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Implementation of Machine Learning Algorithms for Cardiac Arrest Prediction

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Abstract— **Cardiac arrest is a critical medical emergency with potential life-threatening consequences. In this paper, machine learning techniques are used to develop a model for early identification of cardiac arrest for an individual. In this paper we are implementing machine learning and deep learning models like Support Vector Machine (SVM), Logistic Regression (LR), Decision Tree (DT), K-Nearest Neighbour (KNN), Multi-Layer Perceptron (MLP), Convolutional Neural Network (CNN). The main aim of the paper is to know how well the machine learning models are applicable for the prediction of cardiac arrest. Based on the factors accuracy, precision, recall and F1-score the performance will be calculated. These models analyse the health data to identify any uncovered signs that could signal a future cardiac arrest.**

Keywords — Cardiac arrest, Machine Learning, Deep Learning.

I. INTRODUCTION

Cardiac arrest is a life-threatening condition where the heart's pumping action abruptly stops. This leads to a complete cessation of blood flow to the vital organs, including the brain. Without immediate intervention, it can quickly result in irreversible damage and death within minutes.

Tragically, cardiac arrest claims millions of lives globally each year, making it a major public health concern. Often, there are no warning signs or symptoms before a cardiac arrest event. This makes early detection and intervention particularly challenging.

With advancements in technology, machine learning algorithms are emerging as promising tools in the fight against cardiac arrest. These algorithms can analyse vast amounts of clinical data, including vital signs, electrocardiograms (ECGs), and medical history, to identify subtle patterns and risk factors associated with potential cardiac arrest events.**Benefits of Machine Learning:**

- **Early Detection:** By analysing data with greater sensitivity and sophistication than traditional methods, machine learning algorithms can potentially detect early signs of impending cardiac arrest, allowing for earlier intervention andpossibly saving lives.
- **Improved Risk Assessment:** These algorithms can personalize risk prediction for individual patients, taking into account a wider range of factors beyond demographics and traditional risk scores. This allows for more targeted interventions and optimized resource allocation.
- **Real-time Monitoring:** Utilizing wearable devices and continuous data streams, machine learning can enable real-time monitoring of patients at risk, facilitating immediate action upon detecting warning signs.

The subsequent sections are as follows: Section 2 is about Literature Survey, Section 3 is about Methodology which includes description and implementation of machine learning and deep learning algorithms. Section 4 is about Results which includes evaluation of performance of each model and Section 5 is conclusion of the paper.

II. RELATED WORKS

There are several existing methodologies that have developed models to predict the Cardiac arrest. Here are some existing works:

[1] This study presents an innovative application of machine learning to predict cardiac arrest within emergency departments, by integrating patient baseline characteristics and sequential vital sign data. In this study, Data is taken from hospitals which includes patient demographics, vital signs, and cardiac arrest outcomes. Three distinct machine learning algorithms—Random Forest (RF), recurrent neural network (RNN), and logistic

regression (LR)—are employed. These algorithms are trained and optimized using sequential data vectors derived from temporal vital sign measurements. Among all the 3 algorithms RF algorithm emerges as the most effective predictor, demonstrating superior accuracy with AUROC and AUPRC values of 0.97 and 0.86, respectively.

[2] The main aim of this paper is to create model for predicting in-hospital cardiac arrest using heart rate variability(HRV) from ECG data. Data is taken from over 5000 ICU patients' ECG recordings then the study extracted 43 HRV metrics from 5-minute ECG segments and then narrowed down to 33 using the Boruta SHAP algorithm for feature selection. LGBM model was developed and trained on the chosen features. The LGBM model, leveraging 33 HRV measures, achieves an AUROC of 0.881 and an AUPRC of 0.104, indicating strong discriminatory and precision-recall performance for predicting in-hospital cardiac arrest in ICU patients.

