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A realistic ECG signal noise removal and its analysis using AlexNet CNN deep learning technique

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Abstract

ECG signals are playing an important key role in medical industry to diagnosis the brain and metal condition of humans. The signal processing tools can remove the noise and train the samples for getting accurate outcomes. The available methods for speech de-noising are outdated and facing many limitations. PSO, GA, RFO, CNN deep learning and ML models based de-noising is very complex. Therefore, an advanced deep learning model is necessary to cross over the following limitations. So that in this research work An AlexNet based CNN deep learning model is proposed and same time comparing the measures with earlier techniques. Finally comparing performance metrics like accuracy recall F measure and sensitivity and conclude that proposed model is outperformed.

Keywords: ECG, AlexNet, CNN, Speech de-noise.

Introduction

Cardiovascular disorders and its complications are now among the leading causes of mortality worldwide. As a result, an appropriate approach for determining the patient's heart status is required. One of the approaches is to examine the ECG. Electrocardiography (ECG) is a technique for determining the health of the heart. Electrodes positioned at different sites on the body surface record the electrical signals (activity) produced throughout the cardiac cycle. A patient's ECG is visually inspected in the time domain. However, there is a lot of noise in this ECG, which may be decreased with signal processing. In the realm of biomedical engineering, signal processing is an essential and visible technique. The biological signal processing stream has now progressed to the point where signal processing and pattern analysis methods are being used in real-world applications.

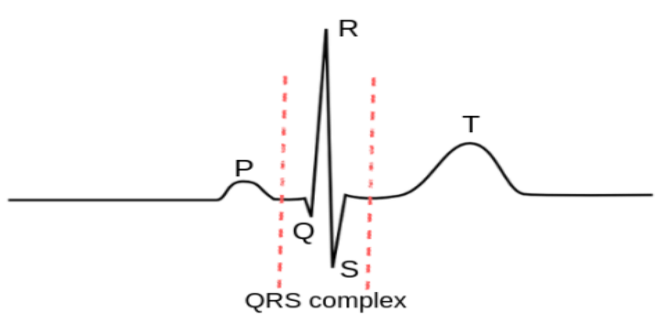

Figure 1. ECG signal

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The ECG signal is a graphical depiction of cardiac activity that is used to evaluate a variety of heart problems. P wave, QRS complex, and T wave are the typical components of an ECG signal, and any variation in these characteristics may anticipate and explain cardiac problems. Baseline wander commonly contaminates electrocardiogram (ECG) readings (BW). Perspiration, patient movement, and breathing modify the electrode-skin impedance, contributing to baseline wander. Baseline wander has an impact on computer-based processing. To allow the ECG signal to be automatically processed by a computer and then interpreted by a cardiologist, noise such as BW and power interference must be reduced. The elimination of different disturbances is one of the first processes in ECG processing, not just before further automated processing, but also before visual diagnosis. The goal of this kind of diagnostic is to make processing simpler and to allow for accurate ST segment readings [1]. Several forms of artefacts taint ambulatory ECG recordings, which are made by putting electrodes on the subject's chest. ECG artefacts are irregularities in an ECG, which is a measurement of the human body's cardiac potentials. Artifacts may cause normal ECG components to be altered. Artifacts are rather prevalent, and a thorough understanding of them is required to avoid misunderstanding of a patient's ECG. Electrical interference from outside sources, electrical noise elsewhere in the body, inadequate contact, and machine failure may all cause artefacts. The QRScomplexalternas is enhanced in a positive stress ECG test, indicating that the patients may have substantial coronary artery disease.

Literature Survey

Alquran, H.,et al [2019]The major contribution of this research is to construct a reliable and adaptable deep learning classification approach by combining pre-trained convolutional neural networks with a mixture of higher-order spectrum estimates of arrhythmias ECG information. When employing third cumulants and GoogleNet, the highest average accuracy was reached at 97.8%. The suggested technique is an efficient automated cardiac arrhythmia classification method, and it delivers a dependable identification system based on well-established CNN architectures rather than training a deep CNN from scratch, as shown by these findings.[1]

