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AI Driven ECG Arrhythmia Diagnosis

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***Abstract*— The patient management needs to have quick and accurate diagnosis of cardiac rhythm abnormalities to achieve effective clinical results. Although, arrhythmias interpretation in case of ECGs recordings is a complicated task, usually, it should be performed by experts, which may introduce delays and a risk of diagnostic variability. In order to address these challenges, Deep Learning based framework offer as-tudy which can conduct automed ECG analysis and diagnosis. The model suggested relies on the utilization of the sophisticated convolutional neural network designs which have been trained on a massive dataset of real world ECG data. This enables one to have a powerful and reliable prediction model. The system can identify hidden biomarkers and also crystalize irregular patterns by direct processing raw ECG signals which is incredibly sensitive and also learns to recognize irregular patterns. As a result, it is able to identify a broad range of arrhyth-mias effectively and with high accuracy even in cases where the waveform features vary to a large extent. Gandhi and Gandhi (2017) also introduce a user-friendly dashboard, which enables medical practitioners to upload ECG recordings and receive diagnosis in-formation on the spot. This will help to make clinical decisions faster, support timely triage, and help make treatment plans more personal. Notably, the model is also data-driven because it focuses less on a black box. It brings out the important sig-nal characteristics affecting its predictions and clearly explainable in a human understandable manner, therefore increasing the confidence and ease of use by the clinicians.**

***Keywords*— Arrhythmia, ECG signals, Deep Learning, Concurrent Neural Network, ECGSignals.**

I. Introduction

Issues with the heart rhythm are not the things you want to play around with. When doctors fail to notice them, things can run out of control within a short period of time. They normally, how-ever, use the ECGs to pick these problems but to tell the truth, these spike like lines are not al-ways easy to interpret. The professionals may ignore things themselves too or get lost in wait of the outcome. We resolved therefore to do something about it. Our AI system is designed to detect arrhythmias of its own through incorporating deep learning. It reads the ECG and detects any-thing unordinary. The concept is easy to understand, accelerate and reduce manmade errors. In order to do it correctly, we trained the model using hundreds of la-beled ECG recordings. Thus, it gets to know how to distinguish between regular patterns and major trouble. The health care workers can now only post the ECG data in an interface and receive immediate feedback. There is no longer sifting for hours to find a better or quicker answer and better care.

This project demonstrates that AI can in fact simplify the process of diagnosing heart rhythm issues a great deal, faster, and more efficiently.

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II. LITERATURE SURVEY

Several investigators have attempted the applications of varying machine learning methods to identify arrhythmias in ECG information [1]. AlexNet and SVM and LSTM models were worked on to classify ECG signals of different types. Their feature extraction was very accurate, which resulted in solid accu-racy. Nevertheless, they had not actually discussed the amount of computing power that they required and had bypassed any actual clini-cal testing. Autoencoder that is an LSTM trained on arrhythmia classification using SVM. It was superior to noise, it did not overfit, but consumed too many computa-tional resources, and it did not readily lend itself to understanding how the model arrived at its deci-sions. Later on in 2021, a medi-cal diagnosis system based on Artificial intelligent and built on AlexNet and VGGNet is constructed[2]. The precision was also good, yet they did not have a large sample to train their model, thus it is hard to admit whether their model would perform well with more patients., CNN, SVM, and DNN are tested on the ECG heartbeat data set in 2021[3,4,5]. The combination of these approaches escalated their performance, however, it was difficult and placed the model at risk of over-fit-ting. Lastly, the paper presents a proposed deep learning approach in 2022 with CNN and RNN to detect arrhythmia[7]. They appeared to have their results that had potential to be used in clinical prac-tice, but the results oscillated depending on the dataset and preprocessing technique they employed.

