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ECG TIME–FREQUENCY DOMAIN FUSION AND CONVOLUTIONAL NEUROLOGICAL NETWORK ARRHYTHMIA DISEASE DIAGNOSIS

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Abstract: Electrocardiogram (ECG) signs will be utilized to distinguish arrhythmia side effects right off the bat in cardiovascular conclusion to further develop treatment and limit unfortunate results. ECG determination moves toward that underuse time-recurrence space data are drowsy and wasteful. A remarkable system utilizing Convolutional Neural Networks (CNNs) to research improved arrhythmia discovery strategies tends to this limitation. The undertaking means to make a solid arrhythmia location framework utilizing time-frequency space information to further develop effectiveness and exactness. CNN, LSTM, CNN + LSTM, Voting Classifier (Random Forest and AdaBoost), and Stacking Classifier are carried out during model-building. Beginning MIT-Touch and PTDBD preliminaries show great outcomes with the CNN model getting 99.43% exactness. Ensemble techniques like CNN+LSTM, Voting Classifier, and Stacking Classifier mean to further develop accuracy. This study progresses cardiovascular diagnostics by utilizing deep learning and group ways to deal with streamline ECG signal data for better quiet results.

INDEX TERMS: Time–frequency domain fusion, convolutional neural networks, ECG diagnosis.

1. INTRODUCTION

Arrhythmia, a CVD, compromises human existence and wellbeing [1], [2], [3], [4], [5]. It and cerebrovascular sickness cause the most mortality and inability internationally [6]. CVD is the main source of early mortality in north of 70 nations [7], [8]. Successful treatment and avoidance of serious arrhythmia side effects need early recognizable proof because of its critical impact on mortality and grimness [9]. In cardiology, analysis, anticipation, emergency vehicle, and treatment of heart issues are critical.[34]

ECG signals are fundamental for cardiovascular analysis and observing [10]. These signs show the heart's electrical movement and have a ton of natural wellbeing data [11,36]. ECG signals assist specialists with diagnosing ventricular atrial growth, myocardial ischemia, and arrhythmias [12]. ECG signals are easier to distinguish and examine than other bioelectrical signals, making them fundamental in medication [13].

A few examinations have utilized ECG signs to evaluate heart wellbeing [14], [15], [16], [17], [18]. ECG signal bunch waves P, Q, R, S, T, and U each uncover heart data. P waves address atrial depolarization, while QRS edifices show ventricular depolarization. Ventricle repolarization causes T and U waves. Doctors assess ECGs utilizing convoluted include extraction techniques [21].

Customary ECG analysis depends on human expertise and requires arduous component extraction [21]. Deep learning calculations for ECG signal order are acquiring prominence. Cui et al. [22] arranged ECG information utilizing CNN and SVM to further develop conclusion exactness. Zeng et al. [23] distinguished heartbeat types utilizing VMD and ANN. Jikuo et al. [24] fostered a CNN engineering for ECG signal classification with Non-local Convolutional Block Attention Module (NCBAM). Subasi et al. [25] utilized iterative help and NCA-based highlight choice followed by DNN grouping for proper finding. Sinha et al. [26] utilized 12-lead ECG information to separate SCI and PCI for myocardial dead tissue conclusion in a SVM structure. Amrani et al. [27] utilized a VDCNN to remove ECG signal elements and work on indicative execution through include combination and grouping.

