. By addressing these areas, the paper aims to improve understanding, better clinical management and recovery of patients affected by the dual impact of COVID-19 and heart complications. The use of artificial intelligence to find new ways of handling the challenges reposed by COVID-19 re-affirms the benefits of application of AI/ML and allied technologies in diagnostics and therapeutic use cases [6]. The researchers aimed to clarify the prognostic significance of a new marker for coronary artery disease inflammation by its tomographic visuals in COVID-19 patients. These markers are likely to help the patients severely needing hospitalization. These markers may be used effectively in AI/ML based support systems also [7]. In the study [8], researchers have concentrated on critical elements and employing machine learning approaches to predict survival outcomes for COVID-19 patients.

Results showed that the DNN algorithm outperformed the random forest algorithm by achieving better precision and recall. In the framework of COVID-19, Lungs Ultrasound (LUS) was identified as a potentially useful diagnostic tool that help to distinguish the pattern of diffused interstitial pulmonary syndrome and direct patient care [9]. The researchers [10] emphasized the importance of data science in managing the overwhelming amount of clinical data. They highlighted that machine learning insights can support clinicians by identifying key factors affecting patient outcomes and revealing previously unnoticed clinical patterns. During the COVID-19 pandemic, the study showcased a collaboration between clinicians and data scientists to identify high-risk patient sub-groups using a random forest classifier model for early prediction of adverse outcomes. The results were further analyzed through unsupervised clustering to understand patient risk factors. This approach is valuable for generating hypotheses and supporting clinical decisions in various healthcare challenges, including future public health crises. The results of preceding study indicate that a non negligible percentage of individuals who are recovering from Covid-19 are experiencing long Covid pain symptoms, despite the fact that these symptoms are not well described.

This emphasizes the significance of future inquire about endeavors to center on this component [11]. The author in his book remarked that many individuals who succumbed to COVID-19 were also vulnerable to pre-existing health conditions such as heart disease, diabetes, hypertension, and others [12]. The study evaluated the frequency, individual risk, and onset of cardiovascular disease that developed after COVID-19 in a sizable primary care database. The Healthcare Research Datalink in the UK provided the data that were taken from. Within 180 days following the infection, rates of arterial events, inflammatory cardiovascular disease and newly developed atrial fibrillation were estimated [13]. After that, data from 220,751 persons who had COVID-19 infection before December 1, 2020, were used to create multivariable logistic regression models. The researchers suggested a hybrid approach combining DEA and ensemble machine learning techniques. DEA was used to assess the efficiency of vaccine in states based on aggregated county-level data. Machine learning techniques were then applied to predict vaccine efficiency. The findings disclosed significant differences in performance among U.S. states, with only 16 states achieving efficient vaccination performance. The Random Forest and XGBoost models yielded the favorable outcomes out of other ensemble machine learning techniques which are used [14]. The past review explores advanced analytical aspects of COVID-19, covering various techniques for classification, segmentation, prediction, and feature selection used in diagnosing, detecting, and predicting the disease [15]. The authors' goal was to examine the performance evaluation measures, modeling strategies, and study designs of studies that developed clinical forecasting models for COVID-19 using machine learning techniques. The researchers searched four databases for articles describing how to use machine learning technique to develop multivariable prediction to predict various outcomes in individuals with COVID-19 [16]. The survey highlights the role of imaging that can play in the treatment of comorbid patients [17]. In study [18], author found that 17% of patients in a sports engineering for featuring aggressive athletes who were referred to the sports hospitals after found athlete testing positive for COVID-19 and doctors found that CMR findings also recommendation for myocardial diseases and 38.8% patient also have the presence of previous heart attack system. The past study introduces an explainable AI for heart attack prediction that is efficient, and easy to understand [19]. The National Institutes of Health and the American Heart Association publish the latest information on

cardiovascular risk factors, heart disease, and stroke each year [20]. The past study introduced the capability of utilizing the computer based intelligence approach, underscoring AI (ML) in foreseeing feebleness in patients with HF [21].

### 2.3 Autoencoder Based Analysis

The previous models do a pretty good job of detecting normal cases, but they fail to detect anomalies. The anomaly detection accuracy is 73.35% [22]. Experimental results shown in work indicate that the model performs quite well with 76.93% accuracy [23]. Ensemble learning techniques had been used on diabetes prediction to augment accuracy and predictive performance [24]. GAN algorithms are used to figuring out the areas of healthcare area which can be possibly to develop in destiny. It is going to help researchers and developers [25]. The mixing of synthetic intelligence and facts analytics with GIS structures promises to improve predictive competencies, improve decision-making, and foster worldwide collaboration [26]. The study was done to take a look toward investigating the COVID-19 vaccine panorama, in particular specializing in the relationship among the number of vaccine recipients and the incidence of COVID-19 cases [27]. The study aimed to perceive COVID-19 clusters in ASEAN international locations using global Moran's I [28].

