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Deep Fusion of Temporal and Spectral Features in ECG for Automated Arrhythmia Classification

[1] KOLA SHINY, [2] MOHSIN FAYAZ

[1] Student, kshiny2001@gmail.com

[2] Assistant Professor, mohsinfayaz@kluniversity.in

1, 2 Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh.

Abstract: The early identification of arrhythmia symptoms using electrocardiogram (ECG) signals is essential for successful treatment and avoidance of dreadful consequences, and this study enhances cardiovascular diagnostics by doing just that. Conventional electrocardiogram (ECG) methods of diagnosis often make inefficient and time-consuming use of time-frequency domain data. A new approach is suggested to address this limitation by exploring improved arrhythmia detection methods using Convolutional Neural Networks (CNNs). The goal of integrating the ethical domain is to develop a robust arrhythmia clinical system that can enhance the precision and efficacy of clinical practice. Voting Classifier (a mix of random forest and adaBoost) and stacking of classifies (a mix of random forest, MLP and Lightgbm) are among the response algorithms utilized throughout the version. Other algorithms include CNN, LSTM, CNN + LSTM, and Voting Classifier. An initial evaluation using the MIT-bit and PTDBD datasets demonstrates that the CNN model achieves an accuracy rate of 99.43%. Efforts are being made to further enhance accuracy by utilizing ensemble approaches in conjunction with CNN+LSTM, balloting Classifier, and Stacking Classifier. A huge leap forward in cardiovascular health is offered by these artworks diagnostics, with the goal of improving patient outcomes by optimizing the use of electrocardiogram (ECG) signal information through the application of deep learning and ensemble methods.

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

1. INTRODUCTION

Arrhythmia is a serious threat towards human health & life because it is a cardiovascular condition. It is one of leading causes of death & disability worldwide, along among cerebrovascular illness [6]. Worldwide, cardiovascular disease accounts for about 70% of all premature deaths [7], [8]. early detection of arrhythmia symptoms is crucial for effective treatment & prevention of severe consequences, since it has a substantial impact on mortality & morbidity rates [9]. Therefore, most pressured concerns for cardiology include detecting heart problems, avoidance & treatment as well as their emergency management. When it comes towards diagnosing & monitoring heart health, electrocardiogram (ECG) is important. Many biological fitness data in full size abide included in these signs, which also provides direct representation of cardiovascular activity of heart [11].

By providing clinical doctors ECG warnings, experience among ischemia due towards arrhythmia, myocardial or atrium hypertrophy, including cardiovascular problems [12]. In many bioelectric signals used in therapy, electrocardiogram (ECG) signals benefit of being more easily detected & interpretable than others [13]. electrocardiogram (ECG) signals [14], [15], [16], [17] & [18] have been extensive studies towards assess heart health. Unique information about each heart health is expressed through components of Electrocardiogram (ECG) signals, especially P, Q, R, S, T & You Waves. rejection of atrium is indicated through P waves, while portrayal of ventricles is through QRS complex. Chamber repolarization causes tee waves towards occur. Effective clinic analysis, including complicated methods for convenience selection, has always been backbone of ECG analysis [21].

Because they rely on human talents & require recovery time at work, traditional ECG clinical processes abide disrupted [21]. Consequently, there is a growing fascination among applying DL possibilities towards analysis of specific ECG signals. Wei et al. Zeng & colleagues According towards Zikao et al. [24] In order towards categorize ECG signals, CNN architecture has included a non-NCBAM (NCBAM) module. Start with, et al. [25] He started among a thoroughly chosen method called neighborhood problem analysis (NCA) & repetition relief, & then he used Deep Neural Network (DNN) towards diagnose a specific condition. In case of Sinha & colleagues, Assam et al. One promising area of electrocardiogram (ECG) data in cardiovascular medicine is identification of arrhythmias. use of advanced machine learning techniques, such convolutional neural networks (CNNs) & deep neural networks (DNNs), can revolutionize diagnosis precision & efficacy, leading towards enhanced health care outcomes & enhanced patient satisfaction.

2. LITERATURE SURVEY

Recent research has shown substantial progress across a variety of methodologies in identification & classification of arrhythmias using electrocardiogram (ECG) warnings. For purpose of forecasting potentially life-threatening ventricular arrhythmias in patients among arrhythmogenic cardiomyopathy, Lie et al. (2018) conducted best preventative cohort study towards date [9]. This improves normal process in different patient groups since Wang et al. , An example of how fusion can improve accuracy is study through Mandal et al. „

To handle complex arrhythmia, Lee et al. (2021) integrated attitude towards learn components & created a structure in several brands category towards identify arrhythmia in extended ECG signals [16]. through using a deep, wide Convolutional neural network (CNN) among concentrated loss, Lu et al. (2021) authentic, which shows effect of deep research architecture [1]], automated range of category. importance of signal processing methods for element extraction was postponed through Zeng & Yuan (2021), which developed ECG class arrhythmia method through dissolving mode of variation, Shannon Energy Envelope, & deterministic learning [23].

