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EXPLORING MACHINE LEARNING MODELS FOR PREDICTING CARDIOVASCULAR CONDITIONS: A FORWARD-LOOKING FRAMEWORK

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ABSTRACT

Cardiovascular diseases (CVDs) remain one of the leading causes of death worldwide, emphasizing the need for early detection and prediction to improve patient outcomes. This paper explores the application of machine learning (ML) models in predicting cardiovascular conditions, focusing on the development of innovative, forward-looking frameworks for diagnosis and risk assessment. Various ML techniques, including supervised, unsupervised, and deep learning models, are reviewed for their effectiveness in analyzing medical data such as ECG signals, patient history, and diagnostic imaging. We discuss the advantages and challenges of these methods, highlighting their potential to provide real-time, accurate predictions that can assist healthcare providers in identifying high-risk individuals. The paper also explores the integration of ML models with wearable devices and healthcare systems, presenting opportunities for continuous monitoring and personalized treatment. The future of CVD prediction through machine learning promises to revolutionize preventive healthcare and improve clinical decision-making processes.

1. INTRODUCTION

1.1 BRIEF INFORMATION

Cardiovascular diseases (CVDs) are a leading cause of morbidity and mortality globally, contributing significantly to the burden of disease worldwide. The complexity and diversity of CVDs necessitate accurate, early detection methods to prevent complications and improve patient outcomes. Traditional diagnostic methods, while effective, often rely on late-stage detection and are resource-intensive. In recent years, machine learning (ML) has emerged as a promising tool in healthcare, particularly for predicting cardiovascular conditions at an early stage.

Machine learning models, which excel in handling large datasets and identifying complex patterns, can be leveraged to predict heart conditions based on diverse health indicators such as patient demographics, medical history, laboratory tests, and physiological measurements like ECG signals. By analyzing this data, ML algorithms can detect subtle patterns and associations that may go unnoticed by human experts, enabling earlier diagnosis, risk assessment, and personalized treatment.

This paper focuses on the application of machine learning in the prediction of cardiovascular conditions, exploring its potential to revolutionize heart health management. We will discuss various types of machine learning models, their strengths, challenges, and the integration of these models with clinical decision-making tools. Furthermore, the application of these models in wearable devices and real-time monitoring systems offers new avenues for proactive healthcare, potentially reducing the incidence and severity of cardiovascular events.

As healthcare systems increasingly move toward personalized and data-driven approaches, the use of machine learning for predicting heart issues is expected to play a critical role in advancing the future of cardiovascular care. This study aims to explore how these forward-looking technologies can optimize detection and treatment, providing better healthcare outcomes for individuals at risk of cardiovascular diseases.

1.2 PURPOSE

It is feasible to enhance model performance and save a significant amount of runtime by selecting the right subset of features that significantly affect the prediction outcomes. Both of these goals may be accomplished with a method called feature selection. "Filters," "wrappers," and "embedding" are the three most often used feature selection methods. The feature variables in the study were selected using the embedded technique called GBDT. This is due to the fact that embedded approaches outperform filter methods in terms of prediction performance and are significantly quicker than wrapper methods. GBDT use an additive model and a forward stepwise algorithm to achieve learning. These two components work together to accomplish this. The more the weighted impurity reduction that occurs during splitting for non-leaf nodes, the more relevant the features become. As a result, it is not possible to provide a comprehensive explanation of how each attribute affects the overall accuracy of the predictions made by the integrated GBDT. To solve this issue, we use a technique known as feature imputation, where the explanatory model is a linear function of the feature imputation-generated data.

1.3 SCOPE

In order to evaluate the system, 14 important features are selected from the dataset, which consists of 76 variables and contains the anticipated traits that lead to heart disease in people. The inventor is left with a less effective system when all the qualities are considered. The purpose of attribute selection is to increase productivity. In this instance, selecting n features is necessary to assess the model that offers more accuracy. Certain features of the dataset are removed since their correlations are almost equivalent. If every feature in the dataset is taken into account, the efficiency drastically drops. The accuracy of the seven machine learning methods is compared, and a prediction model is produced. In order to properly anticipate the sickness, the goal is to apply a range of evaluation measures, including the confusion matrix, accuracy, precision, recall, and f1-score. When comparing all seven, the extreme gradient boosting classifier has the highest accuracy (81%). 14 important variables that are necessary for evaluating the system are selected from the dataset, which comprises 76 features and includes the expected components that affect heart disease in patients. The inventor is left with a less effective system when all the qualities are considered. The purpose of attribute selection is to increase productivity. In this instance, selecting n features is necessary to assess the model that offers more accuracy. Certain features of the dataset are removed since their correlations are almost equivalent. If every feature in the dataset is taken into account, the efficiency drastically drops. The accuracy of the seven machine learning methods is compared, and a prediction model is produced. In order to properly anticipate the sickness, the goal is to apply a range of evaluation measures, including the confusion matrix, accuracy, precision, recall, and f1-score. When comparing all seven, the extreme gradient boosting classifier has the highest accuracy of 81%.