III. DESIGN

A. Dataset

In this project, we referred to Massachusetts Institute of Technology - Beth Israel Hospital Arrhythmia Dataset[6], - almost an efficient standard of ECG studies. It contains 48 half-hour recordings of ECGs of actual patients, all of which were consciously stamped up by professional cardiologists. There you will get all kinds of heartbeats: normal, ventricular ectopic and a few other arrhythmias. The signals are received at a frequency of 360 hertz meaning that you are receiving a lot of information. We split the data into 80, 20 to be used as training and testing respectively. The range of these ECG patterns is enormous and it is in this data that one can easily create an arrhythmia detection model that can work in reality

B. Algorithms used

One of the most prevalent artificial intelligence machines is the Convolutional Neural Networks / CNN:
The suggested ECG arrhythmia detection framework is composed of Deeplearning alogotithms includ-ing CNN and LSTM that are automatically requested to retrieve the spatial features of ECG waveforms, including the shape and morphology of the P, T -waves, QRS complex. The characteristics aid in the detection of structural abnormalities with each heartbeat.
The timing and rhythm of ECG signals are followed up by LSTM layers. Arrhythmias do not appear to be an issue of a single heartbeat, they are about beats in time. LSTMs identify the shifts and patterns which are more extended in time. Combining CNNs and LSTMs, the model can enjoy both the benefits of learning the specifics with every heartbeat and following the evolution of the beats with time. Such a combination renders the classification of arrhythmias much more precise. SVM forms an entry point in comparison. It performs reasonably well when you have a smaller range of features, although as soon as you have large, noisy ECG data the CNN-LSTM model simply outperforms it. All of these algorithms form a strong system of automatic and reliable spotting of arrhythmias.

IV. IMPLEMENTATION

A. Data Collection

Obtain a good collection of ECG images, but, again, ensure that every image is labeled with normal beats, various types of arrhythmia, the entire spectrum of possible arrhythmia. Here, you are to have diversifications, so be sure to have several ages, backgrounds and medical conditions. In our project, we have borrowed some data provided in the Physionet MIT-BIH arrhythmia data-base. It has 48 rec-ords with 30-minute long each, and all of them were recorded between 1975 and 1979 year. Should you want to have a look at it yourself, it is on the MIT-BIH site which anyone may access.

B. Data Preprocessing

The first is clearing up raw ECG signals, extracting the gunk, cleaning things up. Baseline drift is eliminated by high-pass filter[8], and powerline buzz is eliminated by a notch filter. and then you may hunt with R-peaks To nail every beat of the heart. Next up is feature extraction: draw information aside out of the time domain, frequency domain as well as provide some morphological features. You like to mix it up by adding some noise, distorting the data, skewing time, etc. to make the dataset more interesting. Then you normalize and lastly you can split data in to various images as training =, valida-tion and training.

C. Classification

Diagnostics of ECG arrhythmias, signal processing is the initial stage. Firstly, we extract important features of the ECG data such as amplitude, duration, and slope together with some statistics mean standard deviation and higher moments. We also examine R-R intervals in order to pin down heart rate variability and other tim-ing information. All these are combined to provide a good foundation to the next step. We will then trial some of the various models of classification CNN,LSTM networks, KNN,SVM. CNN model is excellent at identifying patterns in space, which comes in convenient since the ECG data might resemble the images greatly. LSTMs are very effective in term of recognition of the order and rhythm of the signal. KNN makes things easy and readable and classifies the data using the ones that are near to each other. SVM operates high dimensional spaces and boundary drawing to cut the various classes. These models then at the end are fed with the features extracted and are used to classify the ECG signals into their classes.

