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Deep Learning-Based Analysis of ECG Images for Intelligent Cardiovascular Diagnosis

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Abstract: Cardiovascular disorders are among the primary causes of mortality and morbidity globally. Early detection requires consistent monitoring of several clinical and lifestyle variables. This explains the increasing number of researches aimed at automating the prediction of cardiac disorders, starting with the analysis of ECG pictures, which is the first diagnostic test administered to patients and is also the most straightforward and cost-effective to execute. Current study presents various heart disease diagnostic systems using diverse advanced methodologies; however, enhancing these procedures remains a compelling research domain. This study proposes a smart healthcare system for diagnosing heart illness via ECG data. This paper presents a deep learning system for detecting cardiovascular problems using electrocardiogram (ECG) pictures. The Convolutional Neural Network (CNN) was trained and assessed, reaching a classification accuracy of 99.1%. The suggested approach illustrates the capability of deep learning models in facilitating cardiovascular diagnostics and underscores the need of accessible deployment tools. Subsequent study will concentrate on more extensive datasets, supplementary heart diseases, and model interpretability using explainable AI methodologies.

Keywords: Smart Systems, Convolutional Neural Networks (CNN), Deep Learning, ECG Signals, Heart Disease, Medical Images.

1. Introduction

Cardiovascular illnesses are among the primary causes of sickness, disability, and death. Consequently, prompt prediction of illness onset is crucial [1]. The majority of disorders are detected by the analysis of the electrocardiogram (ECG), a graphical representation of the heart's electrical activity throughout its function. An ECG is a diagnostic technique using one or more sensors to capture and visually display the heart's rhythm and electrical activity. To record an ECG, 12 electrodes are typically placed on the body's surface to detect voltage fluctuations, which are then represented in an ECG picture, allowing for the visualization and quantification of the acquired signal. An ECG picture captures the bio-electrical activity of the cardiac system, and in the presence of heart illness, some signals from the electrodes deviate from their normal condition. ECG is favoured over other diagnostic modalities, including cardiac magnetic resonance, diagnostic coronary angiography, or myocardial scintigraphy, for several reasons: the procedure is completed within minutes, the report is available within thirty minutes, it is applicable to individuals of all ages, and it is a non-invasive examination. Consequently, ECGs are essential in scientific study and have been extensively examined. Cardiac illness may be diagnosed by the analysis of the ECG pattern; specifically, a "arrhythmia" refers to a series of abnormal cardiac impulses.

Recently, the advent of deep learning methods has significantly transformed medical imaging, offering potential options for automating illness identification with remarkable accuracy. Deep learning models may discern complex patterns immediately from raw data, obviating the need for human feature extraction, hence making them very successful in interpreting ECG pictures [7][8]. This study focuses on developing a machine learning system capable of autonomously detecting cardiovascular problems using electrocardiogram (ECG) pictures. The convolutional neural network (CNN) was trained and assessed using a dataset consisting of four categories: myocardial infarction (MI) patients, individuals with a history of MI, irregular heartbeats, and normal ECGs. The proficient models exhibited exceptional classification accuracy, with the bespoke CNN model attaining an impressive accuracy of 99.1% on the test dataset. To connect research with clinical usefulness, the trained models were implemented via an intuitive online application developed using Stream lit, allowing real-time predictions on fresh ECG pictures. A majority voting strategy was used to enhance the system's dependability by integrating the benefits of many models [12].

2. Related Work

Numerous researches in the relevant literature focus on the automated detection of cardiac disease using ECG signals [13]. The attributes obtained from the cardiac rhythm and the chosen classification algorithms are the two most essential elements of a heart disease prediction system [14]. Numerous factors have been extracted from the ECG to classify heartbeats: morphological characteristics, wavelet transformation, Fourier transform, and statistical metrics [15]. In recent decades, the research community has focused on Artificial Intelligence (AI) to establish a connection between humans and technology, concentrating on digital image processing, sound recording, clinical data, and various data types to diagnose different cardiac pathologies. Concerning ECG pictures, recent research indicates that they are often transformed into signals for analysis rather than used as images in their original form [19]. In the majority of studies, these signals are examined using Deep Learning (DL) methodologies. Deep learning processes multidimensional ECG data as a time series classification and is the predominant AI-based approach for detecting cardiopathies; also, deep learning has shown significant growth potential with outstanding outcomes in medical picture recognition and classification applications. The Convolutional Neural Network (CNN) is recognized as a state-of-the-art approach for the detection and classification of cardiac signals, having been investigated in several forms, including one-dimensional (1-D), two-dimensional (2-D), or a combination of both.

Acharya et al. [26], 2017, introduced a CNN-based architecture for classifying arrhythmias using ECG data, exhibiting enhanced performance compared to conventional classifiers. In a similar vein, Kiranyaz et al. [27]. Implemented a 1D CNN model for individualized arrhythmia detection, demonstrating strong real-time performance. Recent studies have concentrated on using 2D CNNs for ECG image data, converting ECG signals into visual formats for picture-based categorization. AlexNet and its variants, including SqueezeNet and ResNet, have shown effective performance in biological image classification tasks owing to their robust feature extraction abilities [29]. Yildirim [30] used a mix of wavelet transformations and a Bi-directional Long Short-Term Memory (BiLSTM) network for the categorization of ECG signals. Their hybrid approach effectively incorporated both spatial and temporal characteristics, enhancing the overall model performance across various arrhythmia classes. Islam et al. [31] used conventional machine learning classifiers to forecast cardiovascular risk based on demographic and ECG-derived characteristics. Although less precise than deep learning approaches, their research highlighted the significance of feature engineering and ensemble methodologies. Recent research by Li et al. [32] concentrated on implementing lightweight CNNs for edge devices, tackling the issue of computing constraints in rural or mobile healthcare settings. Their methodology effectively classified ECGs on CPUs with little compromise to accuracy.