1.4 MOTIVATION

Weng et al. (31) evaluated four different models using clinical data from over 300,000 homes in the UK. The findings demonstrated that NN produced the best accurate CVD prediction results when a larger amount of data was evaluated. Dimopoulos et al. used ATTICA data with 2020 samples for the small CVD dataset to test and evaluate three traditional machine learning models: K-Nearest Neighbour (KNN), Random Forest (RF), and Decision Tree. In comparison, the HellenicSCORE tool—a calibration of the ESC Score—showed that RF had produced the best outcomes. Because machine learning techniques are so prevalent, Mohan et al. proposed a hybrid HRFLM approach as a means of further increasing the model predictions' accuracy. This is because machine learning methods are increasingly being used in Internet of Things applications. Akash et al. examined an IoT-ML method to predict the condition of the cardiovascular system in humans. The algorithm model uses machine learning (ML) techniques to compute and predict the patient's cardiovascular health after obtaining important data from the human body. This information includes the patient's cholesterol, heart rate, and ECG signal. In the context of Yang et al.'s evaluation of local regions utilising independent prediction models, LR was utilised to evaluate 30 cardiovascular disease-related factors employing over 200,000 high-risk individuals in eastern China. Based on the results of the testing, an RF model that is more suitable for eastern China was developed. For the first time in the research of CVDs, Yang et al. proposed the idea of a stacking model. Data on weather and air pollution were considered in order to better understand the impact of the stacking model on the daily hospitalisation rate for CVDs. Initially, a foundational level of five fundamental learners was established to aid in the development of the stacking model.

2. LITERATURE SURVEY

The application of machine learning (ML) in predicting heart issues has garnered significant attention in recent years, with numerous studies demonstrating the potential of ML algorithms to improve cardiovascular disease (CVD) prediction accuracy. A comprehensive literature survey reveals the breadth of research in this area, focusing on various algorithms, datasets, and real-world applications.

Machine Learning Algorithms for Cardiovascular Disease Prediction: Several studies have explored the use of machine learning algorithms for CVD prediction, with a focus on supervised learning methods. Commonly used algorithms include decision trees (DT), support vector machines (SVM), random forests (RF), and neural networks (NN). In particular, a study by Rajpurkar et al. (2017) introduced the use of deep learning methods for analyzing ECG signals to detect arrhythmias, demonstrating that deep neural networks (DNN) outperformed traditional methods in terms of accuracy and efficiency.

Feature Selection and Preprocessing: The performance of ML models heavily depends on the quality of input features. Several studies have explored feature selection techniques to enhance prediction accuracy. For instance, Hernandez et al. (2019) proposed an automated feature extraction method from ECG signals and clinical data, which was then used for heart disease prediction. Another key aspect highlighted in the literature is the importance of data preprocessing, especially dealing with imbalanced datasets and missing values. Techniques such as oversampling, undersampling, and imputation methods have been widely employed to handle these challenges.

Data Sources and Datasets: The availability of comprehensive, high-quality datasets is a critical factor in the success of ML models. The Cleveland Heart Disease dataset, UCI Heart Disease dataset, and Framingham Heart Study dataset are among the most frequently used datasets in CVD prediction research. Studies such as those by Krittanawong et al. (2017) and Liu et al. (2020) have shown that data from wearable devices, such as heart rate monitors and smartwatches, can be integrated into predictive models to provide real-time health monitoring, improving the accuracy of early detection systems.

Hybrid Models and Ensemble Learning: Hybrid models, combining multiple ML algorithms, have also been explored to improve prediction accuracy. For instance, ensemble methods like bagging and boosting, including random forests (RF) and gradient boosting machines (GBM), have shown promise in CVD prediction. A study by Zhang et al. (2020) demonstrated that an ensemble of SVM and random forest classifiers achieved superior performance in terms of accuracy and sensitivity when compared to individual models.