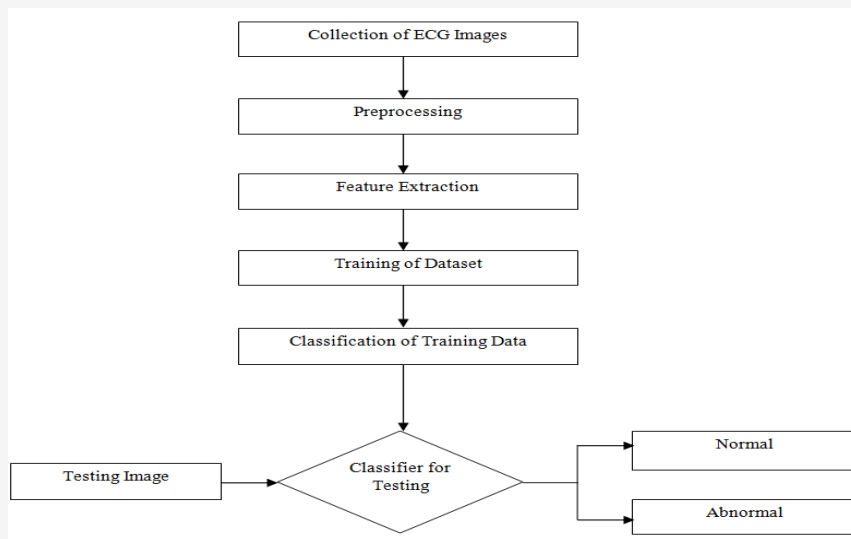
Autoencoders are very useful for detecting unknown post COVID-19 cardiac anomalies. They do not rely on predefined anomaly patterns, they can detect emerging ECG abnormalities linked to different COVID-19 variants. They can easily filters out ECG noise. The result of this study shows that autoencoder based approach produces competitive results. This study demonstrates how deep learning can increase the efficiency and accuracy of detecting abnormal heart rhythms in ECG readings. In summary, our research aims to build upon these prior efforts by employing advanced deep learning technique to predict heart attack risks with 91.11% accuracy, specifically within the context of COVID-19. Table 1 describes summary of literature reviews.

### 3. Proposed Methodology

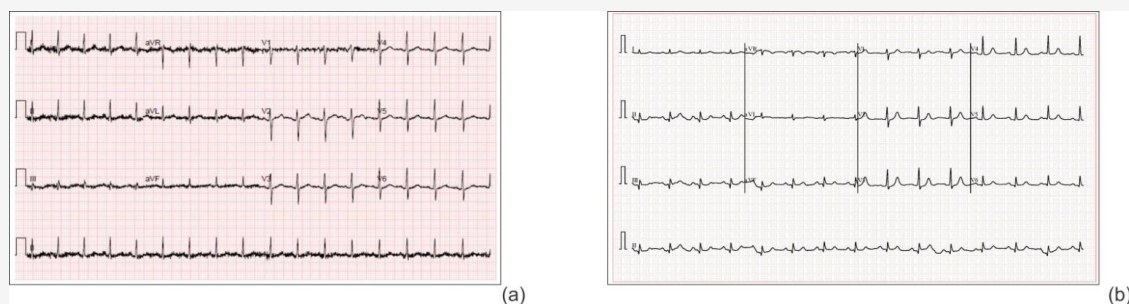
A systematic strategy is necessary in order to use deep learning model in an effective manner. The proposed methodology is shown in Figure 1. The first step is data collection, which entails data gathering in terms of electrocardiogram (ECG) images. Following that, the data is preprocessed using techniques like feature engineering to produce relevant attributes that improve model performance and cleaning to eliminate noise and inconsistencies.

**Table 1:** Summary of reviews done

<b>What has been done?</b>	<b>How it has been done?</b>	<b>What is the outcome/limitations</b>	<b>Reference Number</b>
Despite advances in prevention and treatment, CVDs continue to pose a significant public health burden, with disparities persisting among different population groups.	The report evaluates various sources of data on heart disease and stroke in United States.	The paper aims to provide an updated overview of the current state of heart disease and stroke statistics, including prevalence, risk factors, disparities, and outcomes, to inform healthcare professionals, policymakers, and the general public. The report may not fully capture the experiences and health outcomes of underrepresented populations.	[1]
Numerous heart and brain disorders, such as myocarditis, encephalopathy, stroke, and arrhythmias, can be brought on by COVID-19.	To measure the risk, AI-based tissue characterization is done.	Identify trends suggestive of COVID-19-related heart and brain damage using AI. Medical imaging AI models for COVID-19-related injuries sometimes have weak interpretability and explainability, which makes clinical practice less likely to use them.	[6]
There is growing evidence that cardiovascular consequences, specifically coronary inflammation, are important indicators of poor outcomes in individuals with COVID-19.	The study of strongly association of PCAT (peri coronary adipose tissue) with in hospital mortality in COVID-19 patients was done.	Detection and measurement of coronary inflammation using computed tomography (CT) in individuals with COVID-19. Real time clinical data that includes comorbidities, test results, and treatment plans is not adequately integrated with imaging results in current research.	[7]
The main question addressed by the study is the need to use ML algorithms to evaluate clinical data of understanding COVID-19 disease.	Random Forest classifier is used to predict adverse patients outcomes	Use of large dataset by combining information from various sources has been done to depict the diversity of COVID-19 patient groups. Issues such as inconsistent data, coding, incorrect data entry and missing data should be further investigate.	[10]
The main issue addressed by this study is the need for robust and reliable systems that can ML algorithms to accurately identify people at risk of heart disease.	Logistic Regression, CatBoost Regression, Random Forest Regression, Multilevel Perceptron (MLP) is comparatively tested.	Use of machine learning (ML) system for heart attack prediction. Techniques for hacking machine learning models and drawing important conclusions from predictions need further research especially in clinical settings.	[18]
Inability to identify heart disease early because of mild or ambiguous symptoms	The use of AI with Machine learning is done to predict the frailty syndrome with Heart failure.	Analyzing complicated datasets with AI algorithms to find patterns that human medics cannot see in order to detect cardiac disease early. The combination of more deep learning models or hybrid model is required for better prediction.	[21]