T. Sadad et al. [33] introduced a lightweight CNN including attention modules, attaining a classification accuracy of 98.39% on the ECG Images dataset of cardiac patients. Pre-processing procedures, including brightness modification and scaling, were implemented. A comparable methodology using deep CNNs with normalization and data augmentation enhanced the performance to 97.47% [34]. An augmented version using attention modules had a superior accuracy of 98.73% [35]. Nonetheless, these solutions encountered difficulties related to dataset imbalance and real-time deployment. Y. Liu et al. [36] introduced a multimodal deep learning system that integrated ECG pictures and textual records, attaining an accuracy of 99.63% via data augmentation. Although useful, it may encounter scaling challenges when used to real-time healthcare systems. T. Alsayat [37] presented an ensemble model including Inception, MobileNet, and NASNetLarge, achieving an F1 score of 0.9651 and a balanced accuracy of 0.9640; nevertheless, generalizability was constrained by the use of single-source data. R. Ao and G. He [38] developed a VGG16-based model to identify 13 cardiac disorders from ECG pictures, achieving AUROC values of up to 1.000 for particular situations such as RBBB; nevertheless, the binary classification framework constrained multi-label functionality. A. H. Khan et al. [39] created a heart disease diagnosis method using 12-lead ECG pictures from several formats. They suggested a generalized processing technique using an SSD MobileNet v2-based deep neural network to identify four principal cardiac anomalies (myocardial infarction, arrhythmia, previous myocardial infarction history, and normalcy) with an accuracy of 98%. Utilizing the PhysioNet Challenge 2021 dataset, the model included CNNs for spatial feature extraction and BiLSTM networks for temporal analysis, attaining optimal performance metrics, including 99% accuracy for normal heartbeats and an overall accuracy of 98.5% [42].

3. Heart Disease

An optimal heart delivers the appropriate volume of blood necessary for the proper functioning of the whole body. The many components, of which it consists, function in a coordinated manner at every moment of human existence. In the presence of cardiac lesions or illnesses, the organs fail to obtain the necessary oxygen for optimal function. Cardiovascular illness, including all cardiac diseases, may impair the heart's pumping function. Furthermore, its function may be hindered by structural diseases, such as compromised blood arteries, or by functional disorders, such as electrical system anomalies of the heart, e.g., arrhythmias. Congenital cardiac disease is characterized by abnormalities apparent at birth, often attributable to hereditary reasons. Acquired heart disease is a condition that develops as a consequence of various illnesses resulting from inappropriate activities. Electrocardiography (ECG) is a widely used, non-invasive, and cost-effective diagnostic instrument for detecting cardiac abnormalities, as seen in figure 1.

3.1 Myocardial Infarction

This term denotes myocardial damage characterized by clinical signs of acute myocardial ischemia and the detection of variations in cardiac troponin (cTn) levels. Furthermore, one or more of the following symptoms must manifest: Symptoms of myocardial ischemia include new ischemic electrocardiogram changes, development of pathological Q-waves, imaging evidence of new loss of viable myocardium, new regional wall motion abnormalities consistent with ischemic ethology, and identification of a coronary thrombus via angiography or autopsy.

3.2 Abnormal Heartbeat

The pulse, synonymous with heartbeat rate, refers to the frequency of a person's heartbeats per minute. The standard heart rate varies according to the person. An adult's heart typically beats between 60 and 100 times per minute. An arrhythmia occurs when the heart beats too slowly, too rapidly, or irregularly. Cardiac arrhythmias manifest in various forms: bradycardia, characterized by a heart rate below 60 beats per minute, indicating a slower rhythm; tachycardia (atrial or ventricular), where the heart rate exceeds 100 beats per minute, signifying an accelerated rhythm; and beat arrhythmias, which involve alterations in the rhythm rather than the rate, exemplified by extrasystole, defined as the occurrence of single or repetitive extra beats.

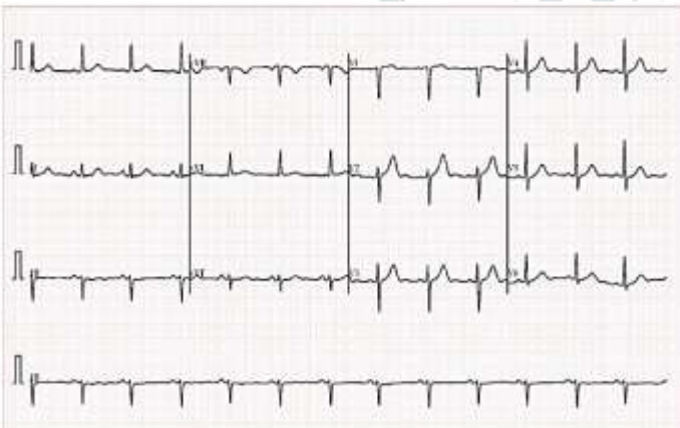

Figure 1: The ECG Image

4. Proposed Framework

4.1 Convolutional Neural Network

Deep learning has seen significant performance improvements in recent years across several domains, including voice recognition, picture identification, and natural language processing [51]. Specifically, Convolutional Neural Networks (CNNs) are one of the most extensively researched types of deep neural networks. A CNN is a feed-forward neural network used to assess visual images via data processing in a grid-like structure. It consists of many stages or layers, each concentrating on a certain functional component. In contrast to the neurons of a conventional neural network, the neurons of a CNN are structured in three dimensions: width, height, and depth. The neurons within a layer will not be fully interconnected with those in the preceding layer; for example, if the input image measures 32x32x3 (width, height, and depth), the final output layer will measure 1x1x10, as the CNN ultimately compresses the entire image into a singular vector of class scores arranged along the depth axis. A CNN generally consists of a sequence of structured blocks, each designated to a layer of the network responsible for transforming the volume of activations into another layer using a differentiable function. Pretrained deep learning models, such as convolutional neural networks (CNNs), have shown efficacy in tasks including electrocardiogram (ECG) picture categorization via transfer learning and feature extraction. These models, first trained on large datasets such as ImageNet, provide robust feature representations that may be used for medical picture interpretation. In transfer learning, the terminal layers of these models are substituted with new layers customized for the target task specifically, the classification of ECG data into distinct cardiovascular conditions, while preserving the convolutional basis to use acquired low- and mid-level characteristics. Fine-tuning these altered models on the ECG dataset enables them to acclimate to the domain-specific patterns inherent in the signals. Furthermore, pretrained networks may serve as static feature extractors by eliminating the classifier head and use the outputs of intermediate layers as inputs for conventional machine learning methods [55]. This method is especially advantageous when using constrained computing resources or datasets, since it significantly decreases training duration and enhances model precision.