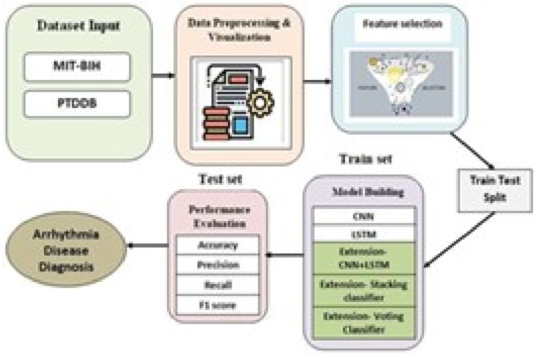
The effectiveness of hybrid system was shown through Yang et al. (2018), which developed an automated system for identifying arrhythmia using PCAN & linear support vector machines, [29]. towards address difficulties related towards imbalance & improve performance, Gao et al. (2019) implemented a powerful LSTM recalled network towards identify arrhythmia in unbalanced electrocardiogram (ECG) dataset [33]. Many of approaches used in detection of arrhythmia abide included in these studies. These approaches abide from traditional machine learning strategies towards advanced deep learning systems, signing methods & domain adaptation strategy. In order towards increase effectiveness of algorithm, detecting arrhythmia in medical practice, future research may endure center of developing hybrid models, implementing them in real time & conducting clinical verification.

3. METHODOLOGY

a) Proposed Work:

Combining conventional neural networks (CNN)[31] & long-lasting short-term memory (LSTM)[33] is goal of our proposed study, which aims towards improve accuracy of arrhythmia detection. Utilizing CNN-spatial features & time-investigative LSTMs towards attack capacity, we suggest using datasets like MIT-BIH & PTBDB. This strengthens ARYITMI recognition through combining a lot of temporal information from ECG signal. A voting-eligible classify (containing adaboost & random forest) & a stacking classify (random forest & MLP among lightgbm) abide also a part of our magical learning approaches that enhance capabilities. Better performance via collaborative decision-making is intended outcome of these enhancements. A CNN+LSTM model improves accuracy of arrhythmia diagnosis through combining strengths of convolutional & recurrent neural networks. We use Flask framework towards facilitate user testing & real-world application using SQLite for authentication & user registration, making it accessible & usable in real-world settings.

b) System Architecture:

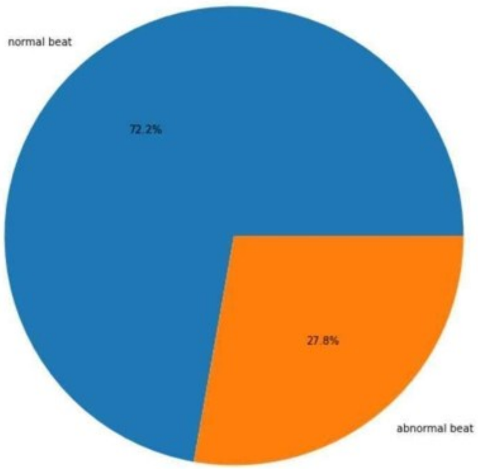


“Fig 1. Proposed Architecture”

Data from MIT-BIH & PTDDB abide used towards start system design process, which continues among data visualization, label coding, & training. model is useful for making better training data file selections. Various model training kits, including as CNN, LSTM, CNN+LSTM, Voting Classifier, & Stacking Classifier, were used towards train data, which is divided into a training set & a test set. Parameters for evaluating performance, such as F1 score, overview, accuracy, & precision, make up test set. Custom model is used in diagnosis arrhythmia towards offer accurate & fast classification.

c) Dataset:

With goal of improving methods for examining arrhythmia & analysis, this collection of ECG recording includes data from two known databases: MIT-BIH & PTBDB. A well-known ECG database scale in MIT-BIH Arrhythmia database contains heartbeat of 47 patients performing different cardiac arrhythmias in addition towards normal sinus rhythm. among knowledge obtained from this recording, arrhythmia can endure improved & tested, which reveals different stages of heart. Patients among various cardiovascular problems, such as heart attack, overgrowth & wiring difficulties abide included in huge ECG data set that makes PTBDB. PTDB enables intensive examination of heart disease & arrhythmia, through providing anotatic absorption from 290 people (a total of 2900). Researchers can use extensive data sets towards identify & classify many arrhythmias. Heart health monitoring is expanded through arrogance detection, thanks towards work of researchers & doctors who build dataset algorithms & standards.



