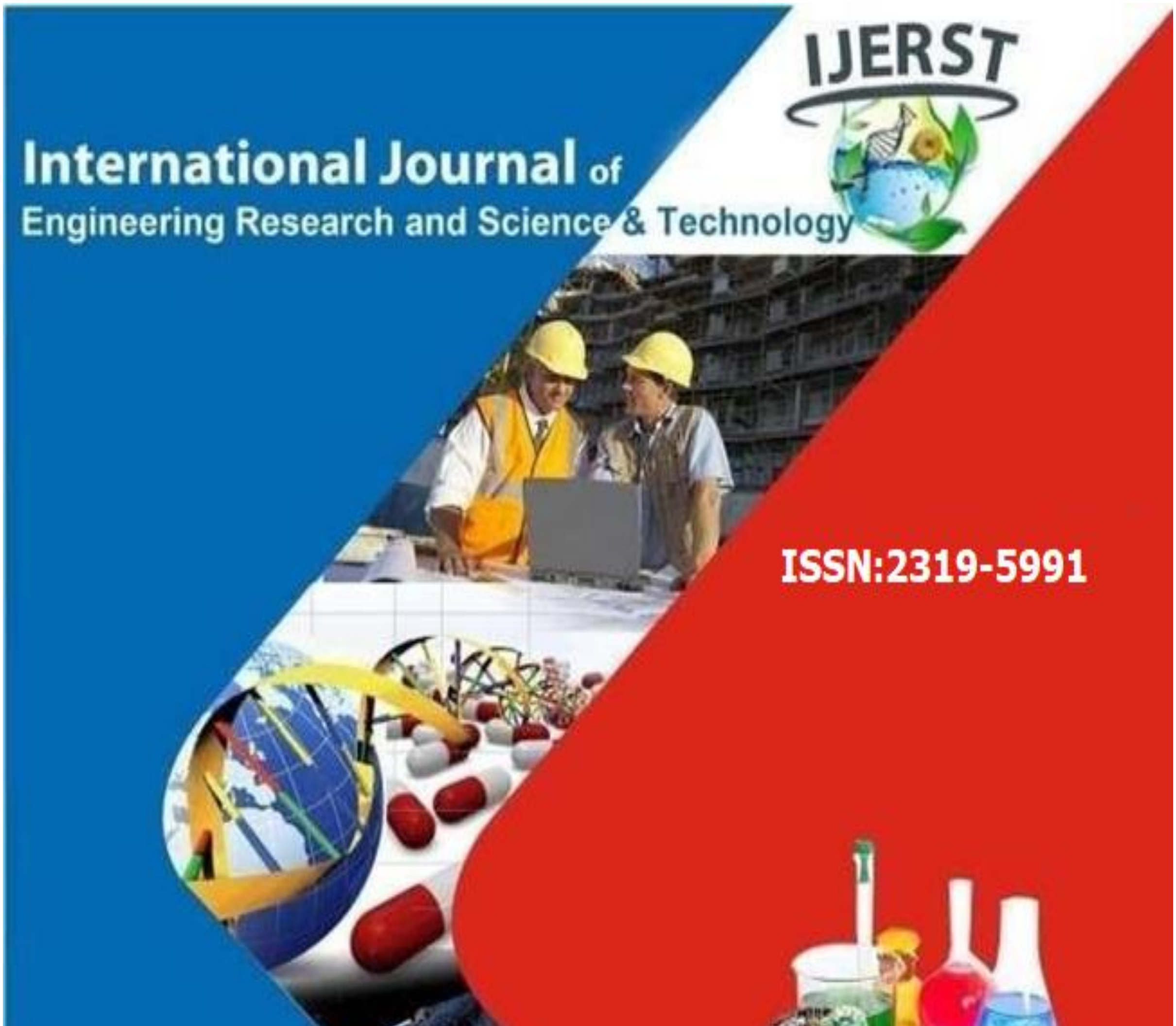

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EFFECTIVE FEATURE ENGINEERING TECHNIQUES FOR HEART DISEASE PREDICTION USING ML