Applications in Clinical Decision Support Systems: Many researchers have emphasized the integration of machine learning models into clinical decision support systems (CDSS), which can aid healthcare professionals in diagnosing cardiovascular conditions. A study by Dey et al. (2020) developed an ML-based CDSS for early detection of heart disease, showcasing how real-time data analysis can support physicians in making timely and informed decisions. ML-based systems have also been employed for risk stratification, allowing for personalized treatment plans and proactive care.

Challenges and Limitations: Despite the progress, challenges remain in the implementation of ML models in real-world healthcare settings. Issues such as interpretability, model transparency, and the need for large and diverse datasets are major obstacles. Studies have shown that while deep learning models achieve high accuracy, they are often seen as "black boxes," making it difficult for clinicians to understand how predictions are made. Research by Ribeiro et al. (2016) and others has focused on developing explainable AI techniques to address these challenges and ensure that ML models are both reliable and understandable to healthcare providers.

Wearable Devices and Real-Time Monitoring: The advent of wearable technology has further enhanced the potential of machine learning in cardiovascular health monitoring. Devices like smartwatches and fitness trackers that monitor heart rate, blood pressure, and other vital signs provide continuous data that can be used in predictive models. A study by Yao et al. (2019) demonstrated how data from wearable devices, when combined with ML models, could predict the onset of cardiac events in high-risk patients, enabling early intervention and reducing hospital readmission rates.

Future Directions and Innovations: The future of machine learning in cardiovascular disease prediction is focused on personalized healthcare and continuous monitoring. Research is increasingly moving towards integrating ML models with Internet of Things (IoT) devices and cloud-based platforms, allowing for real-time, remote monitoring of patients' cardiovascular health. As technology continues to evolve, the use of ML for early detection and prevention of cardiovascular issues is expected to become more widespread, offering a new frontier in proactive healthcare.

Summary: The literature reveals a strong trend towards the use of machine learning models for predicting cardiovascular diseases, emphasizing the importance of algorithm selection, feature extraction, and the availability of high-quality datasets. Hybrid models and integration into clinical decision support systems are gaining traction, while wearable devices offer real-time health monitoring capabilities. Despite the promising advancements, challenges such as interpretability and data diversity remain. Continued research into explainable AI and the integration of IoT and cloud technologies will likely shape the future of ML in cardiovascular care.

3. SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

Using machine learning, the characteristics are analysed and utilised to predict who is most likely to develop heart disease. Machine learning techniques can evaluate enormous volumes of data and identify patterns that people would not see. Processing the constantly increasing amounts of data is frequently done more accurately and efficiently. It also allows for instantaneous adjustment without requiring human intervention. The technique of providing the system with labelled data and output patterns to accomplish a task is known as supervised machine learning. During training, the algorithm searches for data patterns that match the desired result. After training, the supervised learning model can predict the correct label for newly supplied input data. This study compares the classification accuracy of various supervised machine learning algorithms in an effort to identify an effective tactic.

Disadvantages of Existing System

- There will be instances when they must wait for fresh data to be created since it takes additional data sets to train.
- It requires a lot of time and money to accomplish its goals accurately and pertinently.
- It must to be capable of correctly interpreting the outcomes.
- High sensitivity to errors.

3.2 PROPOSED SYSTEM

This study focused on comparing the outcomes of a few categorisation algorithms. The dataset's training and testing portions were divided 70/30. Naive-Bayes, Decision Tree, Logistic Regression, Random Forest, SVM, and KNN classification models were used to predict CVD. Labelling or prediction mistakes can be identified using the confusion matrix. The actual and predicted values are matched using four components: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The seeds for Type-I and Type-II errors are False Positive and False Negative values. The confusion matrix may be used to calculate

Precision, Recall, F1-score, and Accuracy very rapidly.

Advantages of Proposed System

- The performance of Naive Bayes is good for higher dimensional data.
- Decision Tree can tolerate missing values and does not need data normalisation.
- Logistic regression is efficient and does not need input characteristics to be scaled.
- On reduced data and unbalanced datasets, Random Forest performs well.
- SVM uses very little memory.
- KNN is a model that is always changing and does not make any assumptions about the data.

3.5 HARDWARE REQUIREMENTS

The physical computer resources, sometimes known as hardware, are the most typical set of specifications given out by any operating system or software programme. The following sections go into detail about the different hardware requirements.