Yildirim, O.,et al [2019]The use of heart rate (HR) signals collected from electrocardiogram (ECG) data is used in this work to suggest a deep-transfer learning strategy for the automated diagnosis of diabetic mellitus (DM). Deep learning advances have made a substantial contribution to the enhancement of healthcare quality. Large datasets are necessary for training deep learning models in order for them to function successfully. However, in the biomedical profession, there is a scarcity of clinical data that has been annotated by experts. Transferring the weighting established from a big dataset to the current model is a new and widely used strategy for training deep learning models with small datasets. For two-dimensional signals, this deep learning transfer approach is often used. The weighting of pre-trained models utilising two-dimensional big picture data was applied to one-dimensional HR signals in this study. The frequency spectrum pictures of the one-dimensional HR signals were then used to apply to well-known pre-trained models, such as AlexNet, VggNet, ResNet, and DenseNet.[2]

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Ullah, A.,et al [2020]One of the most often utilised signals in the diagnosis and prognosis of cardiovascular disorders is the electrocardiogram (ECG) (CVDs). The ECG readings can detect rhythmic anomalies in the heart, often known as arrhythmias. For accurate diagnosis of patients' acute and chronic cardiac problems, detailed analysis of ECG signals is required. We propose a two-dimensional (2-D) convolutional neural network (CNN) model for categorising ECG signals into eight classes: normal beat, premature ventricular contraction beat, paced beat, right bundle branch block beat, left bundle branch block beat, atrial premature contraction beat, ventricular flutter wave beat, and ventricular escape beat in this study.[3]

Mashrur, F. R.,et al [2019]Atrial fibrillation (AF) is one of the most common cardiovascular illnesses that affects the whole world's population. The majority of existing solutions for automated AF categorization are based on hand-crafted characteristics. The main goal of this project is to develop a deep learning-based technique that will remove the need for human feature identification. We utilised 5,655 single-lead ECG recordings to construct a pre-trained convolutional neural network (CNN) called AlexNet. We first extracted a spectrogram for all 30s signals and used Continuous Wavelet Transform (CWT) to transform them to RGB pictures, which we then passed to AlexNet and trained with various adjustments in requirements. The study's results show that our strategy outperforms all current techniques, achieving a state-of-the-art accuracy of 97.9% and an F1 score of 98.82 percent while having greater overall sensitivity (98.9%) and specificity (90.7%).[4]

Singh, S. A.,et al [2019]Obstructive sleep apnea (OSA) is the most prevalent and severe respiratory disorder, characterised by pauses in breathing lasting more than ten seconds while sleeping. Polysomnography (PSG) is the most common method for detecting OSA. However, this method is both expensive and time-consuming. To address the aforementioned issue, researchers are working on a suitable and new approach for interpreting sleep apnea using ECG recordings. For many years, the approaches for OSA analysis based on ECG have been studied. Early research focused on extracting traits, which are fully dependent on the expertise of human experts. This paper examines a unique strategy for predicting sleep apnea problem based on a convolutional neural network (CNN) with a pre-trained (AlexNet) model.[5]

Ebrahimi, Z.,et al [2020]Deep Learning (DL) has lately been a research issue in a variety of fields, including healthcare, where prompt identification of irregularities on an electrocardiogram (ECG) may be critical in patient monitoring. This work gives a detailed evaluation of contemporary DL approaches that have been applied to ECG signals for classification applications. Convolutional Neural Network (CNN), Deep Belief Network (DBN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit are among the DL approaches investigated in this research (GRU).[6]

Murat, F.,et al [2020]To identify electrocardiogram (ECG) data, deep learning algorithms have become popular. For this application, researchers applied a number of deep learning approaches. This paper provides a thorough evaluation of deep learning algorithms for detecting ECG arrhythmias. The methods utilised by investigators are analysed, as well as their contributions to the discipline. Journal articles were surveyed according to the methodologies employed for this purpose. There are also descriptions and discussions of several deep learning models and experimental experiments. Deep learning approaches were then examined using a five-class ECG dataset comprising 100,022 beats. This dataset was used to test the built models, and the results are reported. As a result, this work includes information on deep learning algorithms for arrhythmia classification, as well as recommendations for future research in this field.[7]