4.2 Dataset

This research used a dataset of 1050 ECG pictures, classified into four unique categories, each corresponding to a particular heart condition: Myocardial Infarction, Abnormal Heartbeat, History of Myocardial Infarction, and Normal Heart Activity. The data were gathered from 1050 individuals, each providing recordings from 12 ECG leads [56]. The dataset comprises 340 photos from patients diagnosed with Myocardial Infarction, 260 images from patients with an Abnormal Heartbeat, 172 images from patients with a History of Myocardial Infarction, and 450 images from persons displaying Normal Heart Activity. The equitable distribution of these classes guarantees a thorough description of the circumstances, which is essential for creating a model that can generalize well across diverse cardiac situations.

4.3 Data Pre-processing

A sequence of image processing procedures was executed to improve data precision and elucidate signal specifics. The photos were first cropped to exclude regions beyond the ECG paper's signal area, concentrating only on the pertinent signal data. The photos were then imported in grayscale format to enable additional processing. Subsequently, Otsu's thresholding technique was used to transform the grayscale pictures into a binary format, accentuating the signal lines by establishing a global threshold that distinguishes the ECG signal (white lines) from the background. Morphological opening was used with a disk-shaped structuring element to eliminate little black spots and noise from the photos. Prior to inputting the photos into the neural networks, many pre-processing procedures were used. Images were scaled to 227×227 pixels and standardized to achieve a zero mean and unit variance using conventional normalization procedures. Data enrichment techniques, including random rotation and horizontal flipping, were used to enhance generalization and mitigate overfitting.

5. Proposed Architecture

The primary objective of a CNN is to autonomously recognize and extract significant and distinctive features from incoming pictures using a hierarchical framework. The essential elements of CNNs are the pooling layers and convolutional layers seen in figure 2. Convolutional layers execute a crucial function of feature extraction by applying filters, also known as kernels, to the input picture. These filters traverse the input spatially, doing element-wise multiplication and aggregating the results to generate feature maps that emphasize certain patterns, such edges, textures, or forms. The convolution process is fundamentally linear, therefore it is usually succeeded by a non-linear activation function, such as ReLU (rectified linear unit) or its derivatives, to include non-linearity, allowing the network to learn intricate mappings. Subsequent to the convolutional layers, pooling layers, including max-pooling, are used to diminish the spatial dimensionality of the feature maps. The down sampling procedure facilitates the extraction of the most prominent characteristics while decreasing computing complexity. This procedure, termed down sampling, reduces the quantity of parameters and calculations inside the network, while enhancing the invariance of features to minor translations in the input. At the conclusion of the network, fully connected layers amalgamate the extracted characteristics for final decision-making, with the last layer often using a SoftMax or sigmoid activation function to provide class probabilities [59]. This organized design allows CNNs to efficiently learn spatial hierarchies of information, making them particularly successful for applications like ECG picture categorization. The suggested convolutional neural network (CNN) architecture comprises 38 layers, which include three max-pooling layers, eight leaky ReLU activation layers, eight batch normalization layers, five dropout layers, six 2D convolutional layers, three fully connected layers, two depth concatenation layers, and a concluding SoftMax output layer. This framework is designed to extract the most significant characteristics from ECG pictures, which may then be used to improve classification accuracy.

The leaky ReLU activation function, with a negative slope coefficient of 0.1, is selected over the normal ReLU to avert the "dying ReLU" phenomenon by permitting a minimal gradient while the unit is inactive. The batch normalization layers equalize the inputs for each mini-batch, enhancing the overall stability and speed of model training. Max-pooling layers use a 6×6 filter with a stride of 3 to down sample feature maps, therefore reducing spatial dimensions, minimizing the number of parameters, and alleviating the computational load [61]. This meticulously crafted architecture allows the model to proficiently acquire hierarchical features from ECG pictures while mitigating challenges such as vanishing gradients and overfitting, hence improving the model's classification accuracy and efficiency. The proposed CNN architecture includes max-pooling layers using a filter dimension of 6x6 and a stride of 3. This stage utilizes 64, 128, and 224 filters to extract complex information from the data in the first, second [62], and third convolutional layers, respectively. The output dimensions of the whole branch of our proposed CNN model are $2 \times 2 \times 224$. The first layer in this branch is a completely linked layer, thus its designation. The completely linked layer in our model has 16 neurons. Conv04 is a convolutional layer with dimensions 322x2, using a stride of 1 and padding of 1, whereas conv05 is a convolutional layer with 64 filters of size 3x3, employing a stride of 2 and padding of 2. The feature maps produced by the two convolutional layers are amalgamated to form a feature map measuring $2\times2\times96$. A dropout layer is then used to mitigate overfitting and address correlated features. The outputs from the two branches are amalgamated to create a feature map measuring $2\times2\times320$. A dropout layer is then included to reduce the model's overfitting. A 1×1 convolutional layer with 256 filters is included to augment the model's nonlinearity and reduce the number of feature mappings. A layer of 512 neurons is included into the fully linked layer to improve the classification process. The output comprises a fully connected layer containing 4 neurons, each corresponding to a class for classification, succeeded by a SoftMax layer to ascertain the anticipated output [63].