- System : CORE i3 Processor.
- Hard Disk : 40 GB.
- RAM : 4 GB.

3.6 SOFTWARE REQUIREMENTS

Software requirements are concerned with specifying the software resources and prerequisites that must be installed on a computer to provide the best possible performance of a programme. These prerequisites must be installed individually before the programme can be installed since they are often not included in the software installation package.

- Operating system : Windows 7 Ultimate(min)
- Coding Language : Python
- Front-End : Python, Django
- Designing : HTML, CSS, JavaScript.
- Data Base : MySQL
- Dataset : Kaggle

4. SYSTEM DESIGN

4.1 SYSTEM ARCHITECTURE

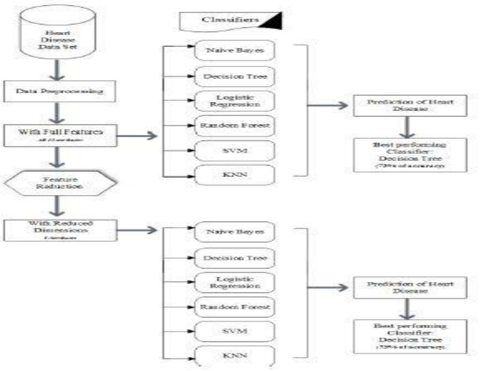


Fig: 4.1 System Architecture

4.2 MODULES

The step of implementation is when the theoretical design is translated into a programmatically-based approach. The application will be divided into a number of components at this point and then programmed for deployment. The following modules make up the bulk of the application. They are listed below.

- Run the decision tree algorithm,
- Generate the train and test data,
- Upload the cardiac dataset, and
- Run the svm method.
- Run the knn algorithm,
- Compare the graph,
- Then run the logistic regression method.

MODULES DESCRIPTION

UPLOAD CARDIAC DATASET MODULE

This module provides information about a patient's id, age, gender, height, weight, blood pressure, cholesterol levels, genetic mutations, smoking, alcohol, etc.,

GENERATE TRAIN AND TEST

This module provides information on the total number of records that were located in the dataset. 80% of the data are utilised to train the machine learning algorithms, whereas 20% of the records are used in the training process.

RUN SVM ALGORITHM

SVM is only 50% accurate, thus proceeding with the other modules as-is.

RUN DECISION TREE ALGORITHM

In the cardiac dataset, our decision tree technique outperforms naive bayes with 90% accuracy.

RUN LOGISTIC REGRESSION

For the cardiac dataset, this Logistic Regression provides 50% accuracy.

RUN KNN ALGORITHM

TFor a cardiac data collection, his KNN technique provides 62% accuracy.

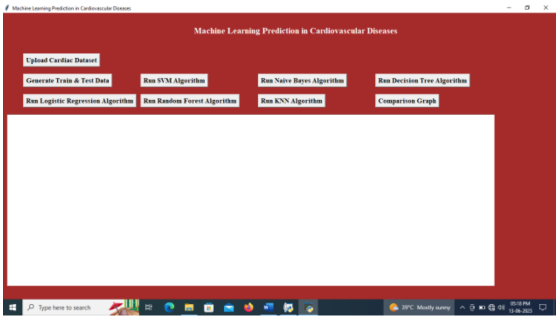
COMPARISION GRAPH

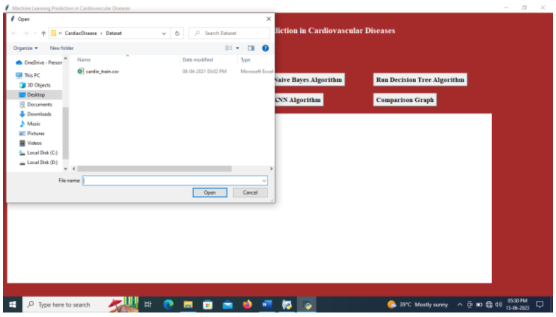
We used a cardiac dataset to train all the algorithms, and the Decision Tree approach had the greatest accuracy. In the comparison graph, the Y-axis represents accuracy, precision, recall, and F-score, and the X-axis the name of the method.