**Figure 1:** Flow chart of proposed methodology



**Figure 2:** ECG Images (a) COVID-19 patient (b) Normal Person

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
0	-1.507674	-3.574550	-4.478011	-4.408275	-3.321242	-2.105171	-1.481048	-1.301362	-0.498240	-0.286928	-0.390031	-0.263842	-0.318024	-0.185916	-0.269790	-0.322245	-0.309253	-0.391101	-0.303259
1	-0.297161	-2.766635	-4.102185	-4.589669	-4.219357	-3.650443	-2.300518	-1.293917	-1.065658	-0.490520	0.050751	-0.076647	-0.094647	-0.158180	-0.068692	-0.140832	-0.069177	-0.134276	-0.059199
2	0.446769	-1.507397	-3.187468	-4.507462	-4.604201	-3.636115	-2.311604	-1.597727	-1.362450	-0.669216	-0.173393	-0.205116	-0.230787	-0.177121	-0.238510	-0.205079	-0.230544	-0.209159	-0.292940
3	0.087631	-1.753490	-3.304473	-4.704657	-4.686415	-3.611817	-2.267268	-1.570893	-1.417790	-0.500788	-0.225177	-0.308834	-0.214733	-0.214509	-0.223121	-0.262336	-0.211816	-0.299099	-0.259956
4	-0.832281	-1.700368	-2.257301	-2.853671	-2.853301	-2.701487	-2.285726	-1.555512	-1.266622	-1.085957	-0.694641	-0.588517	-0.662469	-0.768004	-0.772551	-0.621054	-0.614187	-0.630124	-0.669577

**Figure 3:** Exploratory Data Analysis (EDA)

With the help of autoencoder model, the training of electrocardiogram (ECG) images are done which divides them into two categories (Normal (0) and abnormal (1)). For simplification 82% data is used in training phase and 18 % data is used in testing phase. In Model's evaluation phase, Reconstruction error is calculated by autoencoder using testing image. If testing image is having mean greater than threshold value then it is classified as "abnormal image" means it indicates a good chance of cardiac disease after COVID-19. Finally, model's accuracy is calculated using testing image.

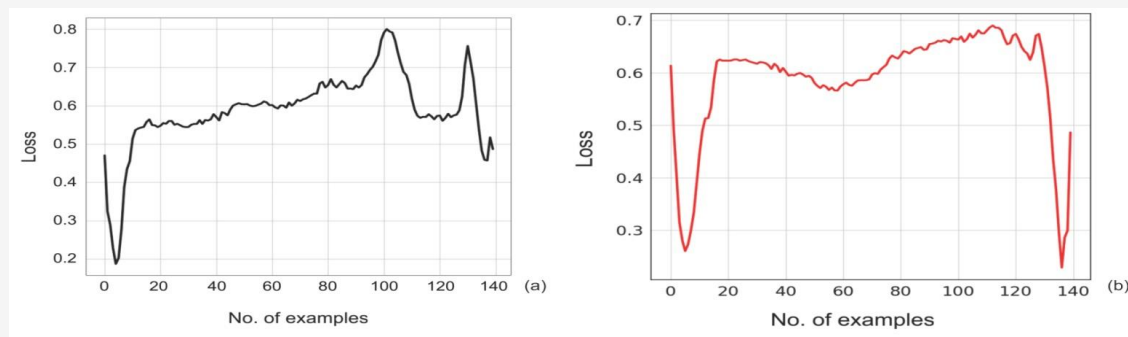
### 3.1 Collection of ECG Images and Preprocessing

In this dataset, there were 450 electrocardiogram (ECG) Images showing the images of pre and post

COVID-19 infected patients. Every image was 256×256 pixels in height and width, making them all two-dimensional. These 450 images are sufficient to detect anomalies based on reconstruction error. In this study, autoencoder uses normal and COVID-19 patients electrocardiogram (ECG) images to detect anomalies. Generally autoencoder requires less data for anomaly detection if it is detected based on reconstruction error. It contains electrocardiogram (ECG) readings of patients shown in Figure 2. Every ECG is having 140 data points. These points are floating point numbers. It is shown in Figure 3. The electrocardiogram (ECG) diagram consists of waves, intervals, and segments representing different phases of the cardiac cycle.