All in all, ECG signals for arrhythmia analysis have extraordinary expected in cardiovascular medication. CNNs and deep neural networks can increment symptomatic accuracy and efficiency, working on persistent results and medical services conveyance.[36]

2. LITERATURE SURVEY

Recent electrocardiogram (ECG) signal-based arrhythmia identification and arrangement research has progressed across a few techniques. An essential preventive partner research by Falsehood et al. (2018) anticipated dangerous ventricular arrhythmias in arrhythmogenic cardiomyopathy patients [9]. A between persistent ECG arrhythmia heartbeat characterization approach in view of solo area variation by Wang et al. (2021) further developed speculation across understanding accomplices [14]. Mandal et al. (2021) utilized pulse changeability signs and ECG beat pictures to distinguish ventricular arrhythmias, demonstrating the way that multimodal information combination can improve precision [15]. In 2021, Li et al. laid out a multi-mark order framework for long haul ECG arrhythmia discovery utilizing highlight figuring out how to handle muddled designs [16]. Lu et al. (2021) utilized a depthwise distinguishable CNN with centered misfortune to group arrhythmia naturally, exhibiting profound learning models' viability [17]. Zeng and Yuan (2021) utilized variational mode decay, Shannon energy envelope, and deterministic figuring out how to characterize ECG arrhythmia, featuring the need of sign handling for include extraction [23]. Yang et al. (2018) applied head part investigation organization and straight help vector machine to consequently perceive arrhythmias, exhibiting cross breed strategies [29]. To recognize arrhythmias on unequal ECG datasets, Gao et al. (2019) recommended a productive LSTM intermittent organization that tends to class unevenness worries for hearty execution [33]. These works display arrhythmia detection approaches going from standard ML to complex deep learning models, signal handling, and space adaption systems. To further develop arrhythmia detection calculations in clinical practice, hybrid models, constant execution, and clinical approval might be created.

3. METHODOLOGY

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a) Proposed Work:

Our recommended strategy incorporates CNN [31] and LSTM [33] models with time-recurrence space combination to further develop arrhythmia location. We use datasets like MIT-BIH and PTBDB to exploit CNNs' spatial element extraction and LSTMs' worldly conditions to further develop arrhythmia discovery by integrating exhaustive time-recurrence data from ECG signals. Our undertaking additionally adds ensemble learning methods like a Voting Classifier (AdaBoost and Random Forest) and a Stacking Classifier (Arbitrary Timberland and MLP with LightGBM). These upgrades further develop execution through cooperative navigation. CNN+LSTM models incorporate convolutional and recurrent neural networks to further develop arrhythmia finding. At long last, we utilize Flask with SQLite for client information exchange and signin to guarantee convenience and availability in true conditions and simplicity client testing and application.

b) System Architecture:

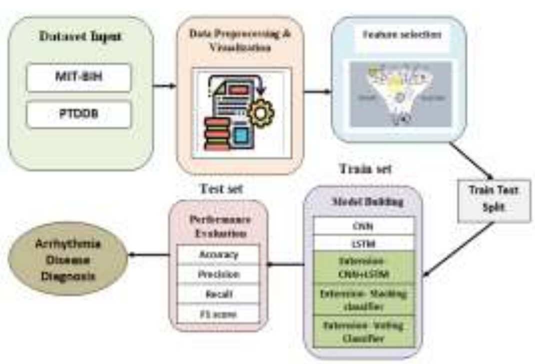

Fig 1. Proposed Architecture

To begin with, MIT-BIH and PTDDB datasets are placed, then, at that point, information arrangement, representation, and name encoding. Highlight determination enhances model preparation datasets. CNN[31], LSTM[33], CNN+LSTM, Voting Classifier, and Stacking Classifier are prepared on the train set. Test set measurements incorporate accuracy, precision, recall, and F1 score. The best model is utilized to analyze arrhythmia condition precisely and really.

c) Dataset:

ECG accounts from MIT-BIH and PTBDB give a complete arrhythmia exploration and investigation assortment. The MIT-BIH Arrhythmia Information base is a well known benchmark dataset with explained ECG accounts from 47 individuals with ordinary sinus rhythm and various arrhythmias. These accounts help construct and assess arrhythmia location calculations by uncovering different heart states. The PTBDB dataset likewise contains ECG accounts from people with myocardial localized necrosis, hypertrophy, and conduction inconsistencies. PTDDB offers an enormous dataset for exploring cardiovascular problems and arrhythmias with more than 2900 explained accounts from 290 members. The dataset's broad explanations permit definite arrhythmia recognizable proof and classification. Specialists and experts might utilize this dataset to make, approve, and benchmark arrhythmia discovery calculations to further develop heart wellbeing observing and analysis.

