Journal of Applied Engineering and Technological Science
Vol 5(2) 2024: 1242-1256

DEEP LEARNING AND ITS ROLE IN DIAGNOSING HEART DISEASES BASED ON ELECTROCARDIOGRAPHY (ECG)

Qaswaa Khaled Abood
Computer Science Department, College of Science, University of Baghdad, Iraq
Qaswaa.k@sc.uobaghdad.edu.iq

Received : 29 November 2023, Revised: 01 March 2024, Accepted : 16 March 2024
**Corresponding Author*

ABSTRACT
Diagnosing heart disease has become a critical topic for researchers specializing in artificial Intelligence because Intelligence is involved in most diseases, especially after the Corona pandemic, which forced the world to turn to Intelligence. Therefore, the basic idea in this research was to shed light on the diagnosis of heart disease by relying on deep learning of a pre-trained model (Efficient B3), which provides the possibility of training in-depth due to the number of layers it contains and the Parameters and reliance on the use of electrical signals from the ECG and ECG segmentation. To feed it into the neural network with only pruning processing operations because it is an electrical signal whose parameters cannot be changed. The data set (China Physiological Signal Challenge - cspsc2018) was adopted, which is considered a challenge for researchers because it includes different age groups. Many diseases and the results obtained by the system were 96% accurate.
***Keywords** : Diagnosing, Heart, CNN, Signal*

1. Introduction

Electrocardiogram (ECG) is a non-invasive diagnostic tool that monitors and documents the heart's electrical impulses(Ibrahim et al., n.d.). The famous Dutch biologist and physician Willem Einthoven invented the ECG recording in 1887 for diagnosis(khiled AL-Jibory et al., 2022). This study revolutionized the diagnosis of heart diseases because of its efficiency and high benefit in monitoring the heart's efficiency(Rahma & Salman, 2022). The ECG's primary purpose was to diagnose the heart's electrical impulses during cardiac systole, evaluate its rhythm, speed, physiological performance, and health, and form a complete picture of its condition. Essential heart and blood vessel disorders with high mortality are diagnosed by cardiologists using ECGs (Ramkumar et al., 2021). The electrocardiogram (ECG) is a vital diagnostic tool for heart disorders in modern medicine. Electrocardiograms (ECGs) show the heart's electrical rhythm in phases(Sandau et al., 2017). Electrodes are inserted into the chest, upper, and lower extremities to obtain an ECG. Electrodes measure electrical potential differences between body parts(Sadiq & Mahmood, 2014). Electrical potential difference measures the voltage differential between two sites. The valuable properties of ECG, which allowed algorithms to be trained and learned, changed the quality of artificial intelligence heart disease diagnosis (Shkara & Hussain, 2018).Deciphering ECG signals is difficult due to their complex and irregular characteristics, which can be tedious and stressful even for experts. The use of computer-assisted methods is crucial to reduce human workload and reduce errors due to fatigue and inter-subject variability(Rahma & Salman, 2022). Deep learning has shown outstanding performance in recent ECG classification studies. The hierarchical structure enables sophisticated feature extraction, improving its ability to extract and classify project features(Mohammed & Essa, 2022) (Abdelghani et al., 2016)Also. A recent study showed more Accuracy and efficiency compared to manual classification by experts. Deep learning is achieved by building artificial neural networks with multiple layers, each of which has its functional function and implicit internal layers, where components in each layer facilitate deep learning, which significantly benefits analyzing and understanding complex data such as the ECG signal(Shkara & Hussain, 2018)(Shahriari et al., 2018). Progressing through each layer allows for more conceptual and advanced features to be extracted, improving classification accuracy. Deep learning is superior to classical machine learning in its ability to model complex data using large data sets (Abd El-Rahiem & Hammad, 2022).The discovery and extraction of features are implicit and do not require algorithms to support their work. It provides speed and

Accuracy. Therefore, researchers have resorted to employing and studying deep learning to diagnose heart diseases(Gimeno-Blanes et al., 2016) (Al-Juboori, 2017).

In this paper, an approach to diagnosing heart disease was proposed. It consists of three primary stages, starting with the processing process, which includes the most critical stage, segmenting the signal and plotting it to unify the inputs to the model. The segmentation process is aided by a set of data with similar wavelengths, plotting these signals and dealing with them because they are images. The input to the model is an image of one size, and Efficient B3 was chosen as a training model because it has several variables of approximately 12M with FLOPs of 1.8B. In this way, the problem of the variable input was solved because it is a signal and cannot be unified because it is raw data and dealt with on the basis that it is an image.

2. ECG Conception

Electrocardiogram (ECG) is a non-invasive diagnostic tool for monitoring and analyzing the electrical impulses of the human heart(Li & Boulanger, 2020). The heart muscle generates electrical signals to control the heart rhythm. Pacemaker cells create electrical impulses. The heart muscle contracts with each beat when the pacemaker cells give off an electrical signal(Sadiq & Mahmood, 2014). A diagnostic electrocardiogram (ECG) records and analyzes the electrical impulses of the heart muscle. Electrodes on the chest and upper and lower extremities produce an electrocardiogram (ECG)(Zontone et al., 2019). Electrodes measure potential changes between parts of the body. Potential difference is the potential difference between two locations(Saranya & Murugan, 2023). Electrocardiogram (ECG) traces show voltage fluctuations. Each electrocardiogram (ECG) wave represents a phase of the heart's electrical cycle. ECG traces have P, Q, R, S, and T waveforms(Abed et al., 2023). The electrical activity of the heart's atria is P waves. The QRS complex indicates decreased electrical activity of the heart's ventricle(Kim et al., 2023). said that the T wave indicates ventricular repolarization. The P wave to the QRS complex is the PR interval. The PR interval is the time it takes for the electrical impulse from the atria to the ventricles(*Methods and Studies for Human Electrocardiogram : A Survey*, n.d.). The QT interval is the period between the QRS complex and the T wave required for cardiac contraction and repolarization(Alqahtani et al., 2023)(Al-Juboori, 2017). All ECG waves are in Figure 1.

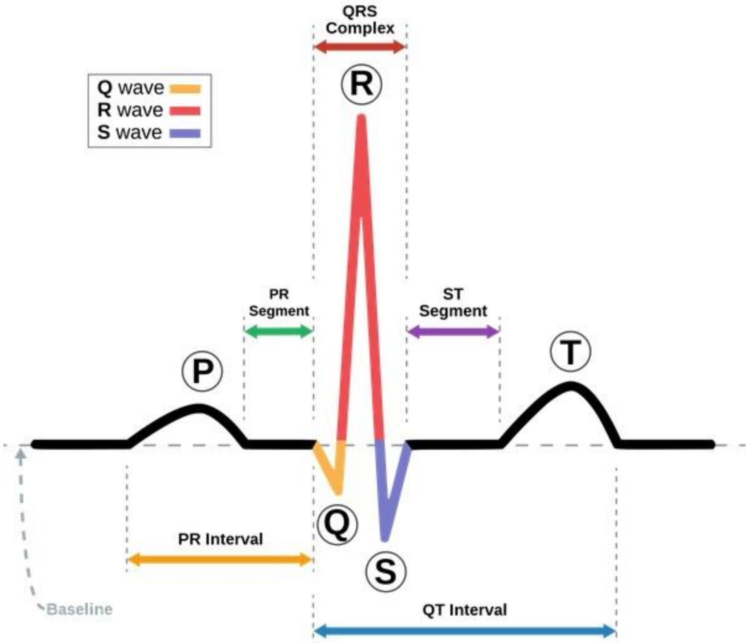

Fig 1. Summarises All Waves in ECG(Borghi de Melo, 2021).