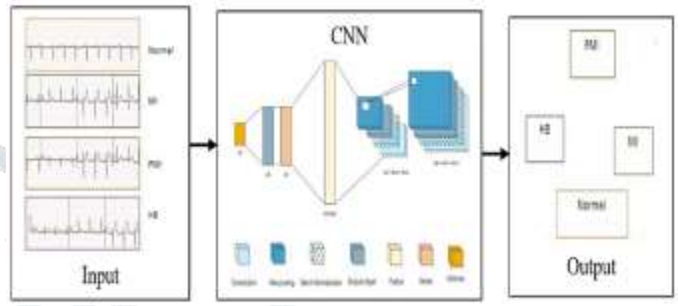

Figure 2: The Proposed Architecture

6. Outcome

This section presents the findings derived from experiments done on the ECG picture dataset with deep learning models based on CNN architecture. The proposed model is assessed using performance metrics including accuracy, precision, recall, F1-score, and confusion matrix, offering insights into its efficacy in diagnosing cardiovascular illnesses [64]. The experimental findings indicate that the suggested framework excels at identifying heart illness using ECG signals. The expectations for this experiment are summarized in the form of confusion matrices shown in figure 3.

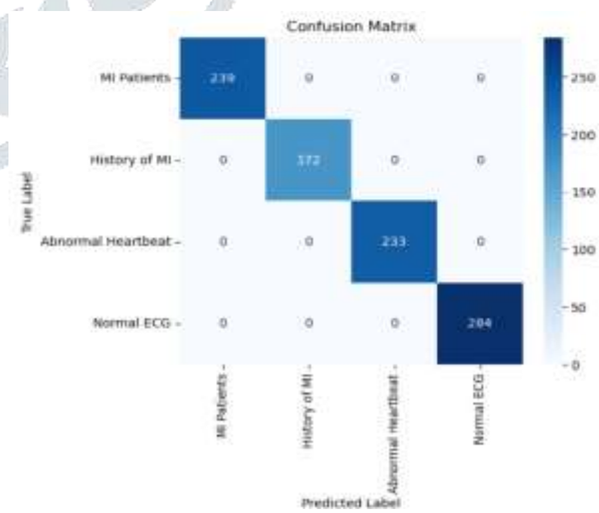

Figure 3: The Confusion Matrix of the CNN

The Custom CNN, constructed with two parallel branches, had exceptional performance. This design enabled the network to concurrently learn both localized and global properties. Methods include batch normalization, leaky ReLU activations, and dropout regularization facilitated effective learning and generalization, mitigating overfitting despite the model's high complexity. To enhance prediction accuracy, a majority voting method was used, whereby the ultimate classification choice is based on the consensus of the CNN architecture models. The CNN achieved a remarkable performance with 99.10% accuracy, attributed to its extensive design and expansive receptive fields seen in figure 4.

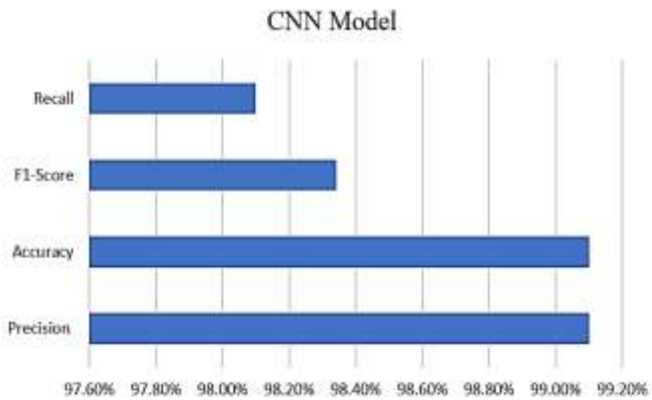

Figure 4: The CNN Model Performance Measures Accuracy, Precision, Recall, F1-Score

The heatmap overlay on the right emphasizes the areas of the ECG that the algorithm concentrated on most during categorization. The regions highlighted in red and yellow on the heatmap indicate the segments of the ECG that had the most effect on the model's judgment, indicating that these locations included essential characteristics pertinent to the classification job. This representation is essential for comprehending how the model analyses ECG data and recognizes clinically relevant patterns that aid in correct diagnosis, as seen in figure 5. Integrating these trained models into a Streamlet-based web application enables real-time inference on supplied ECG pictures, ensuring a smooth user experience. The user interface is deliberately designed to be user-friendly, necessitating little technical skills, hence making it suitable for many environments. This include healthcare institutions with limited resources, mobile diagnostic units, and outpatient clinics, where quick and accurate first assessments may facilitate timely therapeutic decisions.

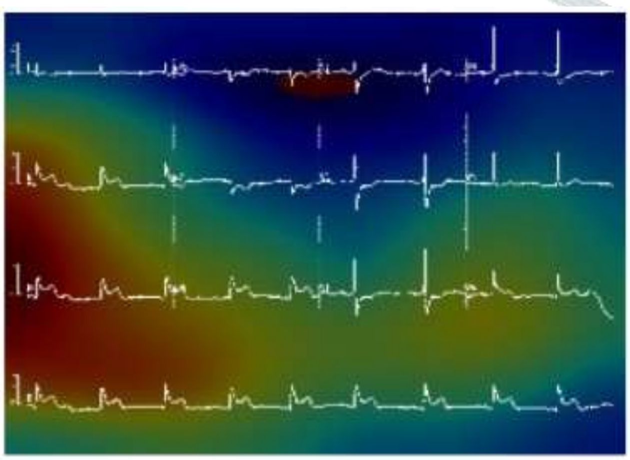

Figure 5: The Heatmap Overlay on ECG Image

7. Conclusion

This study conducted a binary categorization of healthy individuals and those afflicted with a specific kind of cardiac disease. The model used in this work has shown significant efficacy, especially in precisely detecting myocardial infarction and normal instances. Challenges arose in categorizing individuals with a history of myocardial infarction and irregular heart rhythms, highlighting the need for enhancements in the model's overall efficacy. The CNN architecture attains a classification accuracy of 99.10%. The experimental findings illustrate the efficacy of deep learning, especially CNN-based architectures, in discerning intricate patterns from ECG data and delivering precise diagnoses. By facilitating the interpretation of ECG data and identifying aberrant patterns, it may save diagnostic time and enhance assessment accuracy, particularly in resource-constrained environments. These applications together underscore the model's potential influence in enhancing both personal and clinical cardiac care. Our methodology demonstrates that ECG pictures serve as a very effective aid for the efficient categorization of cardiac illnesses, independent of the electrical signals itself. The examination of the various bands also indicates the most effective electrodes for predicting different heart diseases.