123	124	125	126	127	128	129	130	131	132	133	134	135	136	137	138	139	140
-0.107631	-0.161146	-0.101316	-0.095255	-0.069172	0.154878	0.695656	1.214931	1.089068	0.983369	1.014124	0.952629	0.749326	1.007076	1.634990	1.493365	-0.783134	1
-0.332811	-0.410334	-0.406518	-0.337232	-0.386479	-0.082580	0.220316	0.594978	0.581779	0.684406	0.911651	0.979483	1.053458	0.974787	1.110407	1.288165	-0.823386	1
-0.324933	-0.309288	-0.252567	-0.282586	-0.169345	0.258729	0.896627	1.088203	1.001306	1.292059	1.378667	1.014765	0.820793	1.034388	1.258433	0.961215	-0.999476	1
-0.212182	-0.135684	-0.133440	-0.170077	-0.035914	0.332243	1.063251	1.575754	1.709046	2.142926	2.393528	1.925550	1.027624	0.573453	0.192971	-0.648683	-2.441068	1
1.060978	1.116197	1.224351	1.421240	1.644654	2.007181	2.118599	2.028304	2.110504	2.203668	2.227544	2.171733	2.045938	2.126372	2.126852	1.679299	0.965814	1

**Figure 4:** Labelled Data



**Figure 5:** ECG signal (a) normal (b) abnormal

The normal rhythm is regular, with no abnormalities in different P-waves, normal PR/QRS intervals, and normal ST/T waves. The abnormal rhythm is irregular, with no p-waves, with abnormal PR/QRS periods or changes in ST/T waves like peaked or flat T waves.

### 3.2 Feature Selection/Engineering

To understand the connections between the attributes and the objective variable, it is important to conduct an exploratory analysis of the data. This will help in identifying any patterns or relationships that may exist. The label shows whether electrocardiogram (ECG) is normal (0) or abnormal (1). It is shown in 140 column of Figure 4. Additionally, selecting pertinent features with a high degree of predictive accuracy is crucial for building a successful model. By focusing on these key features, we can improve the overall performance and effectiveness of our predictive model.

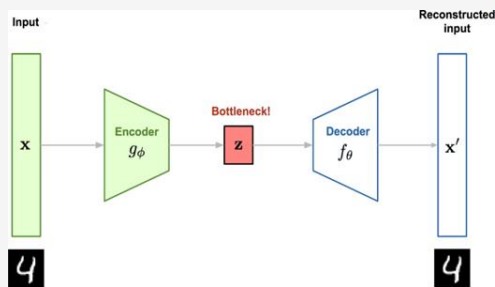
Realistic synthetic electrocardiogram (ECG) images using generative adversarial networks or variation autoencoder (VAEs) are created. GAE is used to generate new high quality synthetic images. TensorFlow and PyTorch Tools are used for this. If abnormal electrocardiogram (ECG) images are underestimated, data augmentation is used to generate synthetic variations. KerasImageDataGenerator tool is used to modify pixel intensities to generalize electrocardiogram (ECG) features. Balanced Target Distribution is taken. Dataset is divided into equal 50-50 % images labeled 0 and 1. 82% data is used for training and

18% data is used for testing purpose. In this step autoencoder is trained using normal rhythm. Normal and abnormal rhythms are separated which are shown in Figure 5.

A normal ECG contains upright and uniform P wave. There is no significant elevation or depression in ST segment. It contains upright T wave. A normal ECG in Figure 5(a) exhibits all these parameters. An abnormal ECG in Figure 5(b) has prolonged PR Interval, abnormal ST segment and T wave.

### 3.3 Model Building

Convolutional neural networks (CNNs) and Long short-term memory (LSTM) usually require large labels that can be expensive and time consuming. Autoencoder can recognize anomalies without the need for labeled data ideal for real scenarios where abnormal electrocardiogram (ECG) samples are lacking in comments or are difficult to comment on. An autoencoder shown in Figure 6 is used to expand the normal data into latent space of larger size than the original data, then go back and measure the difference between the recovered data and original data. The encoder is the part that converts the normal data to a smaller size, while the decoder is the part that return the original size to the compressed format. Hidden variables (Latent variables) are the data shown in the hidden space where the encoder compresses the data. During learning, the autoencoder always extracts the features of the training data and creates a latent space by minimizing the difference between the original data and the recovered data.