The interpretation of the electrocardiogram (ECG) tracing by a healthcare expert who has received specialized training allows for identifying irregularities in the heart's rhythm, pace, and overall functioning(Khanna et al., 2023). Aberrations observed on the electrocardiogram (ECG) have the potential to serve as indicators for a diverse range of cardiac ailments, encompassing(Malakouti, 2023; Yang et al., 2015):

- **Arrhythmias:** Abnormal heart rhythms, such as atrial fibrillation, ventricular fibrillation, and bradycardia.
- **Coronary artery disease (CAD**): A narrowing or blockage of the arteries that supply blood to the heart.
- **Heart attack:** Damage to the heart muscle caused by a sudden blockage in a coronary artery.
- **Heart failure**: A condition in which the heart cannot pump blood effectively.
- **Cardiomyopathy:** A disease of the heart muscle.
- **Heart valve disease:** A condition in which the heart valves do not function properly.
- **Pericarditis:** Pericarditis refers to the inflammation of the pericardium, the membranous sac surrounding and protecting the heart.

3. AI Deep Learning in ECG

Artificial Intelligence mimics the human mind's execution of ideas and finding solutions using algorithms and procedures(Harmon et al., 2022). AI researchers have focused on ECG analysis to improve heart disease diagnosis, detection and clinical assistance(Hannun et al., 2019). AI algorithms can detect subtle changes in complex ECG patterns that may indicate heart disease at diagnosis(Saini & Gupta, 2022). These intelligence algorithms improve the identification of arrhythmias such as AF, VT, and SVT. Deep learning, a type of artificial Intelligence, can improve ECG analysis by learning from vast worldwide ECG data sets collected by specialized centres under medical supervision(Siontis et al., 2021). Deep learning can detect ECG patterns and complex features for doctors to detect. Depending on how specialists use them, ECG analysis systems using AI can evaluate patients' hearts more efficiently and cost-effectively(Lynn et al., 2018). Artificial Intelligence and deep learning algorithms can detect and classify arrhythmias, heart palpitations, intermittent ECGs, migrating beats, and other abnormalities in ECG diagnosis. This highlights the risk of stroke and other problems(Abood, 2023). It can diagnose myocardial ischemia, which reduces blood flow in the heart muscle, by analyzing the ST segment of an EKG. The leading cause of heart attacks can be detected, which is acute coronary syndrome (ACS). HRV, or heartbeat intervals, can be measured using the device(khiled AL-Jibory et al., 2022). HRV measures the heart's pumping performance, autonomic nervous system, and cardiovascular risk. (LVEF) detects heart failure. Artificial Intelligence and deep learning in ECG analysis are constantly increasing and could revolutionize the detection and treatment of heart diseases. Improved and accessible AI algorithms will become more critical in healthcare(Mincholé & Rodriguez, 2019).

4. Related Work

presents an overview of some previously published literature reviews on heart disease diagnosis standard dataset approaches.

In (Terzi & Arikan, 2023), An approach that has the potential to operate technology known as Artificial Intelligence-Based Hybrid Anomaly Detection (AIHAD) has been proposed as a decision support system to enhance clinicians' effectiveness in rapid, early and accurate diagnosis of coronary artery disease (CAD). Particularly in the case of asymptomatic individuals, diagnostic data obtained from electrocardiography (ECG) alone are insufficient to establish a reliable diagnosis of the condition due to its scarcity. Thus, this facilitates immediate medical intervention and significantly reduces the mortality rate associated with cardiovascular diseases based on AI.

In (Shi et al., 2023) present a hyperparameter optimization, feature extraction, and arrhythmia classification method. A hybrid strategy is advised. This method uses a multilayer perceptron for hyperparameter optimization, a restricted Boltzmann machine for feature extraction, and a deep belief network for classification. HybDeepNet will analyze two ECG data sets to test its efficacy. The purpose is to compare the model's performance across the two data sets and ensure correct predictions. Deep learning (DL) models like AlexNet and LeNet can automatically classify ECG signals. Distance learning has efficiently retrieved key features from large datasets to discover correlations. This speeds up and improves diagnosis.

In (Bhanjaa & Khampariya, 2023) The study suggests a multilayer heart attack classification model. To improve heart attack detection with machine learning. A multi-class ECG signal categorization approach for heartbeats is proposed. Improve ECG pulse signal categorization efficiency for best results. Propose an IoT framework with a notification system for real-time medical decision assistance and patient monitoring

In (El Boujnouni et al., 2023) present A capsule network with wavelet decomposed brief ECG segments is presented to classify eight illnesses. The study seeks to automate ECG analysis and cardiovascular disease diagnosis. This can speed diagnosis and reduce errors. Wavelet feature extraction and CapsNet (convolutional capsule network) are breakthrough ECG analysis tools for cardiovascular disease diagnosis. This study seeks new and better ways in this subject.

In (Jayaram et al., 2023) An examination of the numerous varieties of deep learning methods that are capable of predicting cardiovascular illness is presented here. Within the confines of this investigation, the objective is to assess the applicability and precision of employing deep learning models for the purpose of automated heart disease prediction based on electrocardiogram (ECG) data. At first, will investigate the ways in which deep learning can be utilized in this particular domain.

The following is Table 1. Summarized the most citation papers from previous studies.

Table 1 - Summarized The Related Work.