8. Future Work

Subsequent research should concentrate on augmenting the dataset to include more cardiac diseases, hence improving the model's generalizability. Furthermore, transforming the model into a decision support system may enhance the precision and efficacy of cardiovascular disease diagnosis, resulting in improved patient outcomes. This advanced technology may aid physicians in the field, facilitating more efficient and precise decision-making. These enhancements will be essential for the model's successful implementation in practical clinical settings.

References

[1] I. Matias, N. Garcia, S. Pirbhulal, V. Felizardo, N. Pombo, H. Zacarias, M. Sousa, Prediction of Atrial Fibrillation Using Artificial Intelligence on Electrocardiograms: A Systematic Review, vol. 39, Elsevier, 2021

[2] Hassan Serhal, Nassib Abdallah, Jean-Marie Marion, Pierre Chauvet, Mohamad Oueidat, Anne Humeau-Heurtier, Overview on prediction, detection, and classification of atrial fibrillation using wavelets and AI on ECG, Computers in Biology and Medicine, Volume 142, 2022.

[3] Y. Perwej, Firoj Parwej, Nikhat Akhtar, "An Intelligent Cardiac Ailment Prediction Using Efficient ROCK Algorithm and K- Means & C4.5 Algorithm", European Journal of Engineering Research and Science (EJERS), Bruxelles, Belgium, ISSN: 2506-8016 (Online), Vol. 3, No. 12, Pages 126 – 134, 2018, DOI: 10.24018/ejers.2018.3.12.989

[4] Y. Perwej, Mohammed Y. Alzahrani, F. A. Mazarbhuiya, Md. Husamuddin, "The State-of-the-Art Cardiac Illness Prediction Using Novel Data Mining Technique", International Journal of Engineering Sciences & Research Technology (IJESRT), ISSN: 2277-9655, Volume 7, Issue 2, Pages 725-739, 2018, DOI: 10.5281/zenodo.1184068

[5] P. McSharry, G. Clifford, L. Tarassenko, Method for generating an artificial RR tachogram of a typical healthy human over 24-hours, Comput.Cardiol., 29, 2002, pp. 225-228.

[6] Y. Perwej, "An Evaluation of Deep Learning Miniature Concerning in Soft Computing", International Journal of Advanced Research in Computer and Communication Engineering (IJARCCE), ISSN (Online): 2278-1021, ISSN (Print): 2319-5940, Volume 4, Issue 2, Pages 10 - 16, 2015, DOI: 10.17148/IJARCCE.2015.4203

[7] Y. Perwej, Asif Perwej, Firoj Parwej, "An Adaptive Watermarking Technique for the copyright of digital images and Digital Image Protection", International journal of Multimedia & Its Applications (IJMA), which is published by

Academy & Industry Research Collaboration Center (AIRCC) , USA , Volume 4, No.2, Pages 21- 38, April 2012, DOI: 10.5121/ijma.2012.4202

[8] Y. Perwej, Firoj Parwej, Asif Perwej, "Copyright Protection of Digital Images Using Robust Watermarking Based on Joint DLT and DWT", International Journal of Scientific & Engineering Research (IJSER), France, ISSN 2229-5518, Volume 3, Issue 6, Pages 1- 9, 2012

[9] Meenakshi Rani, Elturabi Osman Ahmed, Yusuf Perwej, S V Anil kumar, Dr.Venkatesan Hariram, "A Comprehensive Framework for IoT, AI, and Machine Learning in Healthcare Analytics", Nanotechnology Perceptions, ISSN 1660-6795, E-ISSN:2235-2074, Collegium Basilea, Switzerland, SCOPUS, Volume 20, S 14, Pages 2118-2131, 4 November 2024, DOI: 10.62441/nano-ntp.vi.3072

[10] F. Noman, C. M. Ting, S. H. Salleh, and H. Ombao, Short-segment heart sound classification using an ensemble of deep convolutional neural networks, in Proceedings of the ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 1318–1322, Brighton, UK, May 2019.

[11] N. Akhtar, H. Pant, Apoorva Dwivedi, Vivek Jain, Y. Perwej, "A Breast Cancer Diagnosis Framework Based on Machine Learning", International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Volume 10, Issue 3, Pages 118-132, May-June-2023, DOI: 10.32628/IJSRSET2310375

[12] D. Kaplan, M. Furman, S. Pincus, Techniques for analyzing complexity in heart rate and beat-to-beat blood pressure signals, Comput. Cardiol., 3 (1990), pp. 243-246.

[13] I. Matias, N. Garcia, S. Pirbhulal, V. Felizardo, N. Pombo, H. Zacarias, M. Sousa, E. Zdravevski, Prediction of Atrial Fibrillation Using AI on Electrocardiograms: A Systematic Review, vol. 39, Elsevier, 2021.

[14] Hassan Serhal, Nassib Abdallah, Jean-Marie Marion, Pierre Chauvet, Mohamad Oueidat, Anne Humeau-Heurtier, Overview on prediction, detection, and classification of atrial fibrillation using wavelets and AI on ECG, Computers in Biology and Medicine, Volume 142, 2022.