5.4 OUTPUT SCREENS

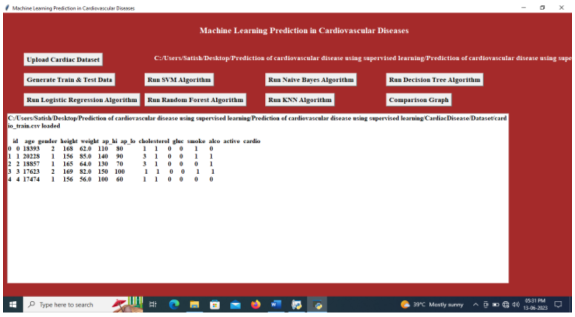
To reach the screen below, double-click the 'run.bat' file to launch the project.

Using the 'Upload Cardiac Dataset' button on the previous screen, upload the dataset.


Machine Learning Prediction in Cardiovascular Diseases
Machine Learning Prediction in Cardiovascular Diseases
Upload Cardiac Dataset
Generate Train & Test Data
Run SVM Algorithm
Run Naive Bayes Algorithm
Run Decision Tree Algorithm
Run Logistic Regression Algorithm
Run Random Forest Algorithm
Run KNN Algorithm
Comparison Graph
Type here to search



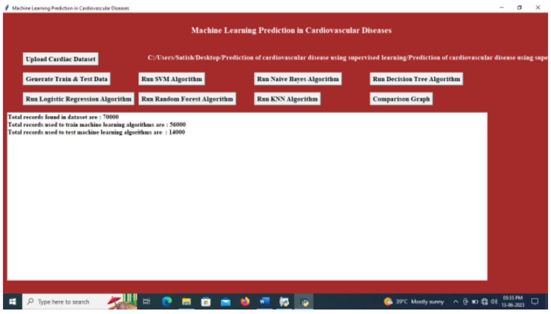
choosing and adding the "cardiac_train.csv" file to the above-mentioned screen, and then clicking the "Open" button to load the dataset and bring up the page below.


Machine Learning Prediction in Cardiovascular Diseases
Machine Learning Prediction in Cardiovascular Diseases
Upload Cardiac Dataset
Generate Train & Test Data
Run SVM Algorithm
Run Naive Bayes Algorithm
Run Decision Tree Algorithm
Run Logistic Regression Algorithm
Run Random Forest Algorithm
Run KNN Algorithm
Comparison Graph
Type here to search

C:/Users/Satish/Desktop/Prediction of cardiovascular disease using supervised learning/Prediction of cardiovascular disease using supe

```
C:/Users/Satish/Desktop/Prediction of cardiovascular disease using supervised learning/Prediction of cardiovascular disease using supervised learning/CardiacDisease/Dataset/card
io_train.csv loaded

   id   age  gender  height  weight  ap_hi  ap_lo  cholesterol  gluc  smoke  alco  active  cardio
0  0  18393      2     168    62.0    110     80          1      1     0      0     1      0
1  1  20228      1     156    85.0    140     90          3      1     0      0     1      1
2  2  18857      1     165    64.0    130     70          3      1     0      0     0      1
3  3  17623      2     169    82.0    150    100          1      1     0      0     1      1
4  4  17474      1     156    56.0    100     60          1      1     0      0     0      0
```

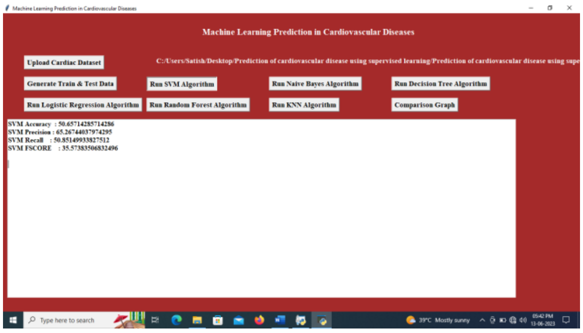
The dataset is imported in the page above, and we can see some of its entries. Next, click the "Generate Train & Test Data" button to split the dataset into two parts: the train portion, which the programme used to train machine learning algorithms, and the test part, which it used to determine how accurate those algorithms were.