Years & Rf.	Method	Limitation	Performance Evaluation
(Terzi & Arikan, 2023)	- Supervised categorization using artificial neural networks (ANNs) to detect CSNA and ECG irregularities. an unsupervised clustering method using: - Gaussian mixture models (GMMs) -Neyman-Pearson criterion to detect coronary artery disease outliers (CAD).	-Sample size: A modest sample size of 260 participants was used to generalize the AIHAD technique's efficacy. A more diverse and extensive dataset may yield a more robust and generalizable model. -Focus on specific disease: The study avoided other cardiovascular disorders and concentrated on CAD detection. AIHAD's efficacy in identifying additional cardiovascular diseases needs more study.	Sensitivity= 98.48 % specificity =97.73 % accuracy= 98.11 %, positive predictive value =97.74 %, negative predictive value 98.47 %, F1-score =98.11 %.
(Ram et al., 2023)	HybDeepNet comprises three deep learning models: - -Restricted Boltzmann Machines (RBMs) - Multilayer Perceptrons (MLPs) - Deep Belief Networks (DBNs).	The study employs a dataset that is extensively utilized in arrhythmia studies but is limited compared to real-world ECG data. This raises questions regarding the model's generalizability to unseen data and its capacity to handle different arrhythmia forms not well documented in datasets. Thus, test data is limited. In addition, the process of dividing data was not explained in a detailed	Accuracy of 97.1%, F1-score =96.4%, AUC =95.3%,

		way to identify the amount of data allocated for training, verification, and testing	
(Bhanjaa & Khampariya, 2023)	-AlexNet - LeNet DL	-Comparison limitations: The study examines deep learning architectures for ECG classification but doesn't compare them to healthcare professionals' ECG analysis methodologies. This makes it hard to compare deep learning models to existing methods. -Specify class count: The study classifies 5 ECG classes, although real-world ECG analysis may include more arrhythmias. Further research should evaluate the model's performance with more ECG classes for a more practical assessment.	AlexNet earned the best classification result accuracy =97.5%, precision=97.61%, recall= 97.42%, F1 score =97.52%
(Shi et al., 2023) 2023	-Genetic Algorithm and Segment Length Optimization (GA-LSLO) - lead attention module (LAM)	-The study validates arrhythmia and myocardial infarction, but not other cardiovascular illnesses. To diagnose more conditions, the algorithm may need refinement and validation. -Overfitting: Machine learning models can overfit when they perform well on training data but poorly on unseen data. Countermeasures like cross-validation and separate test sets can increase the study's generalizability.	accuracy =97.62% F1= 96.25%
(Alnaggar et al., 2023)	-K Nearest Neighbor (KNN) -optimizing hyperparameters with Grid search to enhance classification accuracy	The study detects heart attacks and arrhythmias, thus it may not work for other cardiac diseases. More research is needed to determine the framework's applicability to more heart ailments.	Accuracy when applying (KNN)= 92.3%, (SVM)= 89.51% RF= 90.91% , Gridsearch = 97.5%.
(El Boujnouni et al., 2023)	-ECG signals are preprocessed and segmented into beats segments. - continuous wavelet transform is used to transform the segments into 2D scalograms. -discrete wavelet transform to obtain wavelet coefficient images which are fed to the reformed capsule	The study uses 150 ECG signals, which may be insufficient to build a complicated deep learning model like CapsNet. Overfitting, where the model performs well on training data but badly on unknown data, limits generalizability.	accuracy = 98.6%,

	networks. -The focal loss was applied to mitigate the class-imbalance issue. - The proposed model was trained and tested using 5-fold cross-validation and train-test split techniques.		
(Jayaram et al., 2023)	-Denoising techniques are used to detect QRS complex -ECG signals are filtered using band pass filter. -The techniques like Long short term memory networks [LSTM], Deep Belief Network [DBN], Auto encoders, Convolutional neural network [CNN], Recurrent neural network [RNN] are used for classification of cardiovascular diseases from the extracted features.	The study doesn't specify if cross-validation or an independent test set was employed for validation. The stated results' generalizability and overfitting potential are difficult to judge.	Accuracy of CNN model= 85-88%. Auto encoder= 97%., RNN= 98.4%. , LSTM= 95 %

5. Proposed Methods

Diagnosing heart disease based on artificial Intelligence is a challenging topic for researchers because it contains many dangerous diseases. Therefore, after the Corona pandemic, the entire world turned to artificial Intelligence, so the diagnosis of diseases played a very important role. From this standpoint, the proposed system aims to design an artificial intelligence system based on deep learning. (Pre-trained model) using the most difficult data set and considered a challenge for researchers. Below figure is a that shows the analysis.

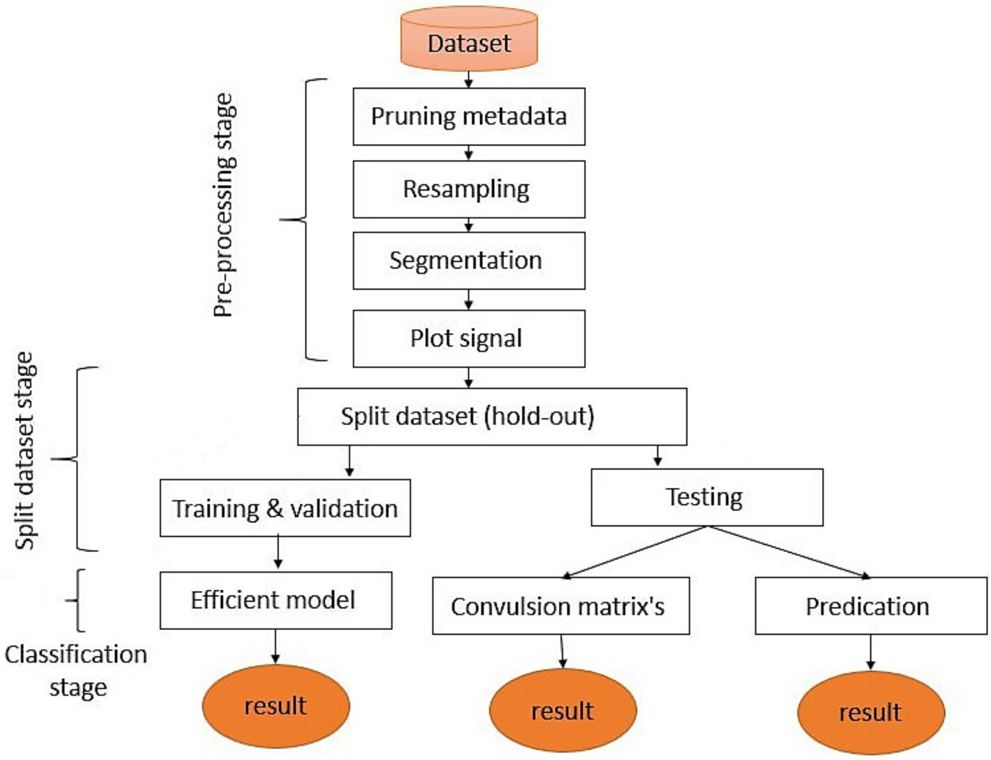

Fig. 2. Proposed System Method

5.1 Dataset

The China Physiological Signal Challenge (CPSC) 2018(Liu et al., 2018) was an academic competition designed to foster the advancement of algorithms in the detection of rhythm and morphological anomalies in 12-lead electrocardiogram (ECG) recordings. The dataset included in the CPSC 2018 study comprises of a single normal electrocardiogram (ECG) type and eight distinct aberrant ECG types. The abnormal cardiac rhythms encompass atrial fibrillation (AF), atrial flutter (AFL), sinus rhythm with premature atrial contractions (PACs), sinus rhythm with premature ventricular contractions (PVCs), sinus tachycardia (SVT), sinus bradycardia (SB), left bundle branch block (LBBB), and right bundle branch block (RBBB). The dataset can be accessed and downloaded without charge from the official PhysioNet website at the following URL: https://physionet.org/.Several research projects have developed and evaluated ECG arrhythmia detection algorithms using the CPSC 2018 dataset. Trials have proven that deep learning algorithms perform this task well. 1,537 people provided 12-lead electrocardiograms (ECGs) for CPSC 2018. The dataset had 45,912 ECGs. The dataset was split into 1,229 training participants and 308 test subjects. The training dataset included normal and abnormal electrocardiogram (ECG) segments, while the test dataset solely included abnormal ones.