Alghamdi, A.,et al [2020]Myocardial infarction (MI), which happens when one or more coronary arteries get blocked, is one of the most prevalent heart illnesses. MI must be treated as soon as possible; even a little delay might have serious repercussions. The key diagnostic technique for monitoring and revealing MI signals is the electrocardiogram (ECG). The complicated structure of MI signals, along with noise, makes it difficult for clinicians to make an accurate and timely diagnosis. Manually analysing huge volumes of ECG data may be time-consuming and laborious. As a result, techniques for automatically analysing ECG data and making diagnoses are required. Many research have been published to solve MI detection, however the majority of these algorithms are computationally costly and suffer from overfitting when dealing with actual data. An efficient computer-aided diagnostic (CAD) system for detecting MI signals using the convolution neural network (CNN) is provided in this study for urban healthcare in smart cities.[8]

Tuncer, S. A.,et al [2019]The majority of society suffers from sleep disturbances, which have a significant impact on an individual's everyday quality of life. Obstructive sleep apnea syndrome (OSAS) is the most hazardous sleep disease, since it reveals itself during sleep and may result in patients' unexpected death. Many essential characteristics relating to the diagnosis and treatment of sleep disorders are investigated at the same time. For experts, this procedure is tiring and time-consuming, and it also requires experience; as a result, it may lead to disagreements among experts. As a result, automated sleep staging systems were created. A decision support system was created in this research to identify OSAS patients.[9]

Amin, S. U.,et al [2019]We propose a cognitive healthcare framework that makes use of cloud-based Internet of Things (IoT) technology. Within the context of a smart city, this framework employs smart sensors for communication and deep learning for intelligent decision-making. The cognitive and smart framework continuously monitors the health of patients and delivers accurate, timely, and high-quality healthcare at a cheap cost. We report the experimental findings of an ECG disease classification approach that employs deep learning to examine the practicality of the proposed framework. To continually capture and monitor multimodal healthcare data, we use a variety of healthcare smart sensors, including an ECG smart sensor. Patients' ECG signals are transferred to the cloud through smart IoT devices, where they are analysed and forwarded to a cognitive module. Sensor data such as facial expressions, voice, ECG, movements, and gestures are used to identify the patient's condition.[10]

Eltrass, A. S.,et al [2021]For the first time, a novel ECG diagnostic method combining Convolutional Neural Network (CNN) and Constant-Q Non-Stationary Gabor Transform is presented in this paper (CQ-NSGT). The CQ-NSGT approach is used to convert a 1-D ECG signal into a 2-D time-frequency representation that will be input into an AlexNet pre-trained CNN model. Extracted characteristics from the AlexNet architecture are employed as relevant features in a Multi-Layer Perceptron (MLP) approach to differentiate between three distinct cases: CHF, ARR, and Normal Sinus Rhythm (NSR). The usefulness of the CQ-NSGT method is shown by comparing the proposed CNN with CQ-NSGT to CNN with Continuous Wavelet Transform (CWT).[11]

Eltrass, A. S.,et al [2022]Using chaos theory and fragmentation analysis, the proposed method improves ECG diagnostic performance by integrating optimal deep learning features with efficient aggregation of

ECG characteristics and HRV values. The 1-D ECG signal is converted into a 2-D picture using the constant-Q non-stationary Gabor transform approach, which is then passed to AlexNet, a pre-trained convolutional neural network structure. To combine the ECG and HRV data, the pair-wise feature proximity technique is used to choose the best features from the AlexNet output feature vector. Condensed characteristics are provided to several kinds of classifiers in order to classify three separate subjects: congestive heart failure, arrhythmia, and normal sinus rhythm (NSR). In comparison to the other classifiers, the linear discriminant analysis classifier has the best accuracy.[12]

Dhar, P.,et al [2021]This research has a common goal – to support physicians and medical professionals – and an essential technology, such as a Cross-wavelet transform (XWT) aided Convolution neural network (CNN) using the AlexNet model to identify irregular heart sounds, which are a sign of cardiovascular illness. To boost system performance, a pre-trained AlexNet model was employed and fine-tuned. The Cross-wavelet spectrum picture is used as an input by a convolution neural network (Alex Net architecture) to prevent and protect people from deadly medical diseases. The suggested approach is used on both raw PCG data and PCG data that has been cleaned of noise.[13]