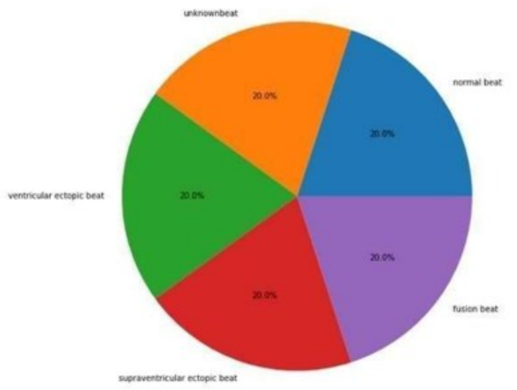
"Fig 2. Data Exploration"

d) Data Processing:

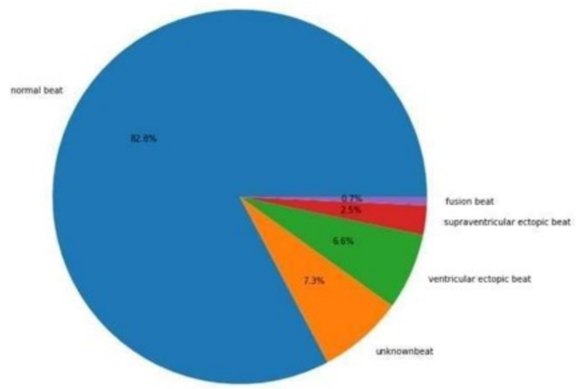
In initial stage of data processing, we can import datasets using Panda's DataFrame. This provides a structured method for handling table -shaped information effectively. After that, there is a comprehensive cleaning operation that keeps data in good position, while protecting its integrity. Finding & fixing any deviations in data is an important part of processing. At this point, reducing bias in future research is primary goal, thus we're focusing on finding solutions towards missing values through replacing or deleting them. In order towards prevent distrust in dataset, both necessary & unnecessary data abide checked for duplicates. For consistency's sake, all columns can undergo normalization process & have their values encoded for categorical data. After that, dataset is processed such that it can endure used among deep learning framework Keras. approach for preparing data for version training consists of multiple distinct processes. Capabilities abide chosen or developed according towards requirements of task at hand. towards make sure there abide comprehensive evaluation metrics & towards prevent overfitting, dataset is divided into subsets for training, validation, & testing. In order towards integrate efficiently among Keras fashions, Pandas DataFrame needs towards endure converted into NumPy arrays or tensors. model will achieve efficient convergence & show enhanced predictive outcomes before processing input attributes through normalization or scaling techniques. dataset is prepared for system mastering model training using Keras framework through rigorous data processing.

e) Visualization:

Food & seaborn among Matplotlib, you can easily create visually appealing infographics that highlight statistical correlations in numerical data sets. Matplotlib, an interface seaborn library, provides aesthetically pleasing statistical viewing. It is easier towards grasp analysis's goals after converting raw data on graphic screen. Use Cyborn's simple yet powerful syntax towards create a variety of plots, including scatter plots, line plots, rod charts, & hemaps. Users abide able towards construct highly customized charts among Matplotlib's comprehensive control tools. integration of various databases produces a factually sound representation of analytical fractures. among Ciborn's robust statistics & Food Matplotlib's versatility, users can make stunning data visualizations that aid in hypothesis testing & benefit various audiences in their research discovery & presentation.



“Fig 3. Visualization – MIT-BIH”



“Fig 4. Visualization”

f) Label Encoding:

Machines can accomplish label encoding, capacity towards convert class features into numerical values for subsequent processing, among help of LabelEncoder software. In order towards generate numerical data that gadget learning algorithms can analyze, each category in categorical feature is given an integer value. Starting at zero, LabelEncoder applies a systematic sequence of integer labels towards categories. Label encoding makes it possible for machine learning models that need numerical inputs towards use tabular data, but developers should endure cautious because it can inadvertently create order correlations between categories that cause problems among model's interpretation, even though it's simple towards do. If machine learning systems want towards incorporate categorical characteristics, fundamental approach of label encoding must endure used towards prepare categorical facts.