[15] Y. Xu, S. Zhang, Z. Cao, Q. Chen, Extreme learning machine for heartbeat classification with hybrid time-domain and wavelet time-frequency features, J. Healthc. Eng., 2021.

[16] Y. Perwej, "The Bidirectional Long-Short-Term Memory Neural Network based Word Retrieval for Arabic Documents", Transactions on Machine Learning and Artificial Intelligence (TMLAI), which is published by Society for Science and Education, United Kingdom (UK), ISSN 2054-7390, Volume 3, Issue 1, Pages 16 - 27, 2015, DOI: 10.14738/tmlai.31.863

[17] Shweta Pandey, Rohit Agarwal, Sachin Bhardwaj, Sanjay Kumar Singh, Y. Perwej, Niraj Kumar Singh, "A Review of Current Perspective and Propensity in Reinforcement Learning (RL) in an Orderly Manner", the International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT), Volume 9, Issue 1, Pages 206-227, 2023, DOI: 10.32628/CSEIT2390147

[18] Aversano, L., Bernardi, M. L., Cimitile, M., Iammarino, M., Montano, D., Verdone, C. (2022, May). Using Machine Learning for early prediction of Heart Disease. In 2022 IEEE International Conference on Evolving and Adaptive Intelligent Systems (EAIS) (pp. 1-8). IEEE

[19] Kajal, Kanchan Saini, N. Akhtar, Devendra Agarwal, Ms. Sana Rabbani, Y. Perwej, "Machine Learning for the Diagnosis and Prognosis of Chronic Illnesses", International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Print ISSN: 2395- 1990 , Online ISSN : 2394-4099, Volume 11, Issue 3, Pages 112-122, May-June -2024, DOI: 10.32628/IJSRSET24113100

[20] Mohit Gupta, Yusuf Perwej, "The Role of OpenCV in Enhancing Brain Tumor Image Segmentation: A Review of Recent Developments and Challenges", International Journal of Creative Research Thoughts (IJCRT), ISSN: 2320-2882, Volume 12, Issue 6, Pages 347 -353, June 2024

[21] Mohit Gupta, Yusuf Perwej, "Brain Tumour Detection Image Segmentation Using OpenCV", International Journal of Creative Research Thoughts (IJCRT), ISSN: 2320-2882, Volume 12, Issue 6, Pages 292 - 301, June 2024

[22] P. Hao, K. You, H. Feng et al., Lung adenocarcinoma diagnosis in one stage, Neuroco., vol. 392, pp. 245–252, 2020.

[23] F. Noman, C. M. Ting, S. H. Salleh, and H. Ombao, Short-segment heart sound classification using an ensemble of deep convolutional neural networks, in Proceedings of the ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 1318–1322, Brighton, UK, May 2019.

[24] R. Priyadarshini, Naim Shaikh, Rakesh Kumar Godi, Yusuf Perwej, P.K. Dhal, Rajeev Sharma, "IoT-Based Power Control Systems Framework for Healthcare Applications", Measurement: Sensors, ELSEVIER, ScienceDirect, SCIE, Web of Science, SCOPUS, ISSN 2665-9174, Volume 25, Pages 1-6, January 2023, DOI: 10.1016/j.measen.2022.100660

[25] N. Akhtar, Hemlata Pant, Apoorva Dwivedi, Vivek Jain, Y. Perwej, "A Breast Cancer Diagnosis Framework Based on Machine Learning", International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Print ISSN: 2395-1990, Volume 10, Issue 3, Pages 118-132, 2023, DOI: 10.32628/IJSRSET2310375

[26]. U. R. Acharya, H. Fujita, S. L. Oh, Y. Hagiwara, J. H. Tan, and M. Adam," Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals," Information Sciences, vol. 415–416, pp. 190–198, Nov. 2017. doi: 10.1016/j.ins.2017.06.027

[27]. S. Kiranyaz, T. Ince, and M. Gabbouj, "Real-time patient-specific ECG classification by 1-D convolutional neural networks," IEEE Transactions on Biomedical Engineering, vol. 63, no. 3, pp. 664–675, Mar. 2016. doi: 10.1109/TBME.2015.2468589

[28] Apoorva Dwivedi, Basant Ballabh Dumka, Nikhat Akhtar, Ms Farah Shan, Yusuf Perwej, "Tropical Convolutional Neural Networks (TCNNs) Based Methods for Breast Cancer Diagnosis", International Journal of Scientific Research in Science and Technology (IJSRST), Print ISSN: 2395-6011, Online ISSN: 2395-602X, Volume 10, Issue 3, Pages 1100 - 1116, 2023, DOI: 10.32628/IJSRST523103183

[29] N. Akhtar, Nazia Tabassum, Dr. Asif Perwej, Y. Perwej," Data Analytics and Visualization Using Tableau Utilitarian for COVID-19 (Coronavirus)", Global Journal of Engineering and Technology Advances (GJETA), Volume 3, Issue 2, Pages 28-50, 2020, DOI: 10.30574/gjeta.2020.3.2.0029

[30]. H. Yildirim,"A novel wavelet sequence based on deep bidirectional LSTM network model for ECG signal classification,"Computers in Biology and Medicine, vol. 96, pp. 189–202, Mar. 2018.

[31] World Health Organization (WHO), "Cardiovascular diseases," Jun. 11, 2021. Accessed: Dec. 27, 2021.

[32] Government of Westren Australia, Department of Health, “Common medical tests to diagnose heart conditions,” Accessed: Dec.29, 2021

[33] Sadad, T.; Safran, M.; Khan, I.; Alfarhood, S.; Khan, R.; Ashraf, I. Efficient Classification of ECG Images Using a Lightweight CNN with Attention Module and IoT. Sensors 2023, 23, 7697.

