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Cardiac Disease Prediction By Analysing Ecg Signal Using Ml And Dl Techniques

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Abstract

The electrocardiogram provides valuable information about the heart. It is used to diagnose various cardiac diseases. This paper proposes a method of detecting arrhythmia using the raw ECG signal. The multiple parameters of an ECG signal are used for assessing the status of heart disease. The disease type that can be detected using these signals is atrial fibrillation, tachycardia, and sinus tachycardia. Early detection of heart disease can save many lives. It can be seen through various means, such as medical examinations, computed tomography scans, and electronic heart signals. In this paper, the objective is to find a way to improve the detection of H.D. data with better accuracy. The proposed classification models are based on the notion of classification.

Keywords: ML(Machine Learning), DL(Deep Learning), Heart, ECG(Electrocardiogram)

LITERATURE REVIEW:

This part aims at reviewing the literature related to the detection of heart disease. It is mainly focused on the techniques used for this purpose. Two papers published on Heart Disease detection were also included in this list. The review papers primarily focused on the use of deep learning techniques for detecting heart disease.

Different variants of input for the Heart Disease detection model have been presented in various papers. The outputs of these experiments have been analyzed using KNN algorithm. Data scientists usually determine the cutoff values for all observations, which are not called anomalies. This eliminates the need for a train-test-split of data.

Push the hidden layer's output to the next layer by taking the dot product with its weights. The use of the DL methods has been reported in various articles. In one study, the detection of atrial fibrillation was achieved by using the LSTM network. A recognition performance of 99.39 percent has been reported for an improved version of the proposed method. A combination of the two approaches is proposed to provide a better detection accuracy. The method involves first extracting various features from the ECG signal and then feeding them to the LSTM model.

INTRODUCTION:

The electro electrocardiogram is a low frequency weak signal that is commonly used for monitoring a person's heart rate. It ranges from 0.01 to 150 Hz and its amplitude is generally between 0.05 and 3V. An automatic electrocardiogram analysis is performed when the computer can detect and record the features of an ECG signal. This procedure is very useful for detecting and monitoring a variety of cardiac conditions. Arrhythmias are any abnormal activation sequence of the myoscardium. Some of these include myocardial infarction, which is caused by the sudden loss of blood supply to the heart. One of the most difficult and essential health problems in the real world is the prediction of heart disease. This condition affects the function of blood vessels and can weaken the body of the patient. According to the WHO, around 18 million people die yearly due to heart disease globally. Due to the increasing prevalence of cardiac diseases, people are prone to prevent devastating event from happening. They are used to diagnose a patient's cardiac condition [1].

Wearable sensors can be used to identify diseases such as heart disease, but they can also be corrupted by signal artifacts. This issue can affect the accuracy of the data and the results of the tests. Data mining and hybrid models have been proposed as possible solutions to predict and diagnose various types of cardiovascular disease. A data mining technique uses textual data to extract various risk factors.

Hybrid models are mainly composed of two main phases. The first one is used to select a feature's subset or weight and the second one is used to predict heart disease. The use of redundant features can create confusion and noise when it comes to defining a target class. Also, their handling can affect the accuracy of classification. Uncertain combination operations are commonly used for distinguishing features from classifications. They can also decrease the accuracy of the model and increase the mean square error. The electrocardiogram is a non-invasive diagnostic tool that records the heart's physiological activities. It can be used to identify various types of cardiovascular abnormalities, including those caused by sudden cardiac arrest (SCA), atrial fibrillation, and myocardial infarction. Due to the rapid emergence and evolution of portable ECG monitors, their continuous analysis has become a challenging task.

Deep learning methods have been widely used in various application areas, such as speech processing, natural language processing, and computer vision. One of their main advantages is that they do not require the use of human experts to extract feature data. Instead, they are performed by models based on their data learning capabilities.

Although there are various papers reviewing machine learning methods for analyzing ECG data, there are no systematic reviews focused on deep learning methods. This leaves us with the impression that there are no promising methods for extracting data from ECG data.

METHODOLOGY:

Convolutional neural networks are widely used in Deep Learning to analyze visual imagery. They are also known as shift-invariant or space invariant systems. Short-term Memory cell is a component that can be used for creating a neural network that can predict sequences of data. It can also be used to generate recurrent neural networks.