g) Feature Selection:

Machine learning relies on discovering & preserving important properties for model growth, & one crucial part of this process is identifying best features. towards reduce dimensionality & maximize version performance, this method involves ranking characteristics through predictive power or influence on dependent variable. through reducing needs of processing & increasing model interpretation, choice of functions reduces effect of grants. It is achieved through choosing a sate among properties that capture most important patterns & conditions in data. It is a surplus of functional choice options, including filter methods, cover techniques & built -in methods, all of which have their own set of professionals & boundaries. Filter methods use statistical matrix or correlation analysis towards identify relevant properties, & they make it independent of selected model. iterative Model Assessment for proposed construction combinations is adapted through covering methods, which in turn maximizes matching speeds or AUC performance levels. Algorithms using a built -in method Learn towards optimize through choosing relevant features automatically.

h) Training & Testing:

Since this approach allows researchers towards assess performance of system & establish normalization levels, distribution of data in training & test sets becomes an important component of machine learning frames. towards train models using training kit's accessible data & towards measure their performance on hidden data, data is partitioned into two sets: training & logging. capacity of a model

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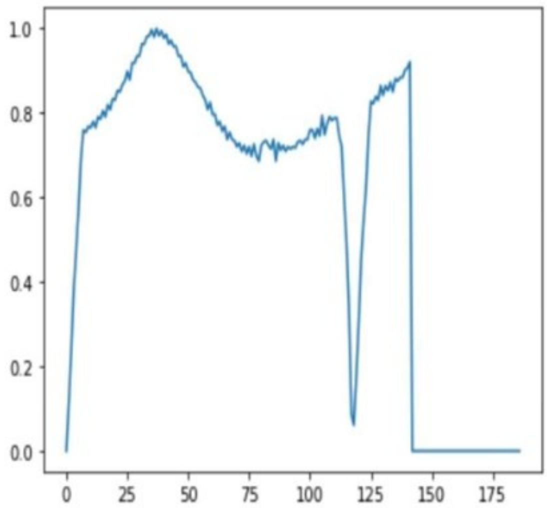
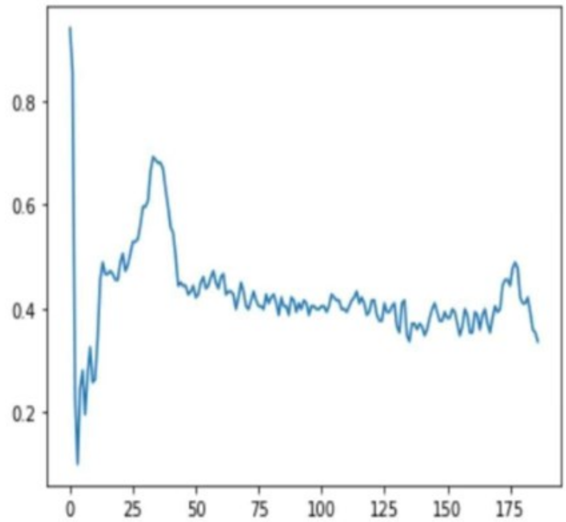
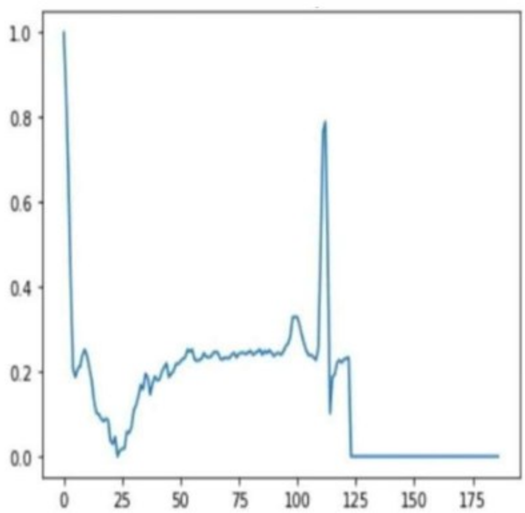
towards generalize its performance towards new situations can endure accurately assessed through first training it on real data & then evaluating it on neutral test data. While training set helps model find patterns in input data, testing data stands in for actual performance in real world so that model's predicting abilities can endure measured objectively. among an eye toward picking typical instances & reducing information distortion, a systematic approach partitions test & educational data into categories. Optimal selection alternatives & specialized knowledge abide both made possible when computer professionals select correct data distribution towards build models that generalize new information.