Author	**Technique**	**Key point**	**Performance**
Gaddam, P. G.,et al 2021 [14]	Using ECG classification, transfer learning, AlexNet , de ep learning	To create a transferable deep learning algorithm for automated classification of the four cardiac illnesses.	accuracy 095.67%
Sai, Y. P.,et al 2022 [15]	Using Machine learning techni ques, pre-trained CNN architectures-AlexNet	Our suggested DeepNet model is efficient, promising, and outperforms all existing models.	accuracy of 99.56%.
Allen, J.,et al 2021 [16]	Using AlexNet CNN	This unique automated technique, which only requires little pre-processing of the pulse waveforms before PPG trace categorization, might be useful for diagnosing PAD in a number of clinical settings where low-cost, portable, and easy-to-use diagnostics are desired.	sensitivity 86.60%, specificity90.20 % and accuracy 88.90%
Ullah, A.,et al 2021 [17]	Using machine learning techniques,A lexNet	To create a reliable system that can reliably categories ECG signals even when there is noise in the surroundings.	accuracy for 1D 97.38% and for 2D 99.02%
Liu, X.,et al 2021 [18]	Using CNN. Alexnet	To discuss our thoughts on the future potential of deep learning in ECG diagnosis.	sensitivity 87.60%, specificity 88.20% and accuracy 88.690%
Ahmad, Z.,et al	Using AlexNet, CNN, ML	Experiment on the PhysioNet	sensitivity

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[2021 [19]		MIT-BIH dataset for five distinct arrhythmias in compliance with the AAMI EC57 standard, as well as the PTB diagnostics dataset for MI classification.	84.60%, specificity 89.30% and accuracy 89.90%
Huerta, Á.,et al 2021[20]	Using AlexNet, deep learning techniques,CNN .	The findings of both instances were compared using the McNemar test, and no statistically significant differences were found, suggesting that the synthetic noisy signals may be utilised to train CNN-based ECG quality indices with confidence.	sensitivity 94.60%, specificity 79.30% and accuracy 84.90%
Jun, T. J.,ET AL 2018 [21]	Using AlexNet, deep learning techniques,CNN .	The proposed CNN classifier using the converted ECG pictures has successfully proven that it can achieve great classification accuracy without any manual pre-processing of the ECG signals such as noise filtering, feature extraction, and feature reduction.	accuracy 99.05% sensitivity 97.85%
Sai, Y. P.,et al 2022 [22]	Using AlexNet, deep learning techniques,CNN Machine learning techniques	The MIT-BIH arrhythmia database is used to assess the models.	sensitivity 95.64%, specificity 82.30% and accuracy 88.90%

Methodology and methods

In this research AlexNet CNN based ECG signal noise removal methods are discussing, same time comparing this analysis with existed method. Deep learning networks are gaining popularity in a variety of domains, including the signal processing of electroencephalography (ECG). These models were able to match conventional methodologies in terms of performance.

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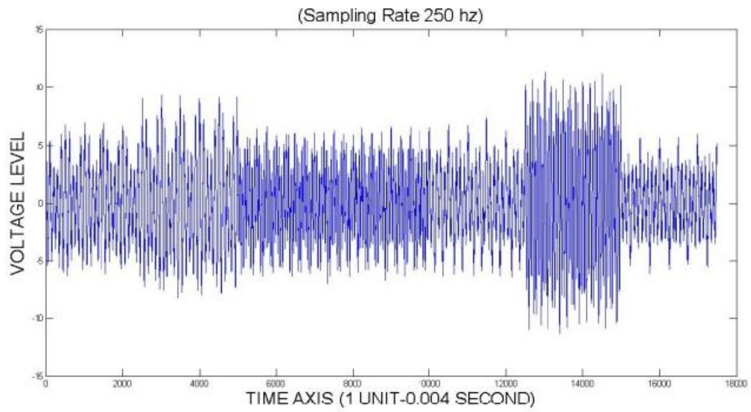

Figure :1 ECG signal

The development of deep learning systems for ECG denoising is currently hampered by a lack of well-structured and standardized datasets with particular benchmarks. ECGdenoiseNet is a benchmark ECG dataset that may be used to train and test deep learning-based denoising models as well as compare their performance.

Deep learning approaches offer a lot of promise for ECG denoising, according to our research, even when there's a lot of noise. here expect that ECGdenoiseNet will help to advance the area of deep learning-based ECG denoising, which is still in its early stages.