CNN LSTMs are designed to aid in the prediction of visual time series events and are also used to generate textual descriptions from sequence of images. This architecture is used for generating a sequence of textual descriptions of images. It was initially referred to as a Long-term recursive network model.

CNN is a feature extraction system that is used for generating caption problems in text-based systems. It can also be used for extracting audio and textual data from audio. CWT and CNN are used to extract time-frequency components from an ECG signal. The CWT component is then used to decompose the signal to obtain its associated features. With the help of Convolution Neural Network, these features can be combined to form an ECG classification layer.

Our method performs well across various parameters, and it has an overall performance of 98.74%. The distribution between A Fib and Normal signals is now evenly balanced in both training and testing sets. With the help of CNN-LSTM networks, we can learn long-term dependencies among data sequences.

Fig 1 :CNN LSTM ARCHITECTURE

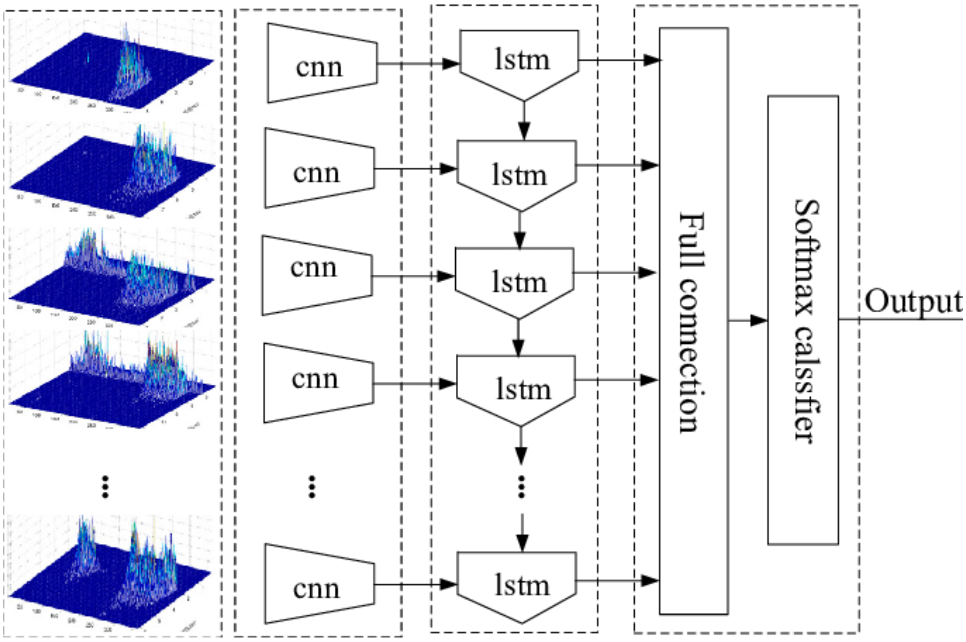
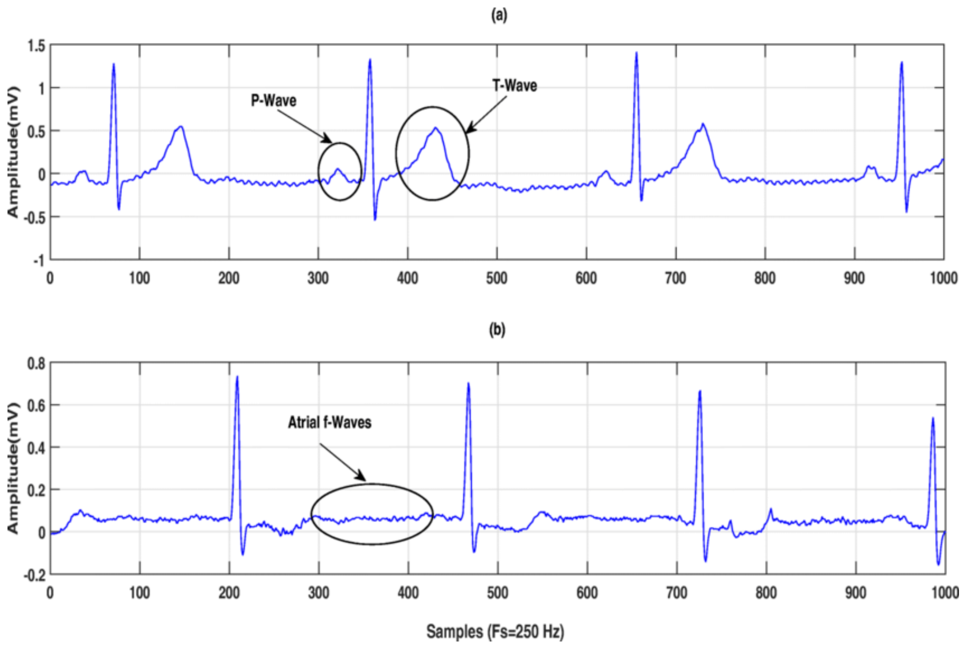