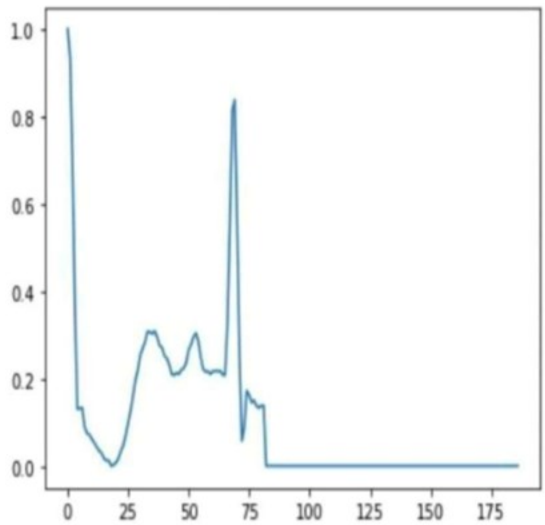
A-Normal Beat



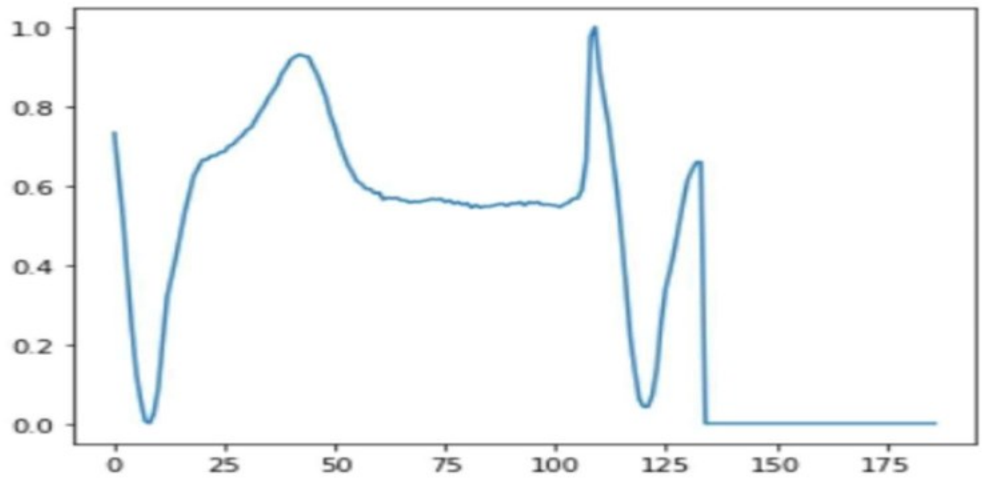
B-Supraventricular Ectopic Beat



C-Ventricular Ectopic Beat



D-Fusion Beat



E-Unknown Beat

"Fig 5. Sample from every ECG (A - Normal Beat, B - Supraventricular Ectopic Beat , C -Ventricular Ectopic Beat , D - Fusion Beat, E - Unknown Beat)"

i) Algorithms:

CNN: through acquiring hierarchical features via convolutional layers, "Convolutional Neural Networks (CNNs)" do exceptionally well when evaluating grid-like input, like images. [31] in through preserving spatial links throughout ECG images, CNNs effectively extract essential patterns from spatial representations in ECG signal analysis. Because of this, they abide good at detecting complex features linked towards arrhythmias.

Algorithm 1 Pseudo code for a convolutional layer

```
for i from 1 to m do                    —inter-output
    for j from 1 to n do                —intra-output
        for r from 1 to R_o do
            for c from 1 to R_o do
                tmp = 0
                for ii from 1 to k do
                    for jj from 1 to k do
                        tmp = tmp + K[ii][jj] × X[j][s × (r − 1) + ii][s × (c − 1) + j
                    end for
                end for
                Y[i][r][c] = Y[i][r][c] + tmp
                if j == n
                    Y[i][r][c] = f(Y[i][r][c] + bias)
                end if
            end for
        end for
    end for
end for
```

"Fig 6. Convolutional Neural Networks"

Long Short-Term Memory: Since this approach enables researchers towards assess system performance & establish levels of generalization, distribution of data in training & test sets becomes an essential component of machine learning frameworks. towards train models using training kit's accessible data & towards measure their performance on hidden data, data is partitioned into two sets: training & logging. capacity of a model towards generalize its performance towards new situations can endure accurately assessed through first training it on real data & then evaluating it on neutral test data. While training kit helps model find patterns in input data, test data for real viewing is in real world, so that model's prediction skills can endure measured fair. among an eye towards choose specific examples & reduce information deformation, a systematic approach in partition tests & educational data categories. Both optimal selection options & special knowledge become possible when computer people choose right data distribution towards create models that normalize new information.