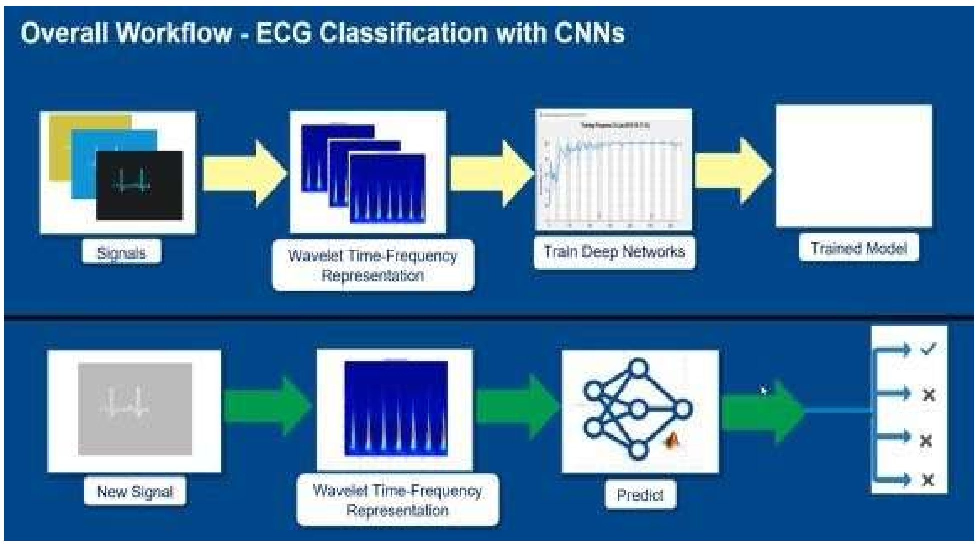


Fig 1: Classification with CNN

D. Testing

In testing arrhythmia with the ECG, you put the trained models on a new test set and observe their per-formance. You consider accuracy and precision, recall and ROC-AUC to make a feel of the success of the same. Confusion matrices can be used to understand where the model is correct or incorrect. In case the results are still not there but you modify the settings of the model or explore ensemble techniques to provide it with a boost then recheck the results. This is a cycle; test, readjust repeat, until you are either sure of solid performance. Lastly, you collaborate with medical practitioners to ensure that the model is actually working in the real world and not only in theory.

E. Evaluation

The model passes a rigorous examination so that it is really viable in the field. First of all, we search the numbers accuracy, the preciseness of everything. But we don't stop there. We consider false posi-tives and false negatives, as well, because they can indeed count in medicine. In order to maintain clari-ty we make use of inter-pretability tools because people would like to see how the model makes deci-sions. When we find a problem, we make modifications to the model and repeat the run to the model to make the model better. We also run it on various data sets to ensure that it is effective in the broad ra-ther than in a limited situation. At any stage, we contend ourselves on what would be truly significant clinical relevance, ethics, feedbacks provided by the users and whether the model is cost effective. All this and then we ensure that the model is not only accurate but also safe in terms of ethics and prepared and equipped to handle the actual workings of the healthcare sector.

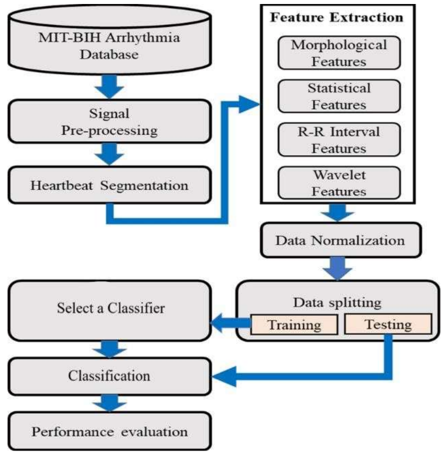
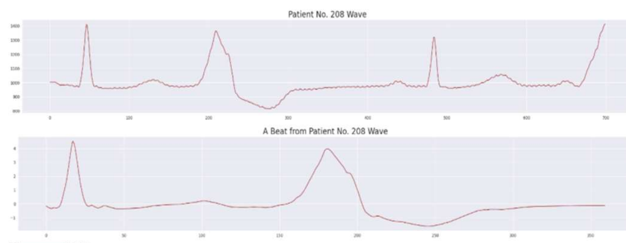