[34] Y. Perwej, “An Optimal Approach to Edge Detection Using Fuzzy Rule and Sobel Method”, International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering (IJAREEIE), ISSN (Print) : 2320 – 3765, ISSN (Online): 2278 – 8875, Volume 4, Issue 11, Pages 9161-9179, 2015, DOI: 10.15662/IJAREEIE.2015.0411054

[35] Khorsheed, M.S.; Karim, A.A. Enhancing Diagnostics: A Novel CNN-Based Method for Categorizing ECG Images with Attention Mechanism and Enhanced Data Augmentation. Ing. Des Syst. d’Information 2024, 29, 2011–2020.

[36] Liu, Y.; Li, D.; Zhao, J.; Liang, Y. Enhancing heart failure diagnosis through multi-modal data integration and deep learning. Multimed. Tools Appl. 2023, 83, 55259–55281.

[37] Alsayat, A.; Mahmoud, A.A.; Alanazi, S.; Mostafa, A.M.; Alshammari, N.; Alrowaily, M.A.; Shabana, H.; Ezz, M. Enhancing cardiac diagnostics: A deep learning ensemble approach for precise ECG image classification. J. Big Data 2025, 12, 7.

[38] Ao, R.; He, G. Image based deep learning in 12-lead ECG diagnosis. Front. Artif. Intell. 2023, 5, 1087370. [CrossRef]

[39] Khan, A.H.; Hussain, M.; Malik, M.K. Cardiac Disorder Classification by Electrocardiogram Sensing Using Deep Neural Network. Complexity 2021, 2021, 5512243. [CrossRef]

[40] Mahmoud AbouGhaly, Nikhat Akhtar, Elturabi Osman Ahmed, Sunny Kumar, Yusuf Perwej, Ratna Kumari Tamma, “Internet of Things Based Devices Designed for Pediatric Therapy to Improve Mobility and Engagement in Children with Cerebral Palsy”, Journal of Neonatal Surgery (JNS), SCOPUS, ISSN: 2226-0439 (Online), Volume 14, Issue S9, Pages 443 - 451, March 2025, DOI: 10.52783/jns.v14.2695

[41] Sunny Kumar, Apoorva Dwivedi, Dr. Yusuf Perwej, Moazzam Haidari, Siddharth Singh, Dr. Nagarajan Gurusamy, “A Smart IoT-Image Processing System for Real-Time Skin Cancer Detection ”, Journal of Neonatal Surgery (JNS), SCOPUS, ISSN: 2226-0439 (Online), Volume 14, Issue S14, Pages 823-831, April 2025, DOI: 10.52783/jns.v14.4330

[42] Omarov, B.; Momynkulov, Z. Hybrid deep learning model for heart disease detection on 12-lead electrocardiograms. Procedia Comput. Sci. 2024, 241, 439–444.

[43] Ferretti, J., Randazzo, V., Cirrincione, G., Pasero, E., 1-D convolutional neural network for ECG arrhythmia classification. In Progresses in artificial intelligence and neural system, In: Progresses in artificial intelligence and neural systems. Springer, Singapore, 2021. p. 269-279.

[44] Hina Rabbani, Sana Rabbani, Dr. Yusuf Perwej, Saurav Kumar, Dr. Nikhat Akhtar, “AI-Driven Enhancement of Diabetes Diagnosis Using Deep Learning Techniques”, Journal of Emerging Technologies and Innovative Research (JETIR), ISSN-2349-5162, Volume 12, Issue 6, Pages 757 - 763, June 2025, DOI: 10.6084/m9.jetir. JETIR2506297

[45] Farheen Siddiqui, Sarvesh Kumar, Dr. Yusuf Perwej, Ankit Shukla, Dr. Nikhat Akhtar, “AI-Enhanced Diagnostic System for Reasonable Evaluation Breast Cancer”, International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT), ISSN: 2456-3307, Volume 11, Issue 3, Pages 816-830, May 2025, DOI: 10.32628/CSEIT25113349

[46] Thygesen, Kristian, et al. ”Fourth universal definition of myocardial infarction (2018).” Journal of the American College of Cardiology 72.18 (2018): 2231-2264.

[47] D. Kumar, P. Carvalho, M. Antunes, P. Gil, J. Henriques, L. Eugenio, ’A new algorithm for detection of S1 and S2 heart sound’, Proceedings of the ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing, 2, IEEE, Toulouse, France (2006), pp. 1180-1183.

[48]Ankit Shukla, Farheen Siddiqui, Yusuf Perwej, Sarvesh Kumar, Nikhat Akhtar, “An Intelligent Framework for Emotion Detection from Speech Signals”, Journal of Emerging Technologies and Innovative Research (JETIR), ISSN-2349-5162, Volume 12, Issue 6, Pages 682 - 688, June 2025, DOI: 10.6084/m9.jetir.JETIR2506069

[49] Anjali Yadav, Shruti Dwivedi, Anubhav Dwivedi, Ujjwal Thakur, Dr. Nikhat Akhtar, “Intelligent Disease Diagnosis: A Multi-Disease Prediction Approach Using Machine Learning”, International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Print ISSN: 2395-1990, Online ISSN: 2394-4099, Volume 12, No. 3, Pages 98 - 109, May 2025, DOI: 10.32628/IJSRSET251235

[50] Himanshu Srivastava, Drishti Tiwari, Prakhar Tripathi, Ramhit Sharma, Nikhat Akhtar, “A Data-Driven Approach to Multi-Cancer Detection Using Machines Learning”, Journal of Emerging Technologies and Innovative Research (JETIR), ISSN-2349-5162, Volume 12, Issue 5, Pages 181 - 189, May 2025, DOI: 10.6084/m9.jetir.JETIR2505617

[51] L. Aversano, M. L. Bernardi, M. Cimitile, M. Iammarino, D. Montano and C. Verdone, ”A Machine Learning approach for Early Detection of Parkinson’s Disease Using acoustic traces,” 2022 IEEE International Conference on Evolving and Adaptive Intelligent Systems (EAIS), Larnaca, Cyprus, 2022, pp. 1-8, doi: 10.1109/EAIS51927.2022.9787728.