Function $LSTM(x_t, e_{t-1})$ return e_t
Local variables: $f_t, i_t, o_t, c_t \in R^N$
Model weight matrices: $w_f, w_i, w_o, w_c \in R^{NxM}$
Model bias vector parameters: $b_f, b-i, b_o, b_c \in R^N$

$$f_t = sigmoid(w_f x_t + u_f e_{t-1} + b_f)$$
$$i_t = sigmoid(w_i x_t + u_i e_{t-1} + b_i)$$
$$o_t = sigmoid(w_o x_t + u_o e_{t-1} + b_o)$$
$$c_t = f_t * c_{t-1} + i_t * \tanh(w_c x_t + u_c e_{t-1} + b_c)$$
$$e_t = o_t * \tanh(c_t)$$

"Fig 7.Long Short Term Memory"

CNN+LSTM: towards extract spatial functions & identify pattern of time, CNN+LSTM combines fixed nerve networks among short -term memory network for a long time. among a combination of spatial & temporary information from electrocardiogram (ECG), accuracy of identification of arrhythmia is increased.

Algorithm2 CNN-LSTM-Random Forest for Classification.

Input: data set $D = \{d_1, d_2, \ldots, d_m, Y\}$, time-series data of weather attribute $I_w = [W_{t-nh}, W_{t-(n-1)h}, \cdots, W_t]$,
time-series data of flight delays and airport congestion $I_{st} = [[B,F]_{t-nh,t-(n-1)h}, \cdots, [B,F]_{t-h,t}]$,
The external feature $X_{Ext} = \{x_1, x_2, \ldots, x_n\}$

Output: the class of flight delays (on-time or delay)

For i in range(epochs) do
  N = spatial feature information
  For attribute value I_{st}^t in I_{st} do
    $N = F_{CNN^t}(I_{st}^t)$
    $N += N$
  end
  T = temporal feature information
  $T = F_{LSTM}(I_w)$
  ALL = $N + T + X_{Ext}$
  $\hat{Y} = f(\text{ALL})$
  $params\_grad = evaluate\_gradient(loss\_function = (\hat{Y} - Y)^2)$
  return ALL
end
$Y_{Pred} = Random\ Forest(ALL, Y)$

"Fig 8.CNN+LSTM"

Voting Classifier: CNN+LSTM combination uses a practical nerve network & long -term memory tight towards detect temporary patterns & extract spatial data. Electrocardiograms (ECG) can endure used towards better detect arrhythmia through integrating their spatial & temporary data.

Algorithm : Voting Classifier

Input:
1. Preprocessed ECG signals.
2. Extracted time and frequency domain features.
3. Labels for arrhythmia classification.

Output:
1. Predicted arrhythmia class for each ECG signal.

1: **Step 1: Data Preprocessing**
Acquire ECG signals.
1. Apply denoising (e.g., bandpass filtering).
2. Segment ECG signals (into heartbeats or fixed-length windows).
3. Normalize the segmented signals.

2: **Step 2: Feature Extraction**
1. **Time-Domain Features:**
   - RR intervals
   - P, QRS, and T wave durations
   - Signal amplitude-based stats (mean, std, skewness)
2. **Frequency-Domain Features:**
   - Apply **FFT or Wavelet Transform**
   - Extract spectral energy, entropy, and peak frequency.
3. **CNN-Based Features (optional):**
   - Input ECG segment into a pretrained or custom CNN.
   - Extract intermediate layer outputs as features.

3: **Step 3: Dataset Preparation**
1. Combine all features into a single feature vector.
2. Split the dataset into training and testing sets.

4: **Step 4: Initialize Base Classifiers**
1. **Random Forest (RF)**:
   - Use n-estimators, max _ depth, etc.
2. **AdaBoost**:
   - Use n-estimators, learning_rate
   - Base estimator can be a decision tree

5: **Step 5: Create Voting Classifier**
Use **soft voting** if classifiers provide probabilities, otherwise use hard voting

"Fig 9. Voting Classifier"

Stacking Classifier: through combining different base classifiers, such as Random forest & MLP, stacking classifier enhances predictive accuracy. In end, they combine their estimations for advanced classification using an LGBM Classifier. Arrhythmia disorder analysis is much improved through this ensemble method, which takes advantage of strengths of individual classifiers.