**Figure 6:** An autoencoder

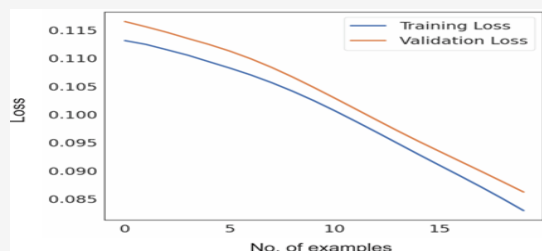
In encoder part, an input layer accepts raw ECG signals then 1D Convolutional layer is used to extract features from ECG signals after that an activation function LeakyReLU is used for batch normalization. Max Pooling layer is used for dimensionality reduction and finally dense layer is used to compress low dimensional representation of the ECG. In decoder part, dense layer expands back to high dimensional feature space. Transposed Conv1D layer expands feature back to original size using activation function LeakyReLU depending on the output format. Finally output layer reconstructs the original ECG signal.

### 3.4 Training of Dataset

Autoencoders are frequently used in unsupervised learning and anomaly detection, especially in the processing of electrocardiogram (ECG) signals. In order to detect irregularities during inference, an autoencoder for electrocardiogram (ECG) data needs to be trained to reconstruct normal electrocardiogram (ECG) waveforms. Reconstruction error between input and output signals decreases during training. The loss function is calculated using following equation 1 [29]:

$$MAE = \frac{1}{N} * \sum_{i=1}^N |O_i - P_i| \quad \text{Equation-1}$$

Where ( $O_i$ ) is observed value and ( $P_i$ ) is predicted value.  $N$  is number of observations. The training and validation loss is shown in Figure 7.



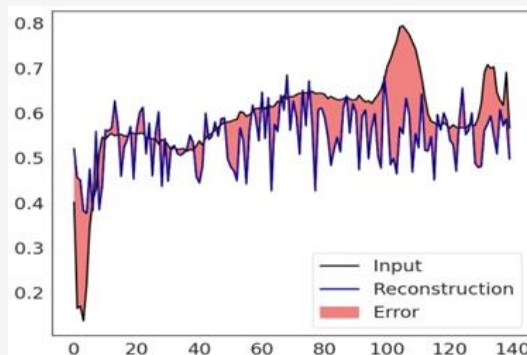
**Figure 7:** Training and validation loss

### 3.5 Model Evaluation

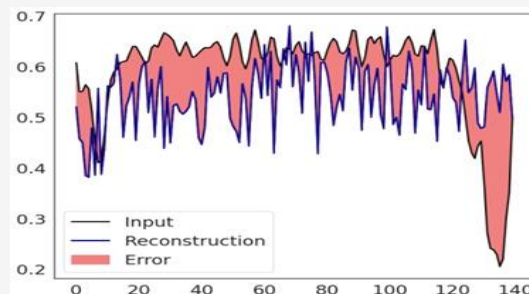
An autoencoder evaluates function and properties by comparing inputs and outputs. The simplest way is to treat the return data and the original data as points in the  $n$ -dimensional space. The input/output difference is represented by distance between two points. Reconstruction error is the name of this measure. If bad quality data is supplied, then compression and recovery cannot be done properly because the autoencoder is used to analyze defects which are taught to recover good quality of data. The bad quality data has a large reconstruction error. If the anomaly score is small, the data is classified as normal, if it exceeds the threshold, the data is classified as abnormal.

## 4. Result Analysis

If the reconstruction error is larger than one standard deviation from the training sample, the electrocardiogram (ECG) is classified as abnormal. We first describe the electrocardiogram (ECG) parameters of the training process, the autoencoder encoding, reconstruction after decision followed by reconstruction error. Normal data is tested and shown in Figure 8. Testing of abnormal data is shown in Figure 9

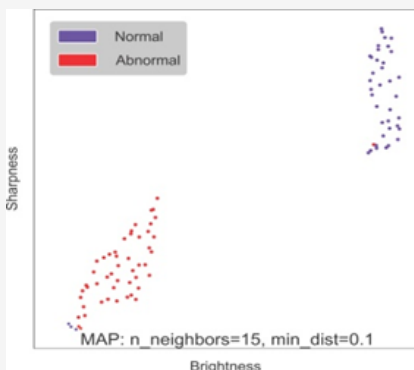


**Figure 8:** Testing of normal data



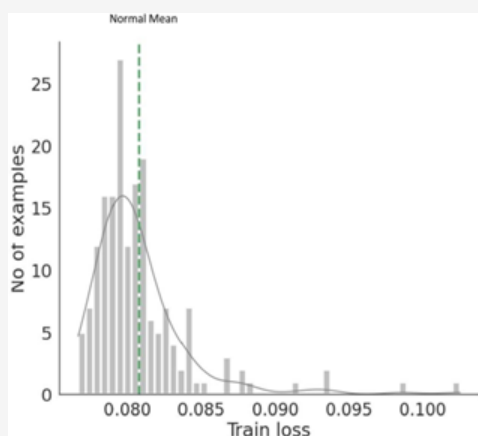
**Figure 9:** Testing of abnormal data

Dimension reduction of latent area for both normal and abnormal data is shown in Figure 10.