5.2 Processing Stage

The data set comprises electrical impulses from an EKG stored in CSV files containing comprehensive patient information such as disease type, age, gender, and other parameters, as presented in Table 2.

Table 2 - Details Of File Metadata

Feature	Description
subject_id	Unique identifier for each subject
recording_id	Unique identifier for each ECG recording
lead	Lead name (lead I, lead II, lead III, etc.)
sample number	Sample number within the ECG recording
amplitude	Amplitude of the ECG signal at that sample
recording time	Time in seconds since the start of the ECG recording
age	Age of the subject in years
sex	Sex of the subject (male or female)
diagnosis	Diagnosis of the subject (normal, atrial fibrillation, ventricular tachycardia, etc.)

In addition to that, the CSV file could have additional columns that are different from one subchallenge to the next. An example of this would be the Comma-Separated Values (CSV) file that pertains to the subchallenge of arrhythmia detection. This file would have a column that indicates whether or not an arrhythmia was present in the electrocardiogram (ECG) segment. Researchers and developers who are working to improve the diagnosis and management of arrhythmias and other electrocardiogram (ECG) issues will find the CSV file that is included in the CPSC 2018 dataset to be an invaluable resource. The method of pruning consisted of removing duplicates and empty files, if any were there, as well as information that was not essential for diagnosis. After that, the Resample command was utilized to generate intervals between the pulses due to the fact that they overlapped one other to a large degree.. Through this, spaces are created that do not affect the signal, but enable the splitting process. It is done smoothly and the signal appears clearly to the eye, and then the segmentation process is performed, which was done based on experience, where the criterion for division was experience and its effect on the training process and its efficiency, since this data set provides a complete reading of the 12 leads completely, and a final step in the processing process is drawing the signal. Electricity by directing the plot signal in Python. Thus, the files were prepared for the process of converting the electrical signal into an image signal by directing the signal to be plotted in the Python library, and thus the new image data was created. Below is a figure 3 that shows how processing works in the proposed system through a sequence of steps.

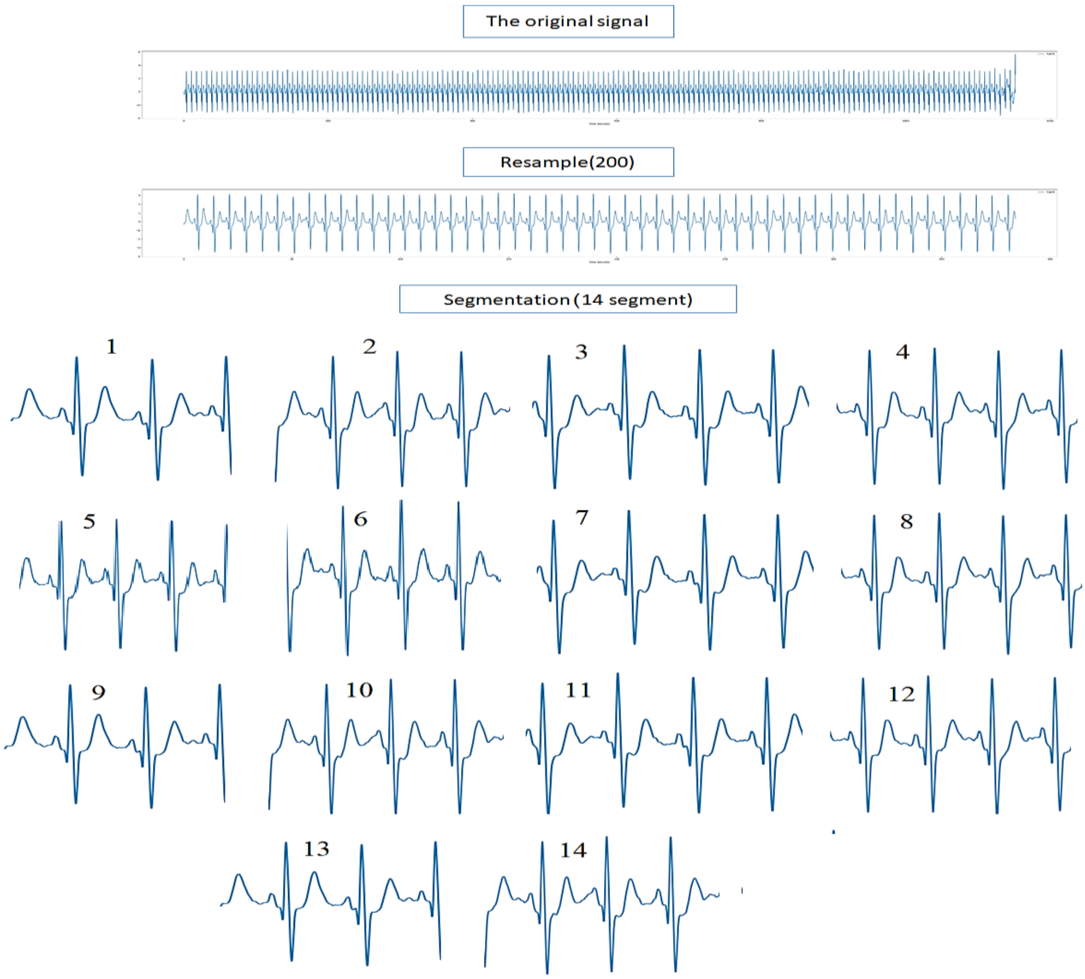

Fig. 3. Steps of Processing Stage in Proposed System.

It was noted that all the pre-processing stages were in the form of restrictions, but they were presented in a pictorial form to clarify the work more accurately, as the last step after the process of segmenting the signal is to draw and generate it on the basis that it is an image, so that the input to the model is an image and it is read on the basis that it is a matrix of one size. In this step, the importance of the idea lies in the fact that if the signal is used as it is (raw), then its measurement in relation to the wavelength cannot be worked by the approved model or others, and if it is divided and entered on the basis of a signal, it also suffers from the issue of standardizing the signal lengths, which causes loss of some information, so resorting was made to it. To the idea of drawing signs and turning them into image.