Machine Learning Prediction in Cardiovascular Diseases
Machine Learning Prediction in Cardiovascular Diseases
Upload Cardiac Dataset
Generate Train & Test Data
Run SVM Algorithm
Run Naive Bayes Algorithm
Run Decision Tree Algorithm
Run Logistic Regression Algorithm
Run Random Forest Algorithm
Run KNN Algorithm
Comparison Graph
Type here to search

C:/Users/Satish/Desktop/Prediction of cardiovascular disease using supervised learning/Prediction of cardiovascular disease using supe

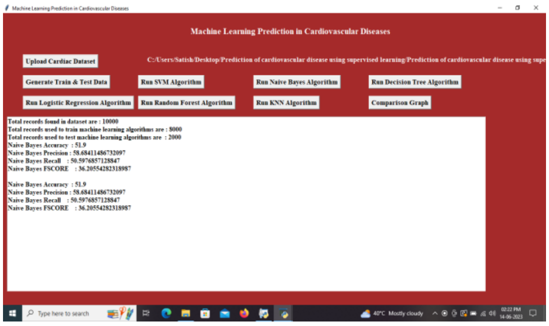
```
Total records found in dataset are : 70000
Total records used to train machine learning algorithms are : 56000
Total records used to test machine learning algorithms are  : 14000
```

The programme uses 8000 records for training and 2000 records for testing from the dataset of 10,000 records shown in the above screen. The features graph is shown below. Any characteristic with a correlation value near to 1 will be considered relevant on the significance graph.


Machine Learning Prediction in Cardiovascular Diseases
Machine Learning Prediction in Cardiovascular Diseases
Upload Cardiac Dataset
C:/Users/Satish/Desktop/Prediction of cardiovascular disease using supervised learning/Prediction of cardiovascular disease using supe
Generate Train & Test Data
Run SVM Algorithm
Run Naive Bayes Algorithm
Run Decision Tree Algorithm
Run Logistic Regression Algorithm
Run Random Forest Algorithm
Run KNN Algorithm
Comparison Graph
Type here to search
39°C Mostly sunny
05:42 PM
13-06-2023

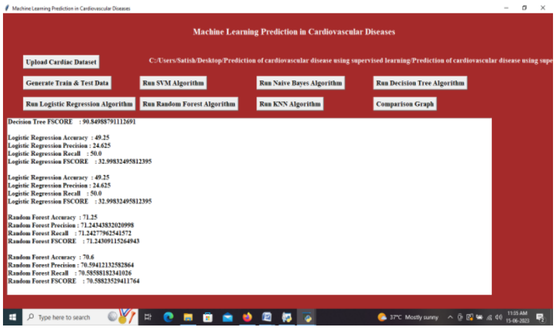
```
SVM Accuracy  : 50.65714285714286
SVM Precision : 65.26744037974295
SVM Recall    : 50.85149933827512
SVM FSCORE    : 35.57383506832496
```

SVM had a 50% accuracy rate on the screen above; to see its accuracy, click the buttons for Nave Bayes and Decision Tree.


Machine Learning Prediction in Cardiovascular Diseases
Machine Learning Prediction in Cardiovascular Diseases
Upload Cardiac Dataset
C:/Users/Satish/Desktop/Prediction of cardiovascular disease using supervised learning/Prediction of cardiovascular disease using supe
Generate Train & Test Data
Run SVM Algorithm
Run Naive Bayes Algorithm
Run Decision Tree Algorithm
Run Logistic Regression Algorithm
Run Random Forest Algorithm
Run KNN Algorithm
Comparison Graph
Type here to search
40°C Mostly cloudy
02:22 PM
14-06-2023

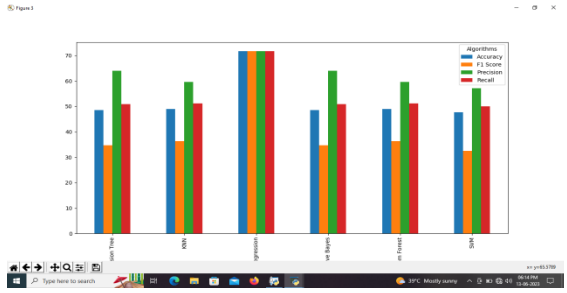
```
Total records found in dataset are : 10000
Total records used to train machine learning algorithms are : 8000
Total records used to test machine learning algorithms are  : 2000
Naive Bayes Accuracy  : 51.9
Naive Bayes Precision : 58.68411486732097
Naive Bayes Recall    : 50.5976857128847
Naive Bayes FSCORE    : 36.20554282318987

Naive Bayes Accuracy  : 51.9
Naive Bayes Precision : 58.68411486732097
Naive Bayes Recall    : 50.5976857128847
Naive Bayes FSCORE    : 36.20554282318987
```

Click the buttons for Logistic Regression, Random Forest, and KNN Algorithms to see their prediction accuracy on the screen above. With Nave Bayes, we achieved 51% accuracy, while with Decision Tree, we achieved 90% accuracy.


Machine Learning Prediction in Cardiovascular Diseases
Machine Learning Prediction in Cardiovascular Diseases
Upload Cardiac Dataset
C:/Users/Satish/Desktop/Prediction of cardiovascular disease using supervised learning/Prediction of cardiovascular disease using supe
Generate Train & Test Data
Run SVM Algorithm
Run Naive Bayes Algorithm
Run Decision Tree Algorithm
Run Logistic Regression Algorithm
Run Random Forest Algorithm
Run KNN Algorithm
Comparison Graph
Type here to search
37°C Mostly sunny
11:35 AM
15-06-2023

```
Decision Tree FSCORE    : 90.84988791112691

Logistic Regression Accuracy  : 49.25
Logistic Regression Precision : 24.625
Logistic Regression Recall    : 50.0
Logistic Regression FSCORE    : 32.99832495812395

Logistic Regression Accuracy  : 49.25
Logistic Regression Precision : 24.625
Logistic Regression Recall    : 50.0
Logistic Regression FSCORE    : 32.99832495812395

Random Forest Accuracy  : 71.25
Random Forest Precision : 71.24343832020998
Random Forest Recall    : 71.24277962541572
Random Forest FSCORE    : 71.24309115264943

Random Forest Accuracy  : 70.6
Random Forest Precision : 70.59412132582864
Random Forest Recall    : 70.58588182341026
Random Forest FSCORE    : 70.58823529411764
```

The accuracy of the logistic regression was 50%, random forest was 71%, and KNN was 62% in the images above. The decision tree method, which we trained on the cardiac dataset on the previous screen to attain the maximum accuracy possible, is shown below in the comparison graph after clicking the "Comparison Graph" button.



The algorithm name is shown on the x-axis of the above graph, while the accuracy, precision, recall, and FSCORE are shown on the y-axis. We may infer from the graph above that decision trees provided improved prediction accuracy.

7. CONCLUSION

The application of machine learning (ML) and deep learning (DL) models for predicting cardiovascular diseases (CVD) represents a significant advancement in healthcare, offering the potential for early detection, personalized treatment plans, and improved clinical outcomes. This literature survey reveals the growing body of research in this domain, showcasing various techniques and approaches that have contributed to the evolving landscape of cardiovascular disease prediction.

The use of traditional machine learning algorithms, such as decision trees, support vector machines, and random forests, alongside deep learning methods like neural networks, has demonstrated great promise in improving the accuracy and efficiency of CVD prediction models. Additionally, hybrid models and ensemble learning approaches have further enhanced prediction capabilities by combining multiple algorithms to achieve superior performance. These advancements have led to improved early detection, enabling timely interventions that can significantly reduce mortality and morbidity rates.

A critical factor influencing the performance of machine learning models is the availability of high-quality, diverse datasets. Publicly available datasets, such as the Cleveland and Framingham Heart Disease datasets, along with data from wearable devices, have played a crucial role in training and validating ML models. Real-time data from wearable technology offers an additional advantage, allowing for continuous monitoring and predictive capabilities that are crucial for at-risk individuals.

Despite the success of these models, challenges remain in the widespread adoption of machine learning in clinical settings. Issues related to model interpretability and transparency persist, particularly with deep learning models, which are often seen as "black boxes." Ensuring that machine learning models are not only accurate but also explainable is crucial for gaining trust among healthcare providers. Efforts are underway to develop explainable AI techniques, allowing clinicians to better understand the rationale behind model predictions and use them in conjunction with their clinical expertise.

Incorporating ML models into clinical decision support systems (CDSS) is a promising avenue for improving patient care. These systems can assist healthcare providers by offering timely insights and personalized recommendations, thus supporting more informed decision-making. The integration of ML with IoT devices, wearable health monitors, and cloud-based platforms presents an exciting future for predictive healthcare, enabling real-time monitoring and proactive interventions.

In conclusion, machine learning and deep learning have the potential to revolutionize cardiovascular disease prediction by enabling early detection, reducing healthcare costs, and improving patient outcomes. Ongoing research and advancements in AI, explainability, and integration with real-time monitoring systems are essential for overcoming current challenges and unlocking the full potential of these technologies in clinical practice. As these models evolve, the future of healthcare will likely see greater personalization, efficiency, and accessibility in the management of cardiovascular diseases.

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