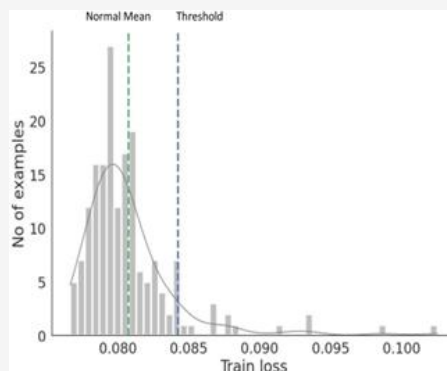
**Figure 10:** Latent Space

By determining whether the reconstruction exceeds the initial threshold, abnormalities can be detected. We calculate the error in the normal sample of the training process, and if the reconstruction error exceeds the standard deviation of the training process, we first record the data as anomaly. Normal mean (0.80) is shown by green line in Figure 11.

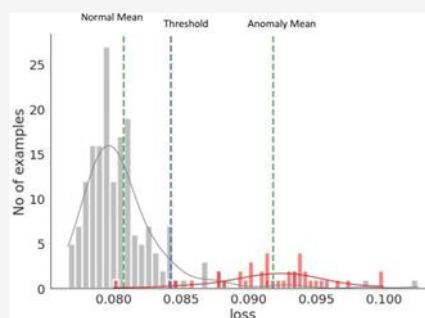


**Figure 11:** Normal Mean

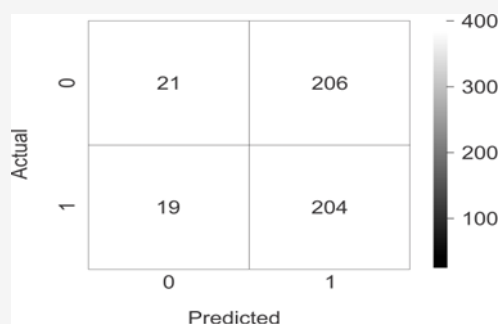
Now select a threshold (0.85) which is having higher standard deviation than mean. It is shown in Figure 12. If the reconstruction error is above the threshold value, the electrocardiogram (ECG) is considered abnormal. It is shown in Figure 13. The confusion matrix for anomaly recognition using electrocardiogram (ECG) images provides insight into the performance of the model by comparing predicted classification with actual classification which is shown in Figure 14.



**Figure 12:** Threshold and normal mean



**Figure 13:** Anomaly mean, threshold and normal mean



**Figure 14:** Confusion matrix

*False Positive (FP):* Normal ECG misclassified as anomaly.

*False Negative (FN):* Anomalous ECG misclassified as normal.

*True Positive (TP):* Anomalous ECG correctly classified as anomaly

Using Equation 1, Model’s accuracy (91%) is calculated. Accuracy, Precision and Recall are shown in following Table 2.

**Table 2:** Display of accuracy, precision and recall

Stats	Value
Accuracy	0.91
Precision	0.91
Recall	0.91

## 5. Conclusion

This study presents a deep learning autoencoder model to detect abnormalities in electrocardiogram (ECG) images of COVID-19 patients, addressing the critical need for effective cardiac care in this vulnerable population. The best accuracy results (91.11%) have been shown by the model compared to previous ones. By reconstruction error, the program learned the normal electrocardiogram pattern and was able to detect a difference that could indicate a problem with the heart. Experimental results demonstrate the model's high accuracy, sensitivity and ability to detect small abnormalities. It highlights its potential to help physicians for early diagnose and treat COVID-19 related problems. Expanding the dataset to improve generalization to a wider variety of patient populations and medical patients is part of future research. Multimodal information such as test results and medical records can increase the prediction accuracy. Additionally, developing hybrid models that combine autoencoders with other machine learning methods could improve the ability to identify complex or unusual heart abnormalities.

## 6. Future Scope

By integrating autoencoder with deep learning techniques like convolutional neural networks (CNNs) and Recurrent neural networks (RNNs), this model can extract more complex pattern from electrocardiogram (ECG) images. Hybrid models can improve the feature learning by reducing the number of false positives or false negatives. Explainable AI is very important for gaining the clinical trust. It can make model's decision more transparent.