[52] Lassoued, Hela, and Raouf KETATA, Artificial neural network classifier for heartbeat arrhythmia detection, Proceedings of Engineering and Tec.-PET. Vol. 22. 2017.

[53] Yusuf Perwej, Prof. Pranati Waghodekar, Mrunal S. Bewoor, Mr. Siddharth Singh, Shubham Jaiswal, Akansh Garg, “Blockchain for Healthcare Management: Enhancing Data Security and Transparency”, South Eastern European Journal of Public Health, (SEEJPH), SCOPUS, ISSN: 2197 - 5248, Volume XXVI, Issue S1, Pages 1173–1184, January 2025, DOI: 10.70135/seejph.vi.3831

[54] Yusuf Perwej, Nikhat Akhtar, Devendra Agarwal, “The emerging technologies of Artificial Intelligence of Things (AIoT) current scenario, challenges, and opportunities”, Book Title“Convergence of Artificial Intelligence and Internet of Things for Industrial Automation”, SCOPUS,ISBN: 978-1-032-42844-4, CRC Press, Taylor & Francis Group, 2024 Link:https://www.taylorfrancis.com/chapters/edit/10.1201/9781003509240-1/emerging-technologiesartificial-intelligence-things-aiot-current-scenario-challenges-opportunities-yusuf-perwej-nikhatakhtar-devendra-agarwal?context=ubx&refId=537f1a8f-6a94-4439-b337-3ad3d1ce8845, DOI: 10.1201/9781003509240-1

[55] N. Akhtar, Kumar Bibhuti B. Singh, Devendra Agarwal, Y. Perwej, “Improving Quality of Life with Emerging AI and IoT Based Healthcare Monitoring Systems”, International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT), ISSN:

2456-3307, Volume 11, Issue 1, Pages 96-107, January 2025, DOI: 10.32628/CSEIT2514551

[56] Peters, N.S.; Kramer, D.B.; Zhang, B.; Wu, H.; Sau, A.; Waks, J.W.; Bajaj, N.; Ng, F.S.; Patel, K.H.K.; Shi, X.; et al. A fully-automated paper ECG digitisation algorithm using deep learning. Sci. Rep. 2022, 12, 20963

[57] Attallah, O. An Intelligent ECG-Based Tool for Diagnosing COVID-19 via Ensemble Deep Learning Techniques. Biosensors 2022,12, 299

[58] Gorriz, J.M.; Alinejad-Rokny, H.; Ling, S.H.; Zhang, Y.-D.;Wang, S.-H.; Alizadehsani, R.; Jafari, M.; Khosravi, A.; Ghassemi, N.;Moridian, P.; et al. Automated diagnosis of cardiovascular diseases from cardiac magnetic resonance imaging using deep learning models: A review. Comput. Biol. Med. 2023, 160, 106998

[59] Simonyan, K.; Zisserman, A. Very Deep Convolutional Networks for Large-Scale Image Recognition, September 2014.

[60] Neha Kulshrestha, N. Akhtar, Y. Perwej, “Deep Learning Models for Object Recognition and Quality Surveillance”, Accepted International Conference on Emerging Trends in IoT and Computing Technologies (ICEICT-2022), ISBN 978-10324-852-49, SCOPUS, Routledge, Taylor & Francis, CRC Press, Chapter 75, pages 508-518, Goel Institute of Technology & Management, 2022, DOI: 10.1201/9781003350057-75

[61] Ö. Yildirim, “A novel wavelet sequence based on deep bidirectional LSTM network model for ECG signal classification,” Computers in Biology and Medicine, vol. 96, pp. 189–202, 2018.

[62] D. Li, J. Zhang, Q. Zhang and X. Wei, “Classification of ECG signals based on 1D convolution neural network,” in 2017 IEEE 19th Int. Conf. on e-Health Networking, Applications and Services (Healthcom),Dalian, China, pp. 1–6, 2017.

[63] N. Akhtar, Saima Rahman, Halima Sadia, Yusuf Perwej, “A Holistic Analysis of Medical Internet of Things (MIoT)”, Journal of Information and Computational Science (JOICS), ISSN: 1548 - 7741, SCOPUS, Volume 11, Issue 4, Pages 209 - 222, 2021, DOI: 10.12733/JICS.2021/V11I3.535569.31023

[64] A. Çınar and S. A. Tuncer, “Classification of normal sinus rhythm, abnormal arrhythmia and congestive heart failure ECG signals using LSTM and hybrid CNN-SVM deep neural networks,” Computer Methods in Biomechanics and Biomedical Engineering, vol. 24, no. 2, pp. 203–214, 2021

[65] M.Kachuee, S. Fazeli and M. Sarrafzadeh, “ECG heartbeat classification:Adeep transferable representation,” in 2018 IEEE Int. Conf. on Healthcare Informatics (ICHI), New York City, NY, USA, pp. 443–444, 2018

[66] S. H. Wang, Y. Zhang, X. Cheng, X. Zhang and Y. D. Zhang, “PSSPNN: PatchShuffle stochastic pooling neural network for an explainable diagnosis of COVID-19 withmultiple-way data augmentation,” Computational and Mathematical Methods in Medicine, vol. 2021, pp. 1–18, 2021

[67] Y. Perwej, Shaikh Abdul Hannan, Firoj Parwej, Nikhat Akhtar , “A Posteriori Perusal of Mobile Computing”, International Journal of Computer Applications Technology and Research (IJCATR), ATS (Association of Technology and Science), India, ISSN 2319–8656 (Online), Volume 3, Issue 9, Pages 569 - 578, 2014, DOI: 10.7753/IJCATR0309.1008

[68] D. Li, J. Zhang, Q. Zhang and X. Wei, “Classification of ECG signals based on 1D convolution neural network,” in 2017 IEEE 19th Int. Conf. on e-Health Networking, Applications and Services (Healthcom), Dalian, China, pp. 1–6, 2017