d) Data Processing:

Bringing in the dataset with Pandas DataFrame gives an organized structure to really handling even information. From that point onward, the dataset is completely cleaned to guarantee information quality and trustworthiness. This involves finding and fixing

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dataset blunders. Significant exercises in this stage incorporate ascription or expulsion of missing factors to diminish predisposition in later examinations. To save dataset exactness and constancy, copy passages are taken out. Segment information types can be changed for consistency and changed, for example, normalizing or encoding unmitigated qualities.[38]

The dataset is then handled for Keras similarity. This requires different techniques to plan information for model preparation. Starting elements are picked or designed relying upon work needs. From that point onward, the dataset is separated into preparing, approval, and testing subsets to limit overfitting and guarantee hearty appraisal measurements. Pandas DataFrames are changed to NumPy clusters or tensors to consolidate with Keras models. At last, input qualities are standardized or scaled to work on model intermingling and expectation execution. The dataset is changed and streamlined for Keras-based ML model preparation utilizing these purposeful data processing strategies.

e) Visualization:

Visualizing data utilizing Seaborn and Matplotlib incorporates building valuable and lovely diagrams to uncover patterns and connections. Matplotlib-based Seaborn gives an undeniable level connection point to making engaging factual visuals. Graphical portrayals improve on information understanding and investigation. Seaborn's lovely and short punctuation creates dissipate, line, bar, and heatmap diagrams with least code. Be that as it may, Matplotlib permits elaborate and profoundly adjustable perceptions with fine-grained plot customisation. These libraries assist with making distribution quality figures that express information bits of knowledge. Seaborn's strong measurable abilities and Matplotlib's adaptability permit clients to make outwardly engaging outlines for information investigation, speculation testing, and public presentation.

f) Label Encoding:

ML utilizes label encoding, supported by LabelEncoder, to communicate unmitigated factors mathematically. This method doles out an interesting number to each all out include class, transforming it into a mathematical portrayal ML calculations can comprehend. LabelEncoder improves on this via consequently requesting whole number marks by class starting from 0. Label encoding lets mathematical ML models utilize absolute information. It's not difficult to carry out. Label encoding might lay out unforeseen ordinal associations between classes, causing model translation mistakes. Label encoding is a fundamental stage in planning straight out information, empowering ML calculations to incorporate downright data.

g) Feature Selection:

ML tasks require feature selection to find and save the most valuable and enlightening data for model preparation. Rank highlights by prescient strength or commitment to the objective variable to diminish dimensionality and work on model execution. Highlight determination decreases the scourge of dimensionality and works on model interpretability by picking a subset of elements that address key information examples and associations. Channel, covering, and incorporated highlight choice methodologies each have their own advantages. Channel approaches utilize measurable measurements or connection investigation to choose huge attributes

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paying little mind to display. Covering approaches train and test models iteratively to improve accuracy and AUC for include subsets. Implanted methods use calculations that favor instructive elements during streamlining to pick includes straightforwardly during model preparation. ML specialists might upgrade model preparation, speculation, and significant bits of knowledge from troublesome datasets via cautiously choosing highlights.[40]

h) Training and Testing:

ML systems need dividing data into training and testing sets to assess model execution and speculation. This technique separates the dataset into two subsets: the training set, used to train the model on available information, and the testing set, used to assess the model on inconspicuous information. Dividing ensures that the model's ability to sum up to new cases is enough inspected via preparing it on a subset of the information and surveying it on another. The testing set is a proxy for true execution, permitting fair-minded gauge of the model's expectation abilities. The preparation set shows the model information examples and connections. The preparation and testing sets' class or result dispersions are painstakingly considered to guarantee representativeness and keep away from predisposition. Viable information parting permits ML experts to foster solid models that sum up to concealed information for informed independent direction and significant bits of knowledge.

i) Algorithms:

Convolutional Neural Network: CNNs use convolutional layers to learn progressive elements to decipher network like info like photos.[31] CNNs succeed at removing key examples from spatial portrayals in ECG signals, holding spatial linkages. Their capacity to perceive confounded arrhythmia characteristics is solid.