5.3 Dataset Split

Dividing the data by following the hold-out method, where the data was divided according to the following mechanism described in following figure 4:

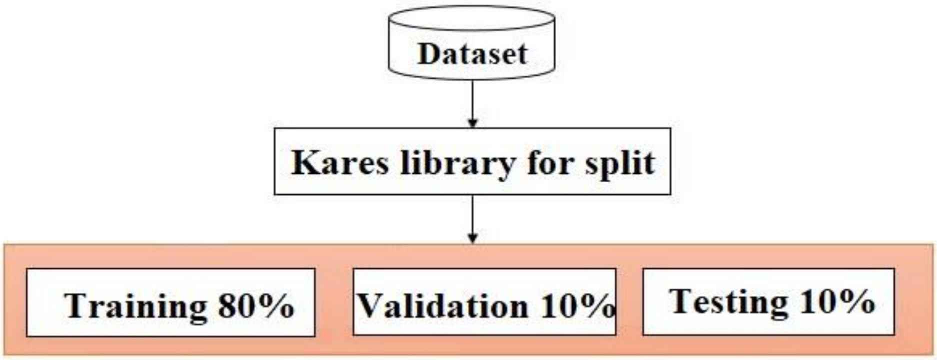

Fig. 4. Split Dataset in Proposed Method.

Based on above figure the number of images that using is:

- Total: 6,877 recordings
- training:5501(80%).
- testing: 688(10%).
- validation: 688(10%).

This method was adopted due to the large volume of data and because this method is recommended by researchers in the event of a large number of data used.

5.4 Training stage

The EfficientB3 model is a convolutional neural network (CNN) architecture developed by Google AI. It is a member of the Efficient model family, which is designed to be efficient and accurate in terms of performance and memory usage. Efficient B-3 is the type of pre-trained model was adopted because most previous researchers used neural networks extensively. Below are the details of the layers used in the proposed system:

Table 3 - Description of layer in EfficientB-3 model in proposed system.

Layer	Type	Activation	Output Shape	Description
Input	Input	None	(batch_size, 28, 28, 1)	Takes an image as input and reshapes it into a 28x28x1 tensor. The batch_size represents the number of images in the batch.
Conv2D_1	Convolutional	ReLU	(batch_size, 28, 28, 32)	Applies 32 3x3 filters to the input tensor. The ReLU activation function is used to introduce non-linearity into the network.
MaxPooling2D_1	Max pooling	None	(batch_size, 14, 14, 32)	Reduces the dimensionality of the tensor by half. This helps to reduce the number of parameters in the network and to make it more robust to noise.
Conv2D_2	Convolutional	ReLU	(batch_size, 14, 14, 64)	Applies 64 3x3 filters to the tensor from the first max pooling layer.
MaxPooling2D_2	Max pooling	None	(batch_size, 7, 7, 64)	Reduces the dimensionality of the tensor by half.
Flatten	Flatten	None	(batch_size, 3136)	Converts the 7x7x64 tensor into a 3136-dimensional vector. This is necessary before the vector can be passed to the fully connected layers.
Dense_1	Dense	ReLU	(batch_size, 128)	Applies 128 fully connected neurons to the vector from the flatten layer. The ReLU activation function is used to introduce non-linearity into the network.
Dropout_1	Dropout	None	(batch_size, 128)	Randomly drops out 50% of the neurons in the vector from the first dense layer. This helps to reduce overfitting.
Dense_2	Dense	Softmax	(batch_size, 10)	Applies 10 fully connected neurons to the vector from the dropout layer. The Softmax activation function is used to produce a probability distribution over the 10 classes

The following Table 4 summarizes Efficient Net b3

Table 4 - Efficient Net

Type	Parameters	FLOPs
EfficientNet-B3	12M	1.8B

Where FLOPS is a unit of measurement that calculates the performance and capability of a supercomputer. Floating-point operations can only be executed on computers with integrated floating-point registers. EfficientNet-B3 has 24 layers in total, including 22 convolutional layers, 1 fully connected layer, and 1 softmax layer, as shown in the following figure5.

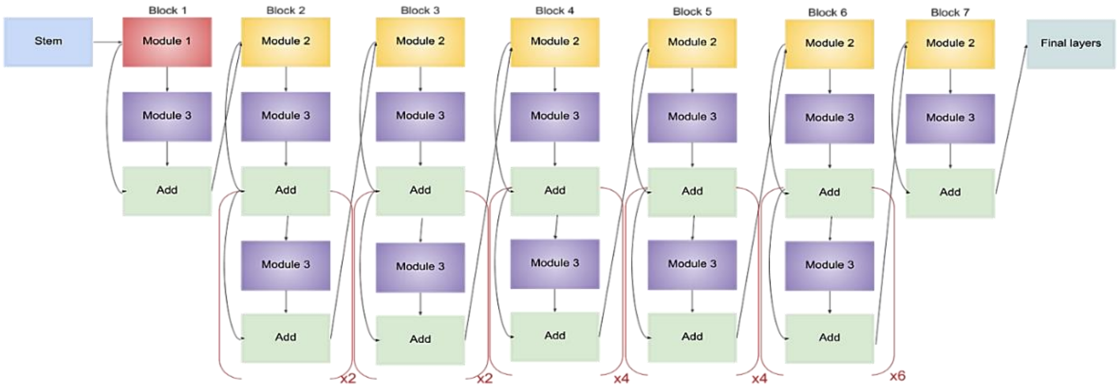

Fig. 5. Training Result of Proposed System Efficient –B3.

The training process in the system had promising and good results, as the following figure 5 shows the results obtained from the proposed system.

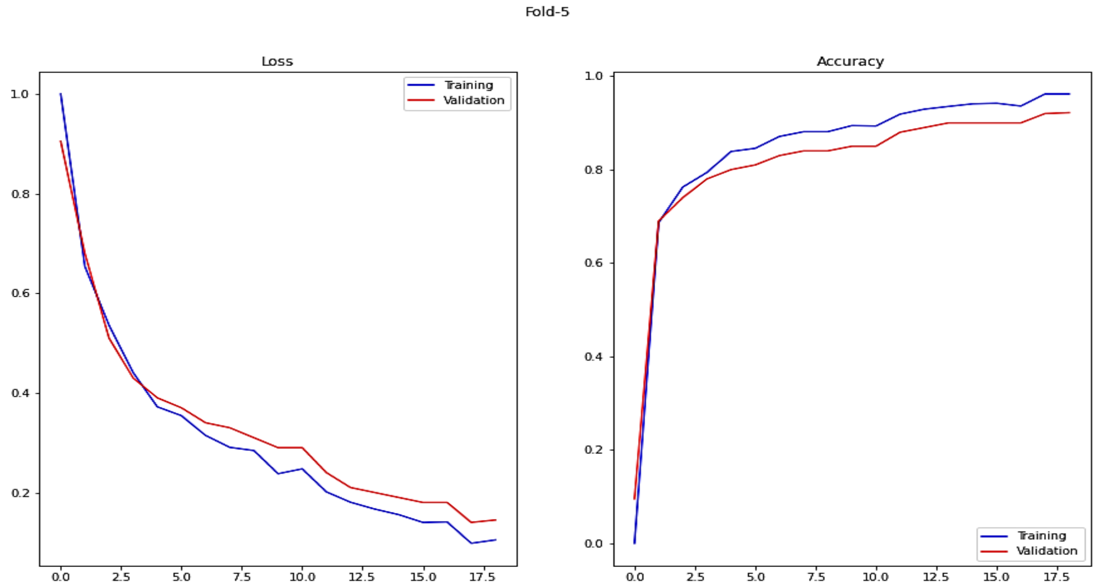

Fig. 6. Training Result of Proposed System.