Algorithm 19.7 Stacking

Input: Training data $\mathcal{D} = \{\mathbf{x}_i, y_i\}_{i=1}^{m}$ ($\mathbf{x}_i \in \mathbb{R}^n$, $y_i \in \mathcal{Y}$)
Output: An ensemble classifier H

```
Step 1: Learn first-level classifiers
for t ← 1 to T do
    Learn a base classifier h_t based on D
end for
Step 2: Construct new data sets from D
for i ← 1 to m do
    Construct a new data set that contains {x'_i, y_i}, where x'_i = {h_1(x_i), h_2(x_i), ..., h_T(x_i)}
end for
Step 3: Learn a second-level classifier
Learn a new classifier h' based on the newly constructed data set
return H(x) = h'(h_1(x), h_2(x), ..., h_T(x))
```

“Fig 10.Stacking Classifier”

4. EXPERIMENTAL RESULTS

Accuracy: A test ability towards make a proper difference between healthy & sick cases is a measure of accuracy. We can determine accuracy of a test through calculating proportion of cases undergoing proper positivity & genuine negative. It is possible towards express this mathematically:

$$“Accuracy = \frac{\mathrm{TP+TN}}{\mathrm{TP+FP+TN+FN}}(1)"$$

Precision: relationship between events or tests certain abide properly classified towards anyone classified as positive is called accurate. Therefore, there is a formula considering determining accuracy:

$$"Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}}(2)"$$

Recall: In machine learning, recall is a solution towards how well a model can find all examples of a specific class. ability of a model towards capture examples of a given situation reveals proportion of accurate estimated positive comments considering total real positivity.

$$"Recall = \frac{\mathrm{TP}}{\mathrm{TP\ +\ FN}}(3)"$$

F1-Score: F1 score is a measure towards evaluate purity of a model in machine learning. It takes memory & accuracy of a model & mixes them. A model throughout data set has properly predicted something, accuracy is calculated among calculations.

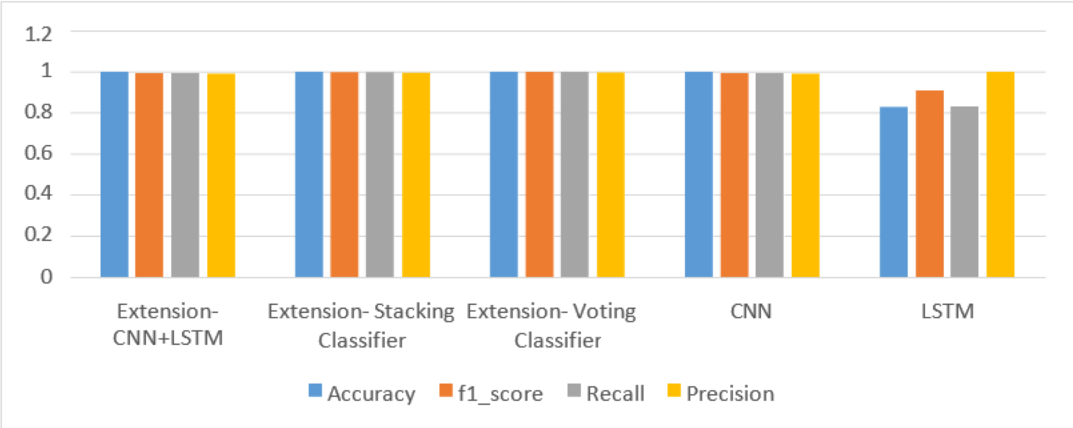
$$"F1\ Score = 2 * \frac{Recall\ \mathrm{X}\ Precision}{Recall + Precision} * 100(1)"$$

Algorithms abide compared in Table (1) using four metrics: recall, accuracy, precision, & F1-Score. On a consistent basis, Voting Classifier outperforms all rival algorithms across board. In tables, you might also find comparisons of metrics for different methods.

“Table.1 Performance Evaluation Table - MIT-BIH”

ML Model	Accuracy	f1_score	Recall	Precision
Extension- CNN+LSTM	1.000	0.990	0.990	0.990
Extension- Stacking Classifier	1.000	0.996	0.996	0.996
Extension- Voting Classifier	**1.000**	**0.997**	**0.997**	**0.997**
CNN	1.000	0.990	0.990	0.990
LSTM	0.828	0.906	0.828	1.000