[3] This paper presents a machine learning system for early detection of cardiac arrest (CA) in emergency department patients. The authors argue that most CA cases exhibit warning signs hours before the event, early detection could improve survival rates and resource allocation. Data is taken from the electronic health records (EHR)s of adult patients who visited NTH's ED. Various machine learning &deep learning models are compared including Random Forest(RF),Logistic Regression (LR),KNN, Naïve Bayes, Decision Tree, Support vector Machine ,LSTM,CNN are evaluated for their predictive performance. Random Forest performs best when predicting cardiac arrest at the time of occurrence (AUROC 0.81).

[4] The study explores predicting cardiac arrest by identifying recurring patterns in sudden death occurrences, stressing the importance of predictive analytics in healthcare. It employs J48 and Naïve Bayes algorithms to construct predictive models, emphasizing the significance of decision model-based techniques in early cardiac arrest detection. Naïve Bayes' shows superior accuracy in forecasting sudden cardiac events, suggesting its viability for timely interventions in critical situations.

[5] The paper mainly focuses on predicting cardiac arrest using machine learning and HRV in critically ill patients, emphasizing HRV's value in risk assessment. Methodology involves analysing data from critically ill ED patients, utilizing short-term ECG recordings and vital signs were used to measure HRV parameters and calculate the ML algorithms for risk prediction. It shows ML score's superiority over MEWS in predicting adverse outcomes.

[6] The paper explores machine learning's role in cardiac arrest prediction, emphasizing the importance of timely detection and understanding heart disease severity. Data collection involves selecting 14 attributes related to heart disease risk factors, followed by pre-processing and evaluation using four machine learning classifiers, including SVM, Naive Bayes, XG Boost, and logistic regression. The XG Boost algorithm demonstrates superior performance in predicting heart disease, achieving a precision level higher than other methods, with model stacking integrating various classifiers for enhanced accuracy.

[7] The paper focuses on predicting cardiac arrest using machine learning algorithms. It explores the application of various prognostic techniques such as logistic regression, random forest, ANN, and XG Boost on heart disease datasets. The dataset is taken from Heart Disease UCI .It encompasses 76 attributes in total, although the analysis focuses on utilizing only 14 pertinent features for heart disease prediction. Machine learning algorithms like logistic regression, random forest, ANN, and XG Boost are used for disease prediction. The results indicate that among the tested algorithms, random forest exhibits the highest accuracy in predicting heart disease.

[8] The authors presented a system that analyses heart sounds to predict the risk of cardiac arrest. They argue that early detection and intervention can significantly improve patient outcomes. Three machine learning algorithms, namely Decision Tree, K-Means Clustering, and Support Vector Machine (SVM), are employed to classify heart sound recordings based on distinct patterns. Among the three models, it was the decision tree algorithm stood out with its superior accuracy (92.5%) in predicting cardiac arrest risk, followed by SVM (78.2%) and K-Means Clustering (71.8%), showcasing the potential of machine learning in early identification of cardiac arrest.

[9] This paper mainly focuses on using machine learning algorithms to forecast the possibility of cardiac arrest considering a range of various patient factors. Data is taken from patients demographics and their B.P, cholesterol, ECG results .All this are employed on Five machine learning algorithms (SVM, Random Forest, Decision Tree, Logistic Regression, ANN).It highlights that ANN's give the highest accuracy in predicting cardiac arrest risk compared to other algorithms.

III. PROPOSED METHOD

This section provides a comprehensive overview of the entire workflow, from preprocessing the input data to predicting the optimal classification model.

A. Description and implementation of machine learning algorithms

Machine learning Algorithms used in this paper are as follows:

Support Vector Machine (SVM**):** SVM is a supervised learning technique is employed for categorization and prediction applications. SVM functions by finding the suitable boundary to accurately separate the data into clear groups. Its objective is to maximize the margin between these groups, this makes them resistant to outliers and its effective in complex data structures.

K-Nearest Neighbors (KNN): KNN is efficient algorithm that predicts outcomes based on the k closest data points, using distance metrics like Euclidean distance. It performs well in both categorization and prediction tasks. KNN operates without assumptions about data distribution, adapting to diverse datasets. While KNN functions lazily, not requiring explicit training, its prediction accuracy relies heavily on selecting the optimal number of neighbors (k). KNN's flexibility and ease of use make it a valuable tool in various problem domains.

Decision Tree(DT): Decision trees are versatile algorithms employed for categorization and prediction tasks. The algorithm constructs a tree-like structure, with each node representing a decision based on specific data features. By iteratively splitting the dataset based on the most discriminative features, it generates leaf nodes containing final predictions.

Logistic Regression(LR): Logistic Regression is a classification model that predicts binary outcomes. It operates as a linear model, estimating event probabilities using a linear equation. The logistic function then converts these outputs into probabilities ranging from 0 to 1. Through optimization, the model adjusts its parameters by minimizing the logistic loss function to enhance predictive accuracy.

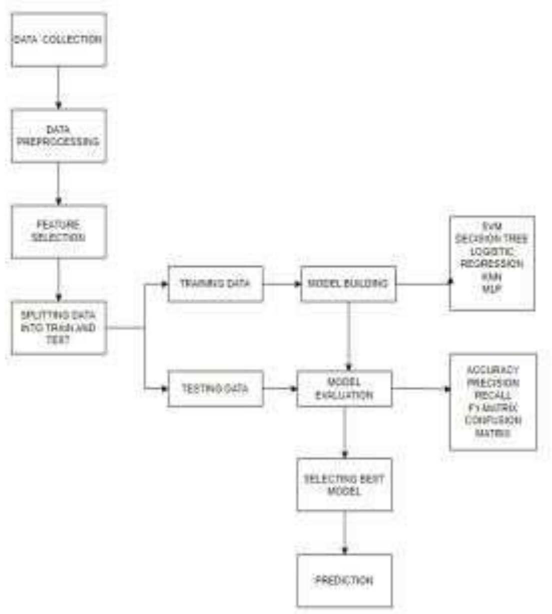

Figure 1: Block diagram of Machine Learning Algorithms

Implementation process using Machine learning models:

In Implementing the machine learning models, the python packages and libraries like Scikit-learn packages, pandas and NumPy libraries are used.

1. Data collection

Data is taken from Kaggle ML repository. The dataset consists of patient demographics and Electrocardiogram (ECG) data. The dataset consists of 452 rows and 280 columns.
Patient demographics consists of age, gender, weight and height of the patient.
Electrocardiogram(ECG) data consists of as follows:

- QRS duration: The time interval between the Q wave to S wave, representing ventricular depolarization.
- P-R interval: The time interval between the P wave and QRS complex, denotes the delay in signal travelling from atria to ventricle.
- Q-T interval: The time between Q wave to T wave, reflecting the contraction and relaxation of ventricles.
- T interval: It indicating ventricular repolarization.
- P interval: The interval between the P wave and the QRS complex, representing atrial depolarization.
- QRS complex: It represents the activation of the ventricles, comprising the Q, R, and S waves.
- T wave: The T wave on an ECG indicates ventricular repolarization, following ventricular activation represented by the QRS complex.
- P wave: It signifies atrial activation, initiating the cardiac electrical activity.
- QRST: The combined QRS-T segment, reflecting the contraction and relaxation of ventricles.
- J wave: It is a small deflection following the QRS complex on an (ECG), associated with hypothermia or other cardiac conditions.
- Heart wave: It represents the electrical activity of the heart, as depicted on an ECG.
- Q wave: First negative shift after the P wave, indicating the beginning of ventricular activation.
- R wave: represents the first positive shit after the Q wave, indicating additional ventricular activation.
- S wave: represents negative shift after the R wave, reflecting the completion of ventricular activation.

2.Data pre processing

It involves filtering, scaling, structuring the original data to make it suitable for analysis. Tasks like handling missing values, making sure all the numbers are on the same scale, and organizing the data for analysis fall under this step.

3.Feature Selection

The process of selecting the most informative attributes from the data, is essential for building models. The main aim of it is to reduce dimensionality and improve model performance by selecting features that have the most predictive power. In this paper, we selected 263 features from data which are relevant for predicting cardiac arrest.

4.Splitting the Data into train and test

For SVM, LR, DT, KNN, MLP models the data is divided, with allocating 80% of the data for the training process and the remaining 20% for testing process.

5.Model Building

In this step, the algorithms SVM, LR, DT, LG, MLP are trained on the training dataset. Here it learns patterns and relationships between input features and the target variable.

6.Model Evaluation

After training the models, they undergo testing, the models undergo rigorous evaluation using metrics like accuracy, precision, recall, F1 score, and the confusion matrix to determine their effectiveness.

7.Selecting the best model

The decision regarding the selection of algorithm is influenced by several factors, including the characteristics of the dataset, complexity of the problem and the desired goals or outcomes of the analysis. Here, the best model is taken into consideration for predicting cardiac arrest to give best results.

B. Description and implementation of Deep learning models.

Convolutional Neural Networks(CNN): CNN is a deep learning algorithm primarily used for image recognition and classification tasks.
The essential elements associated with Convolutional Neural Networks (CNNs) include:

- Input Layer: The first layer represents the input data. For image input it is represented in pixel values.
- Convolutional Layers: These layers execute convolution operations to extract features by applying filters to input data.
- Activation Functions: Rectified Linear Units (ReLU) are utilized to introduce non-linearities following convolutional operations, enhancing the model's capability to learn complex patterns.
- Pooling Layers: These layers down samples the data, reducing its dimensionality and processing cost while preserving important features.
 (e.g. MaxPooling)
- Fully Connected Layers: These layers, positioned towards the network's end, connect every element from one layer to every element in the subsequent layer, facilitating complex combinations and interactions between the extracted features.
- Flattening: Converts multi-dimensional feature maps into a one-dimensional vector before feeding them into fully connected layers.
- Dropout: It is used while learning to mitigate memorization. It randomly deactivates a portion of elements, motivates the system to develop strong and reliable patterns.
- Batch Normalization: It normalizes outputs to speed up learning and prevent vanishing gradients, leading to better model performance.
- Loss Functions: The goal is to minimize the error during training by adjusting the network's internal rules and guidelines. This helps the network learn from its mistakes and ultimately makes its predictions more accurate in the future.
- Optimizer: It reduces loss function and update the model parameters during training, facilitating efficient convergence.
 (e.g.Adam)
- Final layer: This concluding layer generates the model's output, with the activation function and neuron count customized to fit to the task requirements (e.g. softmax for classification).

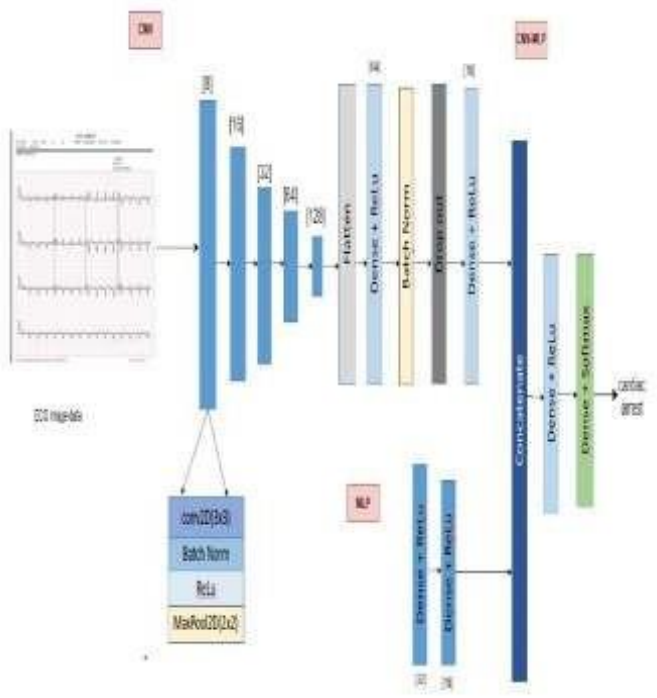

Figure 2: Architecture of CNN-MLP

A hybrid model combining Convolutional Neural Networks (CNNs) and Multilayer Perceptrons (MLPs), where CNNs are specialized in extracting features from images, on other hand MLPs are capable in capturing complex relationships in data.

Implementation process using deep learning models (CNN, hybrid model using CNN-MLP)

Deep learning libraries like TensorFlow and Keras simplify the process of building and training deep neural networks.

1. Data collection

 Image data is taken from google.

2. Data Organizing

The image data is organized into training and testing folders.70% of data is used for training and 30% of data is used for testing.
The data is organized into subfolders within the folder.
The original image has width of 2213 pixels and a height of 1572 pixels, it is resized to dimensions of 600 pixels width and 400 pixels height.

3. CNN

Extract Spatial Features**:** Begin by building a series of convolutional layers with filters. These filters will identify and capture local patterns within specific image regions.

Introduce Non-linearity: Employing the activation functions like ReLu after each convolutional layer to add non-linearity and improve model expressiveness. This allows the network to learn more complex relationships between features.

Down sample and Reduce Computation**:** Utilizing the max pooling layers throughout the CNN architecture makes down samples the spatial dimensions of the data reducing the computational cost and potentially improving generalization.

Stabilize Training **:** Incorporating batch normalization layers after convolutional and activation layers can help to stabilize the training process.

4. Flatten Output

Convert to 1D Vector: After the final convolutional layer, flatten layer reshapes the 2 Dimensional feature maps into a 1 Dimensional vector, thereby readying the extracted features for input into the MLP section.

5. MLP

Capture Global Relationships: Introducing dense layers with powerful activation functions like ReLu. These layers learn complex relationships between the extracted features, capturing more global patterns across the entire image.

Experiment with Neurons: The optimal number of neurons in each dense layer depends on the difficulty of the task.

6. Output Layer

Match Task and Activation: Choose an appropriate activation function for task in the output layer. For multi-class classification, the softmax function is typically used.

7. Compile and Train

Define Model Behaviour: Using a proper optimizer (e.g., Adam) and loss function to compile the model. These parameters influence how the model updates its weights during training.

Train the Model: Adapt the model using fit method, where it is providing the training data and labels.

8. Evaluate the performance

Assess the trained model's effectiveness on a separate test set to examine its applicability on unseen data.

1V. RESULTS

Figure 3: Precision, Recall, F1-Score of Logistic Regression

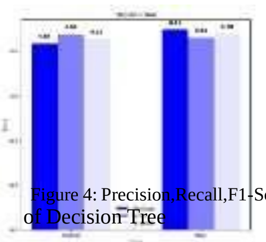

Figure 4: Precision,Recall,F1-Score of Decision Tree

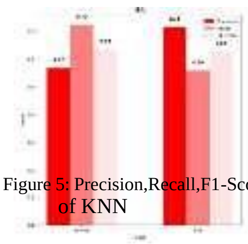

Figure 5: Precision,Recall,F1-Score of KNN

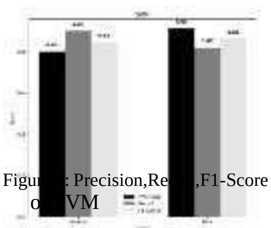

Figure 6: Precision,Recall,F1-Score of SVM

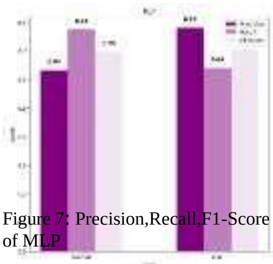

Figure 7: Precision,Recall,F1-Score of MLP

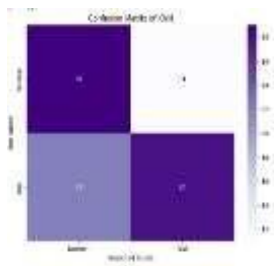

Figure 8: Confusion matrix of of KNN

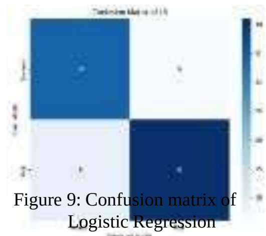

Figure 9: Confusion matrix of Logistic Regression

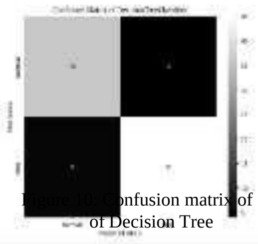

Figure 10: Confusion matrix of of Decision Tree

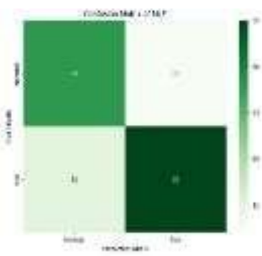

Figure 11: Confusion matrix of MLP

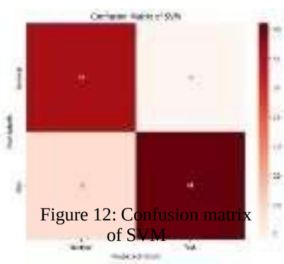

Figure 12: Confusion matrix of SVM

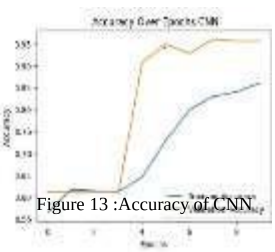

Figure 13 :Accuracy of CNN

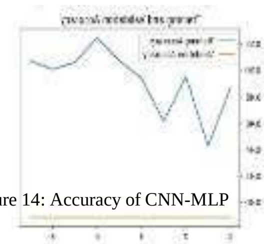

Figure 14: Accuracy of CNN-MLP

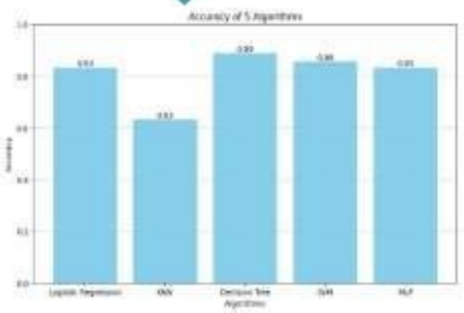

Figure 14: Bar graph

This graph compares the accuracy of five algorithms (SVM, Decision Tree, Logistic Regression, MLP, KNN). Among five algorithms Decision Tree attained the highest accuracy at 89%, followed by SVM at 86%, MLP and LR both at 83%, KNN at 63%.

Deep learning models	Loss	Accuracy	Validation Loss	Validation Accuracy
CNN	0.3137	0.8618	0.1306	0.9573
CNN-MLP	5.2511	0.5071	7.6783	0.3886

Table 1: Results of Deep learning model in prediction of cardiac arrest.

V.CONCLUSION

Machine learning algorithms show promise in predicting cardiac arrest. This paper presents a comparative analysis of four algorithms – Support Vector Machines (SVM), Linear Regression (LT), Decision Trees (DT), and K-Nearest Neighbours (KNN), Multi-Layer Perceptron (MLP) – The algorithms were evaluated according to the performance such as accuracy, precision, F1-Score and recall and found that Decision Trees yielded the highest accuracy and showed better performance among all the four algorithms in predicting arrest events.

Further, in this paper explores the use of deep learning models, like Convolutional Neural Networks (CNNs) and hybrid CNN-MLP models The results indicated that CNNs achieved high accuracy compared to the hybrid models for this specific task.

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