Fig 2: Architectural Diagram

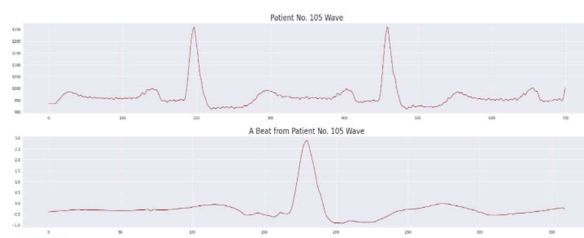
V. RESULT



The heart beat of Patient no. 208 is "Abormal"!

	Predicted	Actual
Atrial premature beat	1	0
Left bundle branch block beat	0	0
Normal beat	1590	1585
Premature ventricular contraction	986	992
Right bundle branch block beat	0	0

Fig 3: 208 Patient result with MIT BIH Dataset



The heart beat of Patient no. 105 is "Normal"!

	Predicted	Actual
Atrial premature beat	11	0
Left bundle branch block beat	8	0
Normal beat	2467	2526
Premature ventricular contraction	81	41
Right bundle branch block beat	0	0

Fig 4: 105 Patient result with MIT BIH Dataset

VI. CONCLUSION

In conclusion, we have developed a new AI system which assists in diagnosing ECG arrhythmias. We combined strong CNNs and LSTMs deep learning architectures with a traditional methods including: KNN and SVM. Having researched the modern world of AI, we realized how AI is transforming healthcare, where Saliency AI and Ezra became the most popular. And what is distinctly different about our system? It is easy to operate as one can actually see how it arrives at the decisions, and it can be sharp enough to pick out even the minute of the abnormalities in the ECG readings. With thoughtful labelling of our dataset of normal and arrhythmic cases we have challenged towards high accuracy in real-time detection. This ultimately provides healthcare providers with a better more rapid means of diagnosing arrhythmias.

REFERENCES

[1] Agrawal, A., Chauhan, A., Shetty, M.K., Gupta, M.D., Gupta, A.: ECG-iCOVIDNet: interpretable AI model to identify changes in the ECG signals of post-COVID subjects. Comput. Biol. Med. 146, 105540 (2022).

[2] Chen, Y.-J., Liu, C.-L., Tseng, V.S., Hu, Y.-F., Chen, S.-A.: Large-scale classification of 12-lead ECG with deep learning. In: 2019 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI), pp. 1–4 (2019).

[3] M. Liu, X. He, X. Yang, and Z. Wang, “Interpretation of report on cardiovascular health and diseases in China 2023,” Chin. Gen. Pract., vol. 28, no. 1, p. 20, 2025.

[4] Moody, G.B.; Mark, R.G. The impact of the MIT-BIH Arrhythmia Database. IEEE Eng. Med. Bi-ol.2001 , 45–50.

[5] Nelson, I.; Annadurai, C.; Devi, K.N. An Efficient AlexNet Deep Learning Architecture for Automat-ic Diagnosis of Cardio-Vascular Diseases in Healthcare System. Wirel. Pers. Commun, 2022 493–509

[6] January CT, Wann LS, Calkins H, Chen LY , Cigarroa J E, Cleveland J C et al. 2019 AHA/ACC/HRS guideline for the management of patients with atrial fibrillation 104-132

[7] Pengfei Li; Yu Wang; Jiangchun He; Lihua Wang; Yu Tian; Tian-shu Zhou et. Al. High-Performance Personalized Heartbeat Classification Model for Long-Term ECG Signal, IEEE Transactions on Bio-medical Engineering,Vol 4 , issue 1 , 2024.

[8] P. de Chazal, “Automatic classification of heartbeats using ECG morphology and heartbeat interval features,” IEEE Trans. Biomed. Eng., vol. 51, no. 7, pp. 1196–1206, Jul. 2004.