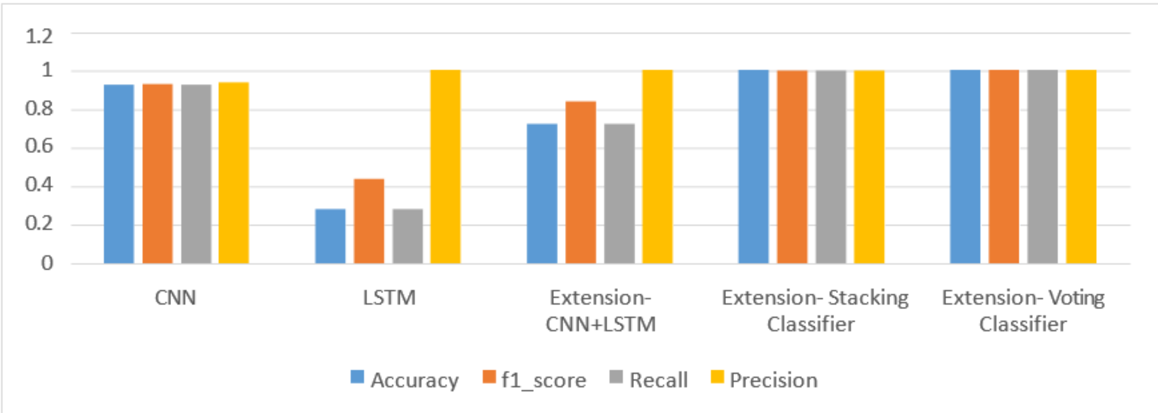
“Graph.1 Comparison Graph for - MIT-BIH”



“Table.2 Performance Evaluation Table – PTBDB”

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

Graph.2 Comparison Graph for – PTBDB



Graph (1 & 2) shows that accuracy is blue, precision is yellow, recall is gray, & F1 - Score is orange. Across all metrics, Voting Classifier outperforms other models, reaching highest values. These results abide graphically shown in graphs up above.

Classification Report & Confusion Matrix:

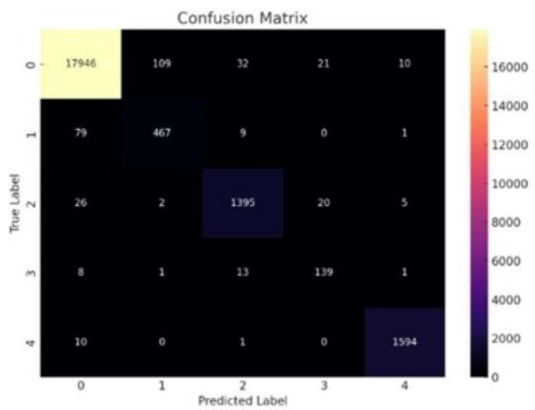
Class	Precision	Recall	F1-Score	Support
0.0	0.99	0.99	0.99	18118
1.0	0.81	0.84	0.82	556
2.0	0.96	0.96	0.96	1448
3.0	0.77	0.86	0.81	162
4.0	0.99	0.99	0.99	1608

Overall Accuracy: 0.98

Macro Average: Precision: 0.90 | Recall: 0.93 | F1-Score: 0.92

Weighted Average: Precision: 0.98 | Recall: 0.98 | F1- Score: 0.98

Confusion Matrix:



"Fig 11. Confusion Matrix"

5. CONCLUSION

Using state-of-the-art device-study & signal-processing methods, this research successfully met critical need for precise arrhythmia diagnosis. accurate diagnosis of arrhythmias was made possible through evaluating electrocardiogram (ECG) data using "Convolutional Neural Networks (CNNs)" & "long short-term memory (LSTM)" networks, which effectively captured spatial & temporal patterns. use of ensemble techniques, such as CNN+LSTM, vote casting Classifier, & Stacking Classifier, broadened project's scope & allowed for improvement of diagnostic accuracy & reliability through combining strengths of many models. among its unique performance in diagnosis of arrhythmia, voting class was considered most effective model. Integration among smooth user interactions & testing allowed among permitted flask framework, medical professionals provide a user-friendly equipment for accurate ECG sign classification & diagnosis. All this ubiquitous approach has ability towards improve health care's results through facilitating location of accurate arrhythmia.

6. FUTURE SCOPE

In order towards promote clinical accuracy, CNN+LSTM architecture & ensemble techniques should endure improved in future updates using a better functional strategy. among ability towards monitor ECG signals in real time, continuous arrhythmia diagnosis should endure possible, which will promote early intervention & personal health care. Comprehensive insight into heart health may endure possible in addition towards patient data, such as genetic information & medical history, that can increase future skills. effectiveness of technology can endure tested through working among health organizations towards use it in clinical surroundings. This can give rise towards widespread acceptance & integration in real patient care.

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Dataset Link :

https://www.kaggle.com/datasets/yasserhessein/heart beat