Fig 2: ECG SIGNAL FOR NORMAL HEART RHYTHM:



Conclusion: Deep learning for ECG data has become more prevalent in recent years. This paper shows that a hybrid approach that combines a recurrent neural network and a convolutional network achieves the best results.

References:

1. S. Jayalalitha, D. Susan, Shalini Kumari and B. Archana, "K-nearest Neighbour Method of Analysing the ECG Signal (To find out the Different Disorders Related to Heart)", Journal of Applied Sciences, 14: 1628-1632.
2. L. N. Sharma, R. K. Tripathy and S. Dandapat, "Multiscale Energy and Eigenspace approach to Detection and Localization of Myocardial Infarction", IEEE Trans. J. Magn, vol. 62, Issue 7, pp. (1827-1837), June 2015.

3. G. K. Sahoo, S. Ari and S. K. Patra, “ECG signal analysis for detection of cardiovascular abnormalities and ischemia episodes”, pp. (1055-1059), April 2013.
4. Ahammad, S.H., Rajesh, V., Rahman, M.Z.U., Lay-Ekuakille, A., "A Hybrid CNN-Based Segmentation and Boosting Classifier for Real Time Sensor Spinal Cord Injury Data", IEEE Sensors Journal,20(17), pp. 10092-10101.
5. Ahammad, S.K.H., Rajesh, V., Ur Rahman, M.Z., "Fast and Accurate Feature Extraction-Based Segmentation Framework for Spinal Cord Injury Severity Classification", IEEE Access 7, pp. 46092-46103.
6. Hasane Ahammad, S.K., Rajesh, V., "Image processing based segmentation techniques for spinal cord in MRI", Indian Journal of Public Health Research and Development, 9(6), pp. 317-323.
7. Ahammad, S.H., Rajesh, V., Neetha, A., Sai Jeesmitha, B., Srikanth, A., "Automatic segmentation of spinal cord diffusion MR images for disease location finding",Indonesian Journal of Electrical Engineering and Computer Science 15(3), pp. 1313-1321.
8. Vijaykumar, G., Gantala, A., Gade, M.S.L., Anjaneyulu, P., Ahammad, S.H., "Microcontroller based heartbeat monitoring and display on PC ", Journal of Advanced Research in Dynamical and Control Systems 9(4), pp. 250-260.
9. Inthiyaz, S., Prasad, M.V.D., Usha Sri Lakshmi, R., Sri Sai, N.T.B., Kumar, P.P., Ahammad, "Agriculture based plant leaf health assessment tool: A deep learning perspective", S.H., International Journal of Emerging Trends in Engineering Research 7(11), pp. 690-694.
10. Kumar, M.S., Inthiyaz, S., Vamsi, C.K., Ahammad, S.H., Sai Lakshmi, K., Venu Gopal, P., Bala Raghavendra, A., "Power optimization using dual sram circuit",International Journal of Innovative Technology and Exploring Engineering 8(8), pp. 1032-1036.
11. Hasane Ahammad, S., Rajesh, V., Hanumatsai, N., Venumadhav, A., Sasank, N.S.S., Bhargav Gupta, K.K., Inithiyaz,"MRI image training and finding acute spine injury with the help of hemorrhagic and non hemorrhagic rope wounds method", Indian Journal of Public Health Research and Development 10(7), pp. 404-408.
12. L. N. Sharma, R. K. Tripathy and S. Dandapat, “Multiscale Energy and Eigenspace approach to Detection and Localization of Myocardial Infarction”, IEEE Trans. J. Magn, vol. 62, Issue 7, pp. (1827-1837), June 2015.
13. H. Ahmed, E.M.G. Younis, A. Hendawi, A.A. Ali, Heart disease identification from patients’ social posts, machine learning solution on Spark, Futur. Gener. Comput. Syst. (2019).
14. Y. Hao, M. Usama, J. Yang, M.S. Hossain, A. Ghoneim, Recurrent convolutional neural network based multimodal disease risk prediction, Futur. Gener. Comput. Syst. 92 (2019) 76–83.
15. J. Jonnagaddala, S.T. Liaw, P. Ray, M. Kumar, N.W. Chang, H.J. Dai, Coronary artery disease risk assessment from unstructured electronic health records using text mining, J. Biomed. Inform. 58 (2015) S203–S210.
16. P. Melin, I. Miramontes, G. Prado-Arechiga, A hybrid model based on modular neural networks and fuzzy systems for classification of blood pressure and hypertension risk diagnosis, Expert Syst. Appl. 107 (2018) 146–164.
17. H. Ahmed, E.M.G. Younis, A. Hendawi, A.A. Ali, Heart disease identification from patients’ social posts, machine learning solution on Spark, Futur. Gener. Comput. Syst. (2019
18. N.C. Long, P. Meesad, H. Unger, A highly accurate firefly based algorithm for heart disease prediction, Expert Syst. Appl. 42 (2015) 8221–8231
19. A.H. Nandhu Kishore, V.E. Jayanthi, Neuro-fuzzy based medical decision support system for coronary artery disease diagnosis and risk level prediction, J. Comput. Theor. Nanosci. 15 (2018) 1027–1037
20. S. Nazari, M. Fallah, H. Kazemipoor, A. Salehipour, A fuzzy inference- fuzzy analytic hierarchy process-based clinical decision support system for diagnosis of heart diseases, Expert Syst. Appl. 95 (2018) 261–271.