Fig 2 Convolutional Neural Networks

Long Short-Term Memory: ECG signs' drawn out conditions are all around caught by LSTMs, recurrent neural networks. LSTMs catch ECG transient connections utilizing memory cells and entryways that store data across lengthy groupings [33]. After some time, they comprehend heartbeat designs and can detect fleeting arrhythmias. CNN and LSTM models utilize spatial and transient information to precisely identify arrhythmias more.

Fig 3 Long Short Term Memory

CNN+LSTM: CNN+LSTM involves CNNs for spatial element extraction and LSTMs for fleeting example acknowledgment. This combination utilizes spatial and fleeting ECG data to further develop arrhythmia recognition.

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Fig 4 CNN+LSTM

Voting Classifier: Combining AdaBoost and RandomForest expectations further develops precision with the Voting Classifier. Different models further develop arrhythmia conclusion by making more accurate forecasts.

Fig 5 Voting Classifier

Stacking Classifier: The stacking classifier further develops expectation execution by combining Random Forest and MLP base classifiers. Last assessor LGBMClassifier gathers expectations for better order. This outfit methodology involves individual classifier qualities to further develop arrhythmia disease distinguishing proof in this exploration.[42]

Fig 6 Stacking Classifier

4. EXPERIMENTAL RESULTS

Accuracy: The model's accuracy is the percentage of true predictions at a grouping position. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

F1-Score: The F1 score captures both false positives and false negatives, making it a harmonized precision and validation technique for unbalanced data sets.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Precision: Precision quantifies the percentage of certain events or tests that are well characterized. To attain accuracy, use the formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{\textit{True Positive}}{\textit{True Positive} + \textit{False Positive}}$$

Recall: ML recall measures a model's ability to catch all class occurrences. The model's ability to recognize

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a certain type of event is measured by the percentage of precisely anticipated positive prospects that turn into real earnings.

$$Recall = \frac{TP}{TP + FN}$$

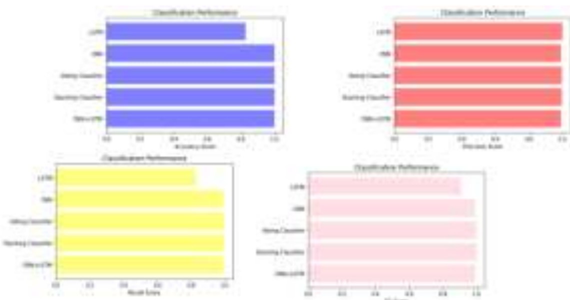

Fig **7** Comparison Graphs MIT-BIH Dataset

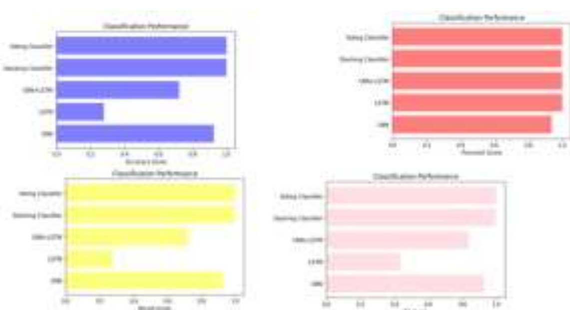

Fig 8 Comparison Graphs PTBDB Dataset

	ML Model	Accuracy	f1_score	Recall	Precision
0	Extension- CNN+LSTM	1.000	0.990	0.990	0.990
1	Extension- Stacking Classifier	1.000	0.996	0.996	0.996
2	Extension- Voting Classifier	1.000	0.997	0.997	0.997
3	CNN	1.000	0.990	0.980	0.980
4	LSTM	0.828	0.908	0.828	1.000