Based on fig5. It is noted that the training results were free of overfitting and underfitting, and the results reach a stage of stability when they reach the stage of results in the nineties. And The results of the training can be summarized in the following table5 .

Table 5 - Result Of Training System.

Accuracy	0.9607250755287009
Precision	0.968944099378882
Recall	0.9512195121951219
Fl-score	0.96

5.6 Evaluation of Test Result

A confusion matrix describes the outcomes of a forecast of classification problems. They used to count numbers to tally and classify the amount of accurate and inaccurate predictions by class (AL-Jibory, 2021). To decipher the confusion matrix, the proposed evaluation method will be used. A confusion matrix summarizes the number of times a classification model accurately or erroneously predicted outcomes (Sansone et al., 2013). Where TP is the True Positive, TN is the True Negative, FP is the False Positive, and FN represents the False Negative. A confusion matrix is a valuable tool for evaluating the effectiveness of a system. Specific fundamental indicators vary depending on the four categories (AL-Jibory, 2021)(Xin et al., 2018):

- **Precision**: Variance is calculated by subtracting the sample standard deviation from the sample mean, whereas bias is determined by comparing the group standard deviation to a known object value. The accuracy equation represents the proportion of a set's data points a classifier correctly labels as positive.
  Precision= $\frac{TP}{TP+FP}$
- **Recall:** The recall metric measures how well a classification system can foretell the number of correct examples.
  Recall(r) = $\frac{TP}{TP + FN}$
- **F1-Score**: Precision and retention, in addition to the Equation flow, are indicated by F1
  F1= $\frac{2rp}{r + p} = \frac{2 \times TP}{2 \times TP + FP + FN}$
- **Accuracy:** Correct forecasts to total predictions are what we measure as Accuracy**;**
  Accuracy= $= \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP++FN}}$

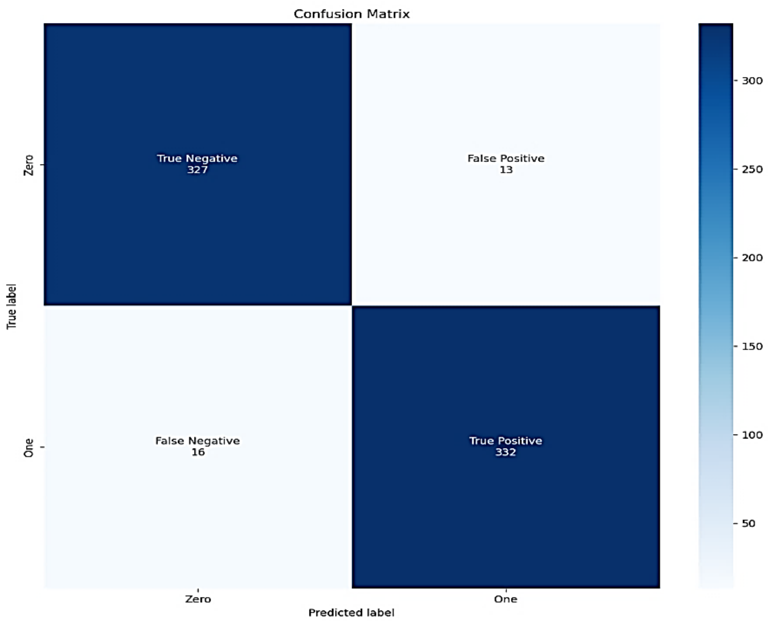

Fig. 7. Confusion Matrix's In Proposed System

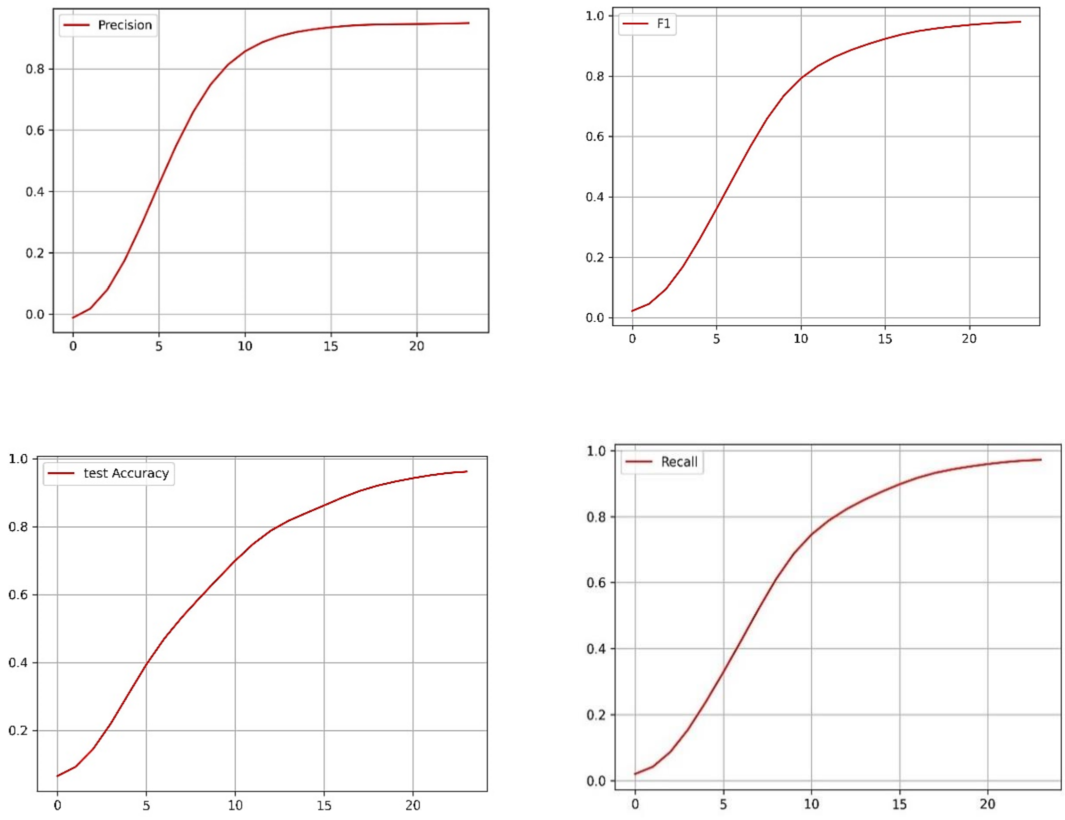

Fig. 7. Result of Testing in Proposed System.

Based on above equation and figure 6 the following table description the result of test part by using confusion matrix's.

Table 5 - Result of Confusion Matrix's in Proposed System.