## References

- [1] Tsao, C., Aday, W., Zaid, I., Alvaro, A., Andrea, Z., Marcio, S., Amelia, K., Alfred, E., April, P. and Yvonne, C., (2022). Heart Disease and Stroke Statistics 2022 Update: A Report from American Heart Association. *Circulation*, Vol. 145(8), e153-e639. <https://doi.org/10.1161/CIR.0000000000001052>.
- [2] Sneha, A., Edzel, L., Arun, M., Inderbir, P., Mahvish, A., Swapna, S., Ayesha, S., Maha, N., Shubhadarshini, P. and Gurpreet, J., (2023). Heart Failure: Recent Advances and Breakthroughs. *Disease-a-Mont*, Vol. 22(6). <https://doi.org/10.1016/j.disamonth.2023.101634>.
- [3] Salvatore, C. and Carlo, S., (2023). A Systematic Review of Multimodal Deep Learning Approaches for Covid-19 Diagnosis. *International Conference on Image Analysis and Processing*, Vol. 9(3), 140-151. <https://doi.org/10.1007/978-3-031-51026713>.
- [4] Antonis, A., Sanjiv, M., Donna, K., Kayte, S., Derrick, A., Leo, A., Paul, A., Michael, H., Jennifer, L. and Anne, E., (2024). Use of Artificial Intelligence in Improving Outcomes in Heart Disease: A Scientific Statement from American Heart Association. *Circulation*, Vol. 149(14), e1028-e1050. <https://doi.org/10.1161/cir.000000000000120>.
- [5] Kumar, S., Tenzin, D. and Gupta, S., (2024). The Clinical Practices and Post- Treatment Care for Covid-19 Patients with Heart Complications. *Clinical Practice and Post-Infection Care for COVID-19 Patients*, Vol. 17(2), 167-189. <http://doi.org/10.4018/978-1-6684-6855-5.ch007>.
- [6] Sharma, H., Birla, R., Biswas, M. and Suri, S., (2023). An Overview of ai Applications in Medical Imaging for Covid-19-Related Brain and Heart Injuries. *Multimodality Imaging*, Vol. 2, 1-1.
- [7] Tuttolomondo, D., Ticinesi, A., Dey, D., Martini, C., Nouvenne, A., Nicastro, M., Filippo, M., Sverzellati, N., Nicolini, F. and Meschi, T., (2024). Coronary Inflammation on Chest Computed Tomography and Covid-19 Mortality. *European Radiology*, Vol. 16, 1-11. <https://doi.org/10.1007/s00330-023-10573-8>.
- [8] Yazdani, A., Erfannia, L., Ali, F. and Ali, O., (2024). Survival Analysis of Patients with Covid-19 Using Deep Neural Network and Random Forest Techniques. *Frontiers in Health Informatics*, Vol. 13. <https://healthinformaticsjournal.com/downloads/files/512.pdf>.
- [9] Granata, V., Fusco, R., Villanacci, R., Grassi, F., Grassi, R., Stefano, F., Petrone, A., Fusco, N. and Ianniello, S., (2023). Qualitative and Semi-Quantitative Ultrasound Assessment in Delta and Omicron Covid-19 Patients: Data from High Volume Reference Center. *Infectious Agents and Cancer*, Vol. 18(1). <https://doi.org/10.1186/s13027-023-00515-w>.