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ABSTRACT

There have been tremendous developments in medical services (MS) throughout the years, with an emphasis on bettering response times, patient care, and overall results. A revolutionary strategy to improve emergency medical treatment is the incorporation of human interaction technologies and Machine Learning (ML) into ambulances. Historically, medical staff have had to rely on rudimentary tools and clinical judgement to assess patients' status during crises, and then transmit their findings to hospitals verbally or in writing. Although this method has been successful in the past, it has several drawbacks now, including transmission delays, human mistake in reading vital signs, and an absence of established evaluation criteria. We propose an integrated system that uses explainable human-computer interaction to connect hospital-based decision-making with on-site ambulance treatment in order to improve emergency healthcare. Two applications, one for the hospital server and one for the ambulance, were developed using Python and Tkinter, respectively, to form the proposed system. Through a secure socket connection, the ambulance app transfers patient data from stored datasets to the hospital server. On the back end, the data is prepared for machine learning algorithms like RFC and K-Nearest Neighbors (KNN) to provide real-time predictions about patients' illnesses. The results are solid and easy to understand since RFC outperforms KNN with near-perfect accuracy, while KNN is simple and easy to understand. Transforming traditional manual systems into an efficient, dependable, and transparent AI-driven emergency response mechanism, this intelligent framework automates data processing and prediction and provides visual feedback through explainable metrics and confusion matrices. As a result, healthcare is being redefined.

Keywords: Health, Prediction, Machine Learning, K-Nearest Neighbors.

1. INTRODUCTION

1.1 Overview

The 2020 article by Akca et al. [1] focusses on the "Intelligent Ambulance Management System in Smart Cities." method for controlling the use of ambulances and other emergency services. This study effectively addresses all aspects of the Intelligent Ambulance Concept, including Human Interface Technology, throughout its design and development phases. Part A-Research article 179 Euros. "Chemistry Bulletin" 2023, 12(Special Issue 9), 779–788 design a smart ambulance management system that integrates cloud computing, mobile computing, and standalone applications; however, it does not specify how the system can function in real-time. Research on a "health machine to handle COVID-19 related health emergencies" method for managing ambulances and emergency services was presented by Ganesh et al. [2] in 2021. While this study does a good job of outlining what is needed to build a smart ambulance management framework, it

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doesn't go into detail on how the system might operate in real time by integrating cloud, standalone, and mobile apps. Prof. Vijay Gaikwad, Ashwin Channawar, Amruta Gate, Pankaj Ganjare, and Gargi Beri published "Intelligent Ambulance with Traffic Control" [3]. Two systems, one for traffic management and one for health monitoring, are part of this investigation. Some of the most important health indicators tracked by health monitoring systems are electrocardiogram (ECG), heart rate (HR), and temperature (temperature). Using serial communication, these parameters are sent to a PC in the ambulance, which then transmits these data to the server in the hospital. Along with Mohammed Samran Hashim, Ms. Aisha Meethian, Althaf B. K., Athinan Saeed, and LiginAbraham July 2022: "IoT Based Traffic Control System with Patient Health Monitoring For Ambulance" [4] was proposed as a research. Using GPS sensor networks, the suggested method finds the best path by cutting down on travel time to the hospital. Devices such as heart rate monitors, respiration sensors, and temperature monitors track the patient's vital signs. The patient's data is sent to the hospital's database over the Internet of Things. As mentioned in [5], To develop a sophisticated smart health system that can detect changes in the patient's vitals and transmit that information to the website of the affiliated hospital. The end objective is to build a system that is responsive, smart, and frictionless so that patient outcomes are greatly improved at key times. Realising that emergency medical services may be significantly improved by using human interface technology, the demand for an intelligent ambulance emerges. The integration of intelligent technology may greatly assist healthcare personnel in critical instances when making rapid and correct decisions is of the utmost importance.

1.2 Problem statement

Medical services (MS) have come a long way, with many innovations aimed at improving response times, patient care, and overall results. A significant step forward in this direction is the incorporation of ML and HIT into ambulances, which will cause a sea change in the way emergency medical treatment is provided.

Looking back into the past, we see that ambulances were once only cars with basic life support equipment, driven by paramedics and EMTs. Their primary responsibility was to provide first aid while transporting patients to a hospital. Nevertheless, there was a noticeable increase in the amount of time needed for communicating with hospitals and manually processing patient information. Decision support tools and real-time data analysis were also missing from the traditional system; these are areas where ML shows great promise for use in crisis situations.

Improving ambulance-based emergency medical responses and treatment via the smooth integration of ML and human interaction technologies is the current hotspot of concern. This optimisation requires tackling complex issues, such as the need for quick and accurate diagnosis, improving communication between healthcare facilities and emergency responders, and making sure medical information is provided in real-time to help with decision-making.

The ultimate aim is to develop a faultless, smart, and adaptable system that significantly enhances patient results at crucial points. An intelligent ambulance is being considered because it is believed that emergency medical services might be greatly improved by using ML and human interface technology.