TP=332	FP=13	FN=16	TN=327
Accuracy		0.958	
Precision		0.962	
Recall		0.954	
Fl-score		0.958	

The above measurements or scale were adopted in order to evaluate the results of the proposed approach and in order to know the percentage of improvement over the previous results of previous work on the subject of heart disease diagnosis. The results were good and promising. The confusion matrix was adopted and applied to the test set that was isolated on the basis that it was unseen data in order to confirm the ability of the proposed approach in diagnosing diseases that were not trained for

6. Conclusion

Diagnosing heart diseases is one of the complex topics that must be worked on because it is developing rapidly and artificial Intelligence, especially deep learning, plays an important and essential role in it. In the proposed approach, basic stages were adopted, which are the initial processing process, data division, and the training stage based on a pre-trained deep learning model. The idea was how to combine several techniques together, where the first step was pruning. In order to get rid of unnecessary restrictions, the data was created and a new file with the .csv extension was created, and the Resample process was used on it. Its purpose was to slow down the width of the signal and the pulses in order to prepare for the division process.

Resample was based on the experiment, and the value 200 was relied upon. After the experiment, the division process was carried out, which was based on the experiment, with (14 divisions) based on the wavelength of the electrical signal, and then the divided signal was drawn, converted into images of one size, and entered into the training model in order to solve the problem of inputs of different size in the signal. Electricity, meaning that as a final stage, these electrical signals were converted into images so that the training process was based on images, and to evaluate the results, the confusion matrix was adopted. As future work, it is possible to work on the captured data. Of patients from local hospitals to continue to support the work, i.e. the application is based on local data that can be collected manually.

References

Abd El-Rahiem, B., & Hammad, M. (2022). *A Multi-fusion IoT Authentication System Based on Internal Deep Fusion of ECG Signals* (Issue October). Springer International Publishing. https://doi.org/10.1007/978-3-030-85428-7_4

Abdelghani, S. A., Rosenthal, T. M., & Morin, D. P. (2016). Surface electrocardiogram predictors of sudden cardiac arrest. *Ochsner Journal*, *16*(3), 280–289. https://doi.org/ 10.1161/CIRCULATIONAHA.112.128413

Abed, R. M., Abdulmalek, H. W., Yaaqoob, L. A., Altaee, M. F., & Kamona, Z. K. (2023). Genetic Polymorphism of TLR5 and TLP6 in Iraqi Patients with Heart Failure Disease. *Iraqi Journal of Science*, 1662–1674. https://doi.org/ 10.24996/ijs.2023.64.4.9

Abood, Q. K. (2023). Predicting Age and Gender Using AlexNet. *TEM Journal*, *12*(1). https://doi.org/ 10.18421/TEM121-61

AL-Jibory, F. K. (2021). Hybrid System for Plagiarism Detection on A Scientific Paper. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, *12*(13), 5707–5719. https://doi.org/10.17762/turcomat.v12i13.9822

Al-Juboori, R. A. L. (2017). Contrast enhancement of the mammographic image using retinex with CLAHE methods. *Iraqi Journal of Science*, 327–336.

Alnaggar, M., Handosa, M., Medhat, T., & Rashad, M. Z. (2023). An IoT-based Framework for Detecting Heart Conditions using Machine Learning. *International Journal of Advanced Computer Science and Applications*, *14*(4). https://doi.org/ 10.14569/IJACSA.2023.0140442

Alqahtani, N., Alam, S., Aqeel, I., Shuaib, M., Mohsen Khormi, I., Khan, S. B., & Malibari, A. A. (2023). Deep Belief Networks (DBN) with IoT-Based Alzheimer's Disease Detection and Classification. *Applied Sciences*, *13*(13), 7833. https://doi.org/10.3390/app13137833

Bhanjaa, M. N., & Khampariya, P. (2023). *Design and Comparison of Deep Learning Model for ECG Classification using PTB-XL Dataset*. https://doi.org/ https://doi.org/10.3390/e23091121

Borghi de Melo, P. H. (2021). Brief Review on Electrocardiogram Analysis and Classification Techniques with Machine Learning Approaches. *U.Porto Journal of Engineering*, *7*(4), 153–162. https://doi.org/10.24840/2183-6493_007.004_0012

El Boujnouni, I., Harouchi, B., Tali, A., Rachafi, S., & Laaziz, Y. (2023). Automatic diagnosis of cardiovascular diseases using wavelet feature extraction and convolutional capsule network. *Biomedical Signal Processing and Control*, *81*, 104497. https://doi.org/ 10.1016/j.bspc.2022.104497

Gimeno-Blanes, F. J., Blanco-Velasco, M., Barquero-Pérez, Ó., García-Alberola, A., & Rojo-álvarez, J. L. (2016). Sudden cardiac risk stratification with electrocardiographic indices - A review on computational processing, technology transfer, and scientific evidence. *Frontiers in Physiology*, *7*(MAR), 1–17. https://doi.org/10.3389/fphys.2016.00082

Hannun, A. Y., Rajpurkar, P., Haghpanahi, M., Tison, G. H., Bourn, C., Turakhia, M. P., & Ng, A. Y. (2019). Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. *Nature Medicine*, *25*(1), 65–69. https://doi.org/10.1038/s41591-018-0268-3. https://doi.org/10.1038/s41591-018-0268-3

Harmon, D. M., Attia, Z. I., & Friedman, P. A. (2022). *Current and future implications of the artificial intelligence electrocardiogram: the transformation of healthcare and attendant research opportunities*. Oxford University Press. https://doi.org/10.1093/cvr/cvac006

Ibrahim, A. E., Abdel-mageid, S., Arabia, S., Nada, N., & Elshahed, M. A. (n.d.). *Human Identification Using Electrocardiogram Signal as a Biometric Trait*. *11*(3), 1–17. https://doi.org/10.4018/IJSDA.287113. http://doi.org/10.4018/IJSDA.287113

T. Tabassum and M. Islam, "An approach of cardiac disease prediction by analyzing ECG signal," 2016 3rd International Conference on Electrical Engineering and Information Communication Technology (ICEEICT), Dhaka, Bangladesh, 2016, pp. 1-5, doi: 10.1109/CEEICT.2016.7873093.

Khanna, A., Selvaraj, P., Gupta, D., Sheikh, T. H., Pareek, P. K., & Shankar, V. (2023). Internet of things and deep learning enabled healthcare disease diagnosis using biomedical electrocardiogram signals. *Expert Systems*, *40*(4), e12864. https://doi.org/10.1111/exsy.12864.

khiled AL-Jibory, F., Younis, M. A., & Al-Tamimi, M. S. H. (2022). *Preparing of ECG Dataset for Biometric ID Identification with Creative Techniques*. https://doi.org/10.18421/TEM114-10, November 2022.