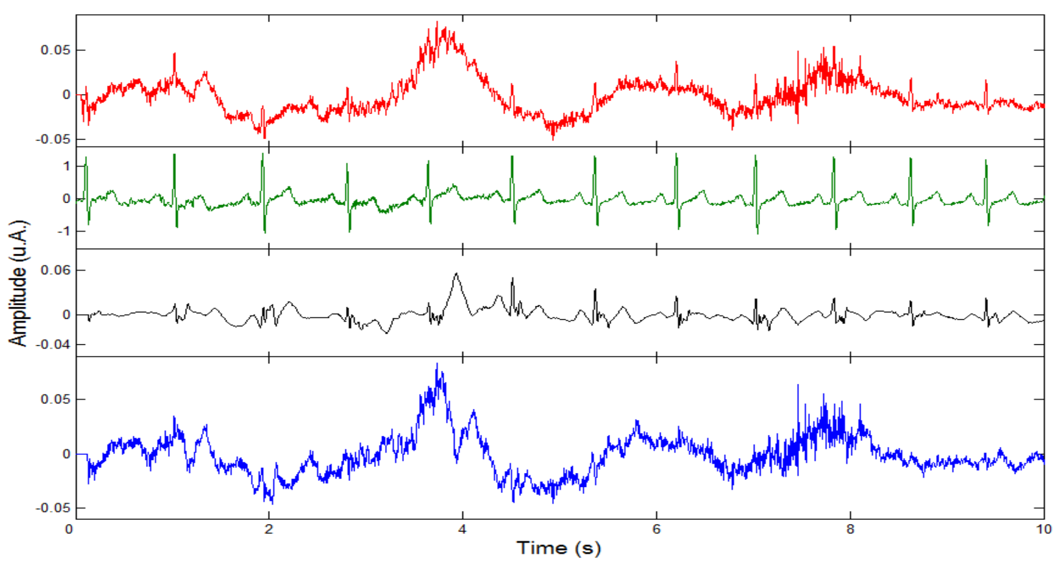

Figure :2 ECG noise signal

ECGdenoiseNet comprises 4514 clean ECG segments, 3400 ocular artefact segments, and 5598 muscular artefact segments, enabling users to synthesis contaminated ECG segments from clean

ECG. The performance of four classical networks was evaluated using ECGdenoiseNet (a fully-connected network, a simple and a complex convolution network, and a recurrent neural network).

Table:2performance measures

S No	Parameter	NN [1]	2D-CNN[2]	AUTOMATED CNN [11]	Proposed
1	**Accuracy**	89.23	91.43	93.27	~98.23 (Expected)
2	**Sensitivity**	91.24	92.45	96.34	~97.28 (Expected)
3	**F measure**	88.23	91.45	91.83	98.12 (Expected)
4	**Recall**	89.23	87.23	93.23	99.23 (Expected)
5	**Hit rate**	84.34	88.94	95.21	97.23 (Expected)