21. O.W. Samuel, G.M. Asogbon, A.K. Sangaiah, P. Fang, G. Li, An integrated decision support system based on ANN and Fuzzy_AHP for heart failure risk prediction, Expert Syst. Appl. 68 (2017) 163–172.
22. Nikolic, G., Bishop, R., Singh, J., 1982. Sudden death recorded during holter monitoring. Circulation 66, 218–225.
23. Hong, S., Wu, M., Zhou, Y., Wang, Q., Shang, J., Li, H., Xie, J., 2017. Encase: An ensemble classifier for ecg classification using expert features and deep neural networks, in: 2017 Computing in Cardiology (CinC), IEEE. pp. 1–4.
24. Hong, S., Zhou, Y., Wu, M., Shang, J., Wang, Q., Li, H., Xie, J., 2019c. Combining deep neural networks and engineered features for cardiac arrhythmia detection from ecg recordings. Physiological measurement 40, 054009.
25. Clifford, G.D., Liu, C., Moody, B., Li-wei, H.L., Silva, I., Li, Q., Johnson, A., Mark, R.G., 2017. Af classification from a short single lead ecg recording: the physionet/computing in cardiology challenge 2017, in: 2017 Computing in Cardiology (CinC), IEEE. pp. 1–4.
26. Ghassemi, M.M., Moody, B.E., Lehman, L.W.H., Song, C., Li, Q., Sun, H., Mark, R.G., Westover, M.B., Clifford, G.D., 2018. You snooze, you win: the physionet/computing in cardiology challenge 2018, in: 2018 Computing in Cardiology Conference (CinC), IEEE. pp. 1–4.
27. Mincholé, A., Camps, J., Lyon, A., Rodríguez, B., 2019. Machine learning in the electrocardiogram. Journal of electrocardiology .
28. Parvaneh, S., Rubin, J., Babaeizadeh, S., Xu-Wilson, M., 2019. Cardiac arrhythmia detection using deep learning: A review. Journal of electrocardiology