Kim, E., Kim, J., Park, J., Ko, H., & Kyung, Y. (2023). TinyML-Based Classification in an ECG Monitoring Embedded System. *Computers, Materials and Continua*, *75*(1), 1751–1764. https://doi.org/10.32604/cmc.2023.031663

Li, H., & Boulanger, P. (2020). A survey of heart anomaly detection using ambulatory electrocardiogram (ECG). *Sensors*, *20*(5), 1461. https://doi.org/10.3390/s20051461

Liu, F., Liu, C., Zhao, L., Zhang, X., Wu, X., Xu, X., Liu, Y., Ma, C., Wei, S., He, Z., Li, J., & Yin Kwee, E. N. (2018). An Open Access Database for Evaluating the Algorithms of Electrocardiogram Rhythm and Morphology Abnormality Detection. *Journal of Medical Imaging and Health Informatics*, *8*(7), 1368–1373. https://doi.org/10.1166/jmihi.2018.2442

Lynn, H. M., Yeom, S., & Kim, P. (2018). ECG-based biometric human identification based on backpropagation neural network. *Proceedings of the 2018 Research in Adaptive and Convergent Systems, RACS 2018*, *1*, 6–10. https://doi.org/10.1145/3264746.3264760

Malakouti, S. M. (2023). Heart disease classification based on ECG using machine learning models. *Biomedical Signal Processing and Control*, *84*, 104796. https://doi.org/10.1016/j.bspc.2023.104796

Abdulla, L. A., & Al-Ani, M. S. (2020). A review study for electrocardiogram signal classification. UHD Journal of Science and Technology, 4(1), 103-117. https://doi.org/ 10.21928/uhdjst.v4n1y2020.pp103-117.

Mincholé, A., & Rodriguez, B. (2019). Artificial intelligence for the electrocardiogram. *Nature Medicine*, *25*(1), 22–23. https://doi.org/10.1038/s41591-018-0306-1

Mohammed, M. K., & Essa, S. I. (2022). Evaluation of the Physical Parameters on Ischemic Heart Disease Patients Using Echocardiography. *Iraqi Journal of Science*, https://doi.org/ 3354–3358. 10.24996/ijs.2022.63.8.10.

Rahma, M. M., & Salman, A. D. (2022). Heart Disease Classification–Based on the Best Machine Learning Model. *Iraqi Journal of Science*, 3966–3976. https://doi.org/ 10.24996/ijs.2022.63.9.28.

Ram, R. S., Akilandeswari, J., & Kumar, M. V. (2023). HybDeepNet: a hybrid deep learning model for detecting cardiac arrhythmia from ECG signals. *Information Technology and Control*, *52*(2), 433–444. https://doi.org/ doi: 10.5755/j01.itc.52.2.32993

Ramkumar, M., Ganesh Babu, C., Karthikeyani, S., Priyanka, G. S., & Sarath Kumar, R. (2021). Probabilistic Feature Extraction Techniques for Electrocardiogram Signal-A Review. *IOP Conference Series: Materials Science and Engineering*, *1084*(1), 012024. https://doi.org/10.1088/1757-899x/1084/1/012024

Sadiq, A. T., & Mahmood, N. T. (2014). A hybrid estimation system for medical diagnosis using modified full Bayesian classifier and artificial bee colony. *Iraqi Journal of Science*, *55*(3A), 1095–1107.

Saini, S. K., & Gupta, R. (2022). Artificial intelligence methods for analysis of electrocardiogram signals for cardiac abnormalities: state-of-the-art and future challenges. *Artificial Intelligence Review*, *55*(2), 1519–1565. https://doi.org/

Sandau, K. E., Funk, M., Auerbach, A., Barsness, G. W., Blum, K., Cvach, M., Lampert, R., May, J. L., McDaniel, G. M., Perez, M. V., Sendelbach, S., Sommargren, C. E., & Wang, P. J. (2017). https://doi.org/ 10.1007/s10462-021-09999-7

Update to Practice Standards for Electrocardiographic Monitoring in Hospital Settings: A Scientific Statement From the American Heart Association. In *Circulation* (Vol. 136, Issue 19). https://doi.org/10.1161/CIR.0000000000000527

Sansone, M., Fusco, R., Pepino, A., & Sansone, C. (2013). Electrocardiogram pattern recognition and analysis based on artificial neural networks and support vector machines: A review. *Journal of Healthcare Engineering*, *4*(4), 465–504. https://doi.org/10.1260/2040-2295.4.4.465

Saranya, R., & Murugan, A. (2023). A systematic review of enabling blockchain in healthcare system: Analysis, current status, challenges and future direction. *Materials Today: Proceedings*, *80*, 3010–3015. https://doi.org/ 10.1016/j.matpr.2021.07.105

Shahriari, Y., Fidler, R., Pelter, M. M., Bai, Y., Villaroman, A., & Hu, X. (2018). Electrocardiogram Signal Quality Assessment Based on Structural Image Similarity Metric. *IEEE Transactions on Biomedical Engineering*, *65*(4), 748–753. https://doi.org/10.1109/TBME.2017.2717876

Shi J, Li Z, Liu W, Zhang H, Guo Q, Chang S, Wang H, He J, Huang Q. Optimized Solutions of Electrocardiogram Lead and Segment Selection for Cardiovascular Disease Diagnostics. Bioengineering (Basel). 2023 May 18;10(5):607. doi: 10.3390/bioengineering10050607. PMID: 37237677; PMCID: PMC10215604.

Shkara, A. A., & Hussain, Y. (2018). Heartbeat Amplification and ECG Drawing from Video (Black and White or Colored Videos). *Iraqi Journal of Science*, 408–419. https://doi.org/ doi: 10.24996/ijs.2018.59.1B.21

Siontis, K. C., Noseworthy, P. A., Attia, Z. I., & Friedman, P. A. (2021). Artificial intelligence-enhanced electrocardiography in cardiovascular disease management. *Nature Reviews Cardiology*, *18*(7), 465–478. https://doi.org/10.1172/JCI178251.

Terzi, M. B., & Arikan, O. (2023). Machine learning based hybrid anomaly detection technique for automatic diagnosis of cardiovascular diseases using cardiac sympathetic nerve activity and electrocardiogram. *Biomedical Engineering/Biomedizinische Technik*, *0*. doi: 10.1515/bmt-2022-0406. Print 2024 Feb 26.

Xin, Y., Kong, L., Liu, Z., Chen, Y., Li, Y., Zhu, H., Gao, M., Hou, H., & Wang, C. (2018). Machine Learning and Deep Learning Methods for Cybersecurity. *IEEE Access*, *6*, 35365–35381. https://doi.org/10.1109/ACCESS.2018.2836950.

Yang, X. L., Liu, G. Z., Tong, Y. H., Yan, H., Xu, Z., Chen, Q., Liu, X., Zhang, H. H., Wang, H. B., & Tan, S. H. (2015). The history, hotspots, and trends of electrocardiogram. *Journal of Geriatric Cardiology*, *12*(4), 448–456. https://doi.org/10.11909/j.issn.1671-5411.2015.04.018

Zontone, P., Affanni, A., Bernardini, R., Piras, A., & Rinaldo, R. (2019). Stress detection through electrodermal activity (EDA) and electrocardiogram (ECG) analysis in car drivers. *2019 27th European Signal Processing Conference (EUSIPCO)*, 1–5. https://doi.org /10.23919/EUSIPCO.2019.8902631