Fig 9 Performance Evaluation Table MIT-BIH Dataset

	ML Model	Accuracy	f1_score	Recall	Precision
0	CNN	0.924	0.927	0.924	0.935
1	LSTM	0.279	0.436	0.279	1.000
2	Extension- CNN+LSTM	0.721	0.838	0.721	1.000
3	Extension- Stacking Classifier	1.000	0.997	0.997	0.997
4	Extension- Voting Classifier	1.000	1.000	1.000	1.000

Fig 10 Performance Evaluation Table PTBDB Dataset

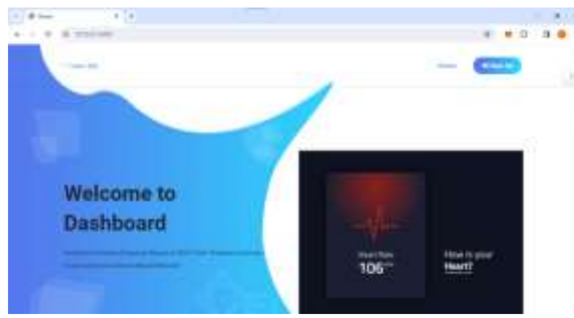

Fig 11 Home Page

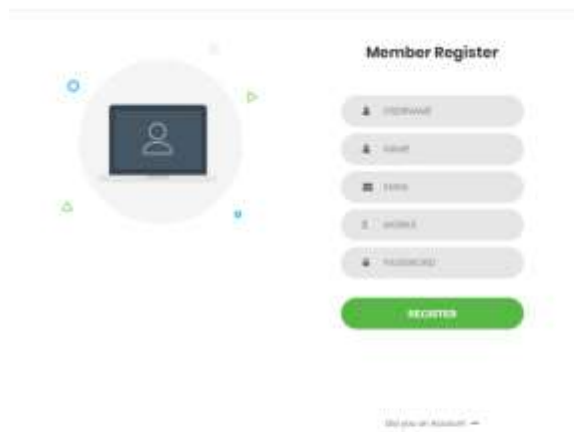

Fig 12 Registration Page

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Fig 13 Login Page

Fig 14 Upload input image

Fig 15 Final outcome

5. CONCLUSION

Taking everything into account, our review utilized strong ML and sign handling strategies to precisely analyze arrhythmia. Electrocardiogram (ECG) information was broke down utilizing Convolutional Neural Networks (CNNs) [31,43] and Long Short-Term Memory (LSTM) [33,44] organizations to catch spatial and fleeting examples and identify arrhythmia. The venture's degree was extended by coordinating gathering approaches including CNN+LSTM, Voting Classifier, and Stacking Classifier to work on symptomatic accuracy and strength. Arrhythmia conclusion was best performed by the Voting Classifier. Medical care specialists could undoubtedly characterize and analyze ECG signals involving a Flask framework for client connection and testing. This complete strategy might further develop medical care results by accurately diagnosing arrhythmia.

6. FUTURE SCOPE

Future CNN+LSTM design and outfit approaches could utilize progressed include designing to increment symptomatic accuracy. Nonstop arrhythmia recognizable proof with continuous ECG signal observing could empower early mediation and individualized treatment. Adding genetic and clinical history information could improve foreseeing capacity and give full cardiovascular wellbeing experiences. Working with medical services organizations to test the innovation in clinical settings would demonstrate its viability, empowering more extensive reception and coordination into patient consideration.

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Dataset Link :

https://www.kaggle.com/datasets/yasserhessein/heartbeat

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