- [10] Cowley, H., Robinette, M., Matelsky, J., Xenes, D., Kashyap, A., Ibrahim, N., Robinson, M., Zeger, S., Garibaldi, B. and Roncal, W., (2023). Using Machine Learning on Clinical Data to Identify Unexpected Patterns in Groups of Covid-19 Patients. *Scientific Reports*, Vol. 13(1). <https://doi.org/10.1038/s41598-022-26294-9>.
- [11] Kerzhner, O., Berla, E., Hareven, E., Ratmansky, M. and Gooraryeh, I., (2024). Consistency of Inconsistency in Long-Covid-19 Pain Symptoms Persistency: A Systematic Review and Meta-Analysis. *Pain Practice*, Vol. 24(1), 120-159. <https://doi.org/10.1111/papr.13277>.
- [12] Rao, V. G. and Rao, D. S., (2023). *Clinical Practice and Post-Infection Care for COVID-19 Patients*, Vol. 5(2), 14-16. <https://doi.org/10.4018/978-1-6684-6855-5>.
- [13] Teeuw, H., Smeden, M., Geersing, G., Klungel, O., Rutten, F., Souverein, P. and Doorn, S., (2023). Incidence and Individual Risk Prediction of Post-Covid-19 Cardiovascular Disease in the General Population: A Multivariable Prediction Model Development and Validation Study. *European Heart Journal Open*, Vol. 3(6). <https://doi.org/10.1093/ehjopen/oad101>.
- [14] Cosgun, O., Kaya, G. and Cosgun, C., (2024). Covid-19 Vaccination Performance of the US States: A Hybrid Model of Deep and Ensemble Machine Learning Methods. *Annals of Operations Research*, Vol. 12(8), 1–31.
- [15] Vetrithangam, D., Pegada, N., Himabindu, R. and Arunadevi, B., (2024). State-of-the- Art Review on the Models, Techniques, and Datasets to Diagnose Covid-19 Disease. *Research Anthology on Bioinformatics, Genomics, and Computational Biology*, Vol. 11(7), 1427–1452. <https://doi.org/10.4018/978-1-6684-6519-6.ch014>.
- [16] Santos, A., Pinhati, C., Perdiga, J., Galante, S., Silva, L., Veloso, I., Silva, A. and Oliveira, E., (2024). Machine Learning Algorithms to Predict Outcomes in Children and Adolescents with Covid-19: A Systematic Review. *Artificial Intelligence in Medicine*, Vol. 14(3). <https://doi.org/10.1016/j.artmed.2024.102824>.
- [17] Suri, J., Puvvula, A., Biswas, M., Majhail, M., Saba, L., Faa, G., Singh, I., Oberleitner, R., Turk, M. and Chadha, S., (2020). Covid-19 Pathways for Brain and Heart Injury in Comorbidity Patients: A Role of Medical Imaging and Artificial Intelligence-Based Covid Severity Classification: A Review. *Computers in Biology and Medicine*, Vol. 124. <https://doi.org/10.1016/j.compbiomed.2020.103960>.
- [18] Manoj, M., Madhuri, M., Anusha, K. and Sree, K., (2023). Design and Analysis of Heart Attack Prediction System Using ML. *2023 IEEE International Conference on Integrated Circuits and Communication Systems (ICICACS)*, Vol. 6(3), 01-06. <https://doi.org/10.1109/ICICACS57338.2023.10099819>.
- [19] Srinivasu, P., Sirisha, U., Sandeep, K., Praveen, S., Maguluri, L. and Bikku, T., (2024). An Interpretable Approach with Explainable AI for Heart Stroke Prediction. *Diagnostics*, Vol. 14(2). <https://doi.org/10.3390/diagnostics14020128>.
- [20] Diwan, S., Thakur, G., Sahu, S., Sahu, M. and Swamy, N., (2022). Predicting Heart Diseases through Feature Selection and Ensemble Classifiers. *Journal of Physics: Conference Series*, Vol. 2273. <https://iopscience.iop.org/article/10.1088/1742-6596/2273/1/012027/pdf>.
- [21] Szczepanowski, R., Uchmanowicz, I., Dixit, A., Sobiecki, J., Katarzyniak, R., Kolaczek, G., Lorkiewicz, W., Kedras, M., Dixit, A. and Biegus, J., (2024). Application of Machine Learning in Predicting Frailty Syndrome in Patients with Heart Failure. *Advances in Clinical and Experimental Medicine*, Vol. 33(3), 309-315. <https://doi.org/10.17219/acem/184040>.
- [22] Kaushik, P. and Sharma, P., (2024). Cutting-Edge Convolutional Neural Network Autoencoders for Anomaly Detection in ECG Signals: Advancements in Early Cardiac Diagnosis. *2024 International Conference on Cybernation and Computation (CYBERCOM)*, Vol. 4(2), 340–344. <https://doi.org/10.1109/CYBERCOM63683.2024.10803240>.
- [23] Agarwal, M., Gill, K., Aggarwal, P. and Rawat, R., (2024). Unveiling Irregular Heart Rhythms: Utilizing a Pretrained Resnet50 Convolutional Neural Network Autoencoder Strategy for Detecting Anomalies in ECG Signals. *2024 2nd World Conference on Communication & Computing (WCONF)*, Vol. 19, 1–4. <http://dx.doi.org/10.1109/WCONF61366.2024.10692242v>.

- [24] Jain, R., Tripathi, N., Pant, M., Anutariya, C. and Suwanchai, C., (2024). *International Investigating Gender and Age Variability in Diabetes Prediction: A Multi-Model Ensemble Learning Approach. IEEE Access*, Vol. 15(4), 76-82. <https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=10534069>.
- [25] Jain, R., Pant, M. and Triapthti, N., (2024). Generative Adversarial Networks in Healthcare Sector. *International Journal of Geoinformatics*, Vol. 20(6), 26-42. <https://doi.org/10.52939/ijg.v20i6.3331>.
- [26] Wongpituk, K., Laosupap, K., Butson, A., Thammaboribal, P., Chankong, W. and Pokomnird, C., (2024). Advancements in Disease Surveillance: The Role of GIS in Global Health Preparedness. *International Journal of Geoinformatics*, Vol. 20(10). 95-108. <https://doi.org/10.52939/ijg.v20i10.3663>.
- [27] Polin, S., Lokavee, S., Sukdee, S., Junpha, J., Harnwungmoung, A., Samngamdee, M., Ampant, P., Thammaboribal, P. and Wongpituk, K., (2024). Assessment of Covid-19 Vaccination Services During the 5th Wave of the Outbreak in Thailand. *International Journal of Geoinformatics*, Vol. 20(3), 28-36. <https://doi.org/10.52939/ijg.v20i3.3125>.
- [28] Thammaboribal, P., Tripathi, N., Junpha, J., Lipilert, S. and Wongpituk, K., (2024). Examining the Correlation between Covid-19 Prevalence and Patient Behaviors, Healthcare, and Socioeconomic Determinants: A Geospatial Analysis of Asean Countries. *International Journal of Geoinformatics*, Vol. 20(3), 95-112. <https://doi.org/10.52939/ijg.v20i3.3159>.
- [29] Paluang, P., Thavorntam, W., and Phairuang, W. (2024). Application of Multilayer Perceptron Artificial Neural Network (MLP-ANN) Algorithm for PM2.5 Mass Concentration Estimation during Open Biomass Burning Episodes in Thailand. *International Journal of Geoinformatics*, Vol. 20(7), 28-42. <https://doi.org/10.52939/ijg.v20i7.3401>.