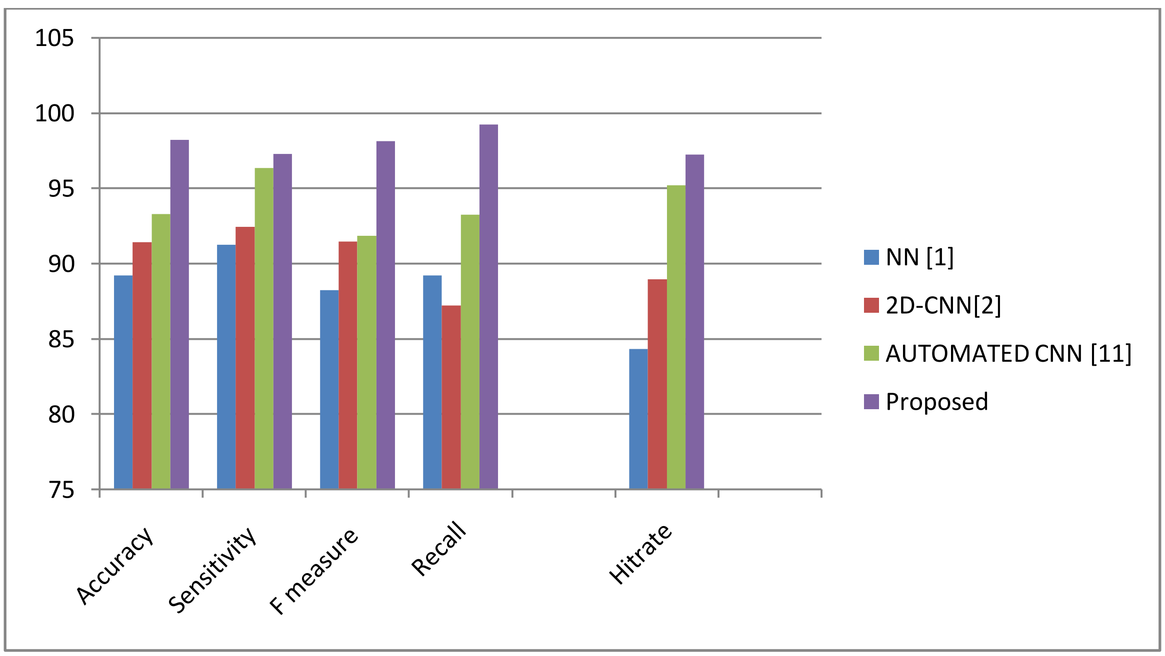

Figure:3performance measures analysis

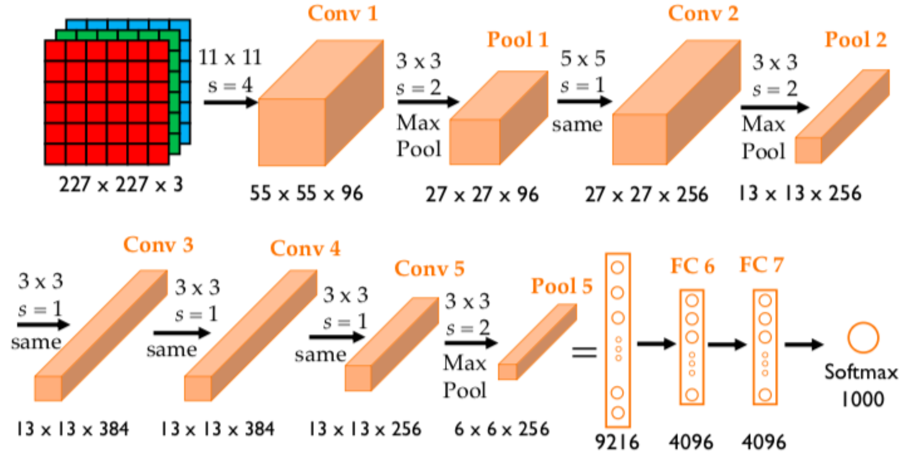

figure:4 AlexNet architecture

AlexNet is the name of a convolutional neural network which has had a large impact on the field of machine learning, specifically in the application of deep learning to machine vision. It famously won the 2012 ImageNet LSVRC-2012 competition by a large margin (15.3% VS 26.2% (second place) error rates) shown in figure 5.

Conclusion

In this research work a brief study on ECG signals have been performed, the earlier models are unable to get deep analysis. The features like alpha, beta, delta and gamma have been analyses and get signal become strong. The earlier models with PSO, GA, RFO and Machine learning are not that much efficient. The measures like accuracy, sensitivity, Recall, F1 measure and throughput can be improved using proposed AlexNet CNN deep learning technology. In upcoming research simulation results and experiment have been presented.

References

1. Alquran, H., Alqudah, A. M., Abu-Qasmieh, I., Al-Badarneh, A., &Almashaqbeh, S. (2019). ECG classification using higher order spectral estimation and deep learning techniques. Neural Network World, 29(4), 207-219.
2. Yildirim, O., Talo, M., Ay, B., Baloglu, U. B., Aydin, G., & Acharya, U. R. (2019). Automated detection of diabetic subject using pre-trained 2D-CNN models with frequency spectrum images extracted from heart rate signals. Computers in biology and medicine, 113, 103387.
3. Ullah, A., Anwar, S. M., Bilal, M., & Mehmood, R. M. (2020). Classification of arrhythmia by using deep learning with 2-D ECG spectral image representation. Remote Sensing, 12(10), 1685.
4. Mashrur, F. R., Roy, A. D., &Saha, D. K. (2019, December). Automatic identification of arrhythmia from ecg using alexnet convolutional neural network. In 2019 4th International Conference on Electrical Information and Communication Technology (EICT) (pp. 1-5). IEEE.