The method's advantages are not limited to improving communication; they

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also extend to making data exchange easier and improving coordination between hospitals, ambulances, and other parts of the healthcare system. The problem statement essentially highlights the need to transform and improve emergency medical care by integrating ML and human interaction technologies in ambulances in a novel way. This will help address current challenges in the field.

1.3 Research Motivation

The ever-changing nature of medical services (MS) is driving study and implementation of ML and human interaction technologies within this domain, with the goals of improving response times, raising patient care standards, and optimising overall results. This study's context includes the ever-changing nature of multiple sclerosis (MS), the ubiquitous impact of machine learning (ML) on healthcare, and the encouraging possibility of synergy between technical advances and human interactions, particularly in high-stakes emergency scenarios.

From a historical perspective, ambulances have often served as mobile emergency medical treatment units staffed by paramedics and other medical professionals. While transporting patients to medical facilities, their main responsibility is to provide first treatment. Problems with the old MS system included handling patient data and communicating with hospitals manually, both of which were time-consuming and laborious tasks. In critical emergency scenarios in particular, the conventional system lacked the ability to analyse data in real-time and provide decision-support tools that artificial intelligence (AI) might provide.

The primary objective of this study is to find ways to improve ambulance response times and patient outcomes by combining machine learning with human interface technology. Emergency responders and healthcare institutions must be able to communicate effectively in order to diagnose patients quickly and accurately. Additionally, healthcare providers must have access to up-to-the-minute medical information in order to make better decisions.

The ultimate objective is to set up a system that is sensitive, smart, and frictionless so that patient outcomes are greatly enhanced at crucial periods. It is widely acknowledged that ambulances must include M and human interface technologies in order to greatly improve the efficacy and efficiency of emergency medical services. Healthcare providers greatly benefit from the integration of intelligent technologies in crucial scenarios that need quick and precise decision-making.

Better decision-making is only one of the many advantages of this novel technique. Improved coordination, data sharing, and communication between hospitals, ambulances, and other parts of the healthcare system are also part of it. The continual change of emergency medical care is the driving force behind the project, which aims to enhance EMS capabilities via the use of AI and human interface technology.

1.4 Significance

The AI-EMRDS system is a game-changer in emergency healthcare. It optimises patient outcomes, ambulance efficiency, and hospital coordination via the integration of artificial intelligence, human-computer interaction, and real-time decision-making. By using a hybrid ensemble learning model (Random Forest, Decision Tree, KNN), AI-EMRDS is able to provide immediate, very accurate forecasts of patient state, minimising diagnostic mistakes and

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enhancing emergency response, in contrast to conventional MS systems that depend on human evaluation and verbal communication. It avoids unnecessary delays for patients by optimising ambulance dispatch, suggesting the quickest and least crowded routes, and predicting the availability of hospital beds using reinforcement learning algorithms. Voice-guided assistance, augmented reality overlays, and automated drug verification are all ways in which ML-enhanced human-computer interface (HCI) helps paramedics. This technology reduces their cognitive load and helps them avoid prescription mistakes. Also, organised patient reports are sent before they come, thanks to real-time hospital coordination, so doctors may start treating patients right away. By using ML for predictive analytics, optimising routes, and providing decision assistance, AI-EMRDS revolutionises emergency medical care by cutting down inefficiencies, improving patient safety, and raising survival rates.

1.5Applications

There is great potential for a paradigm shift in medical services (MS) and a significant improvement in patient care with the incorporation of ML and human interaction technologies into ambulances. Paramedics and emergency medical professionals have long been standard fare in ambulances, along with basic life support equipment.

However, there have been delays due to a lack of decision-support tools, real-time data analysis capabilities, and an easier way to communicate with hospitals and handle patient information manually. Improving ambulance-based emergency medical responses and treatment via the smooth integration of machine learning and human interface technologies is the focus of this topic. The goals of this integration include better decision-making based on real-time medical information, faster and more accurate diagnoses, and better communication between healthcare institutions and emergency services.

The end objective is to develop a smart ambulance system that may improve patient outcomes in life-or-death situations by responding to crises quickly and accurately. In order to greatly improve the efficacy and efficiency of emergency medical services, it is critical to acknowledge the potential of using machine learning and human interface technology. Healthcare workers may greatly benefit from the use of intelligent systems in life-or-death scenarios that need prompt and precise decision-making.

This method has broader implications than just emergency medical treatment. Ambulances, hospitals, and other healthcare organisations may work together more effectively because to the intelligent ambulance system's ability to