5. Singh, S. A., & Majumder, S. (2019). A novel approach osa detection using single-lead ECG scalogram based on deep neural network. Journal of Mechanics in Medicine and Biology, 19(04), 1950026.
6. Ebrahimi, Z., Loni, M., Daneshtalab, M., &Gharehbaghi, A. (2020). A review on deep learning methods for ECG arrhythmia classification. Expert Systems with Applications: X, 7, 100033.
7. Murat, F., Yildirim, O., Talo, M., Baloglu, U. B., Demir, Y., & Acharya, U. R. (2020). Application of deep learning techniques for heartbeats detection using ECG signals-analysis and review. Computers in biology and medicine, 120, 103726.
8. Alghamdi, A., Hammad, M., Ugail, H., Abdel-Raheem, A., Muhammad, K., Khalifa, H. S., ... & Ahmed, A. (2020). Detection of myocardial infarction based on novel deep transfer learning methods for urban healthcare in smart cities. Multimedia tools and applications, 1-22.
9. Tuncer, S. A., Akılotu, B., &Toraman, S. (2019). A deep learning-based decision support system for diagnosis of OSAS using PTT signals. Medical hypotheses, 127, 15-22.
10. Amin, S. U., Hossain, M. S., Muhammad, G., Alhussein, M., & Rahman, M. A. (2019). Cognitive smart healthcare for pathology detection and monitoring. IEEE Access, 7, 10745-10753.
11. Eltrass, A. S., Tayel, M. B., & Ammar, A. I. (2021). A new automated CNN deep learning approach for identification of ECG congestive heart failure and arrhythmia using constant-Q non-stationary Gabor transform. Biomedical Signal Processing and Control, 65, 102326.
12. Eltrass, A. S., Tayel, M. B., & Ammar, A. I. (2022). Automated ECG multi-class classification system based on combining deep learning features with HRV and ECG measures. Neural Computing and Applications, 1-21.
13. Dhar, P., Dutta, S., & Mukherjee, V. (2021). Cross-wavelet assisted convolution neural network (AlexNet) approach for phonocardiogram signals classification. Biomedical Signal Processing and Control, 63, 102142.
14. Gaddam, P. G., &Sreehari, R. V. (2021, November). Automatic Classification of Cardiac Arrhythmias based on ECG Signals Using Transferred Deep Learning Convolution Neural Network. In Journal of Physics: Conference Series (Vol. 2089, No. 1, p. 012058). IOP Publishing.
15. Sai, Y. P., & Kumari, L. R. (2022). Cognitive assistant DeepNet model for detection of cardiac arrhythmia. Biomedical Signal Processing and Control, 71, 103221.
16. Allen, J., Liu, H., Iqbal, S., Zheng, D., &Stansby, G. (2021). Deep learning-based photoplethysmography classification for peripheral arterial disease detection: a proof-of-concept study. Physiological Measurement, 42(5), 054002.
17. Ullah, A., Tu, S., Mehmood, R. M., &Ehatisham-ul-haq, M. (2021). A hybrid deep CNN model for abnormal arrhythmia detection based on cardiac ECG signal. Sensors, 21(3), 951.
18. Liu, X., Wang, H., Li, Z., & Qin, L. (2021). Deep learning in ECG diagnosis: A review. Knowledge-Based Systems, 227, 107187.
19. Ahmad, Z., Tabassum, A., Guan, L., & Khan, N. (2021, June). Ecg heart-beat classification using multimodal image fusion. In ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 1330-1334). IEEE.
20. Huerta, Á., Martínez-Rodrigo, A., Rieta, J. J., & Alcaraz, R. (2021, September). ECG Quality Assessment via Deep Learning and Data Augmentation. In 2021 Computing in Cardiology (CinC) (Vol. 48, pp. 1-4). IEEE.

ISSN- 2394-5125 VOL 7, ISSUE 01, 2020

21. Jun, T. J., Nguyen, H. M., Kang, D., Kim, D., Kim, D., & Kim, Y. H. (2018). ECG arrhythmia classification using a 2-D convolutional neural network. arXiv preprint arXiv:1804.06812.
22. Sai, Y. P., & Kumari, L. R. (2022). Cognitive assistant DeepNet model for detection of cardiac arrhythmia. Biomedical Signal Processing and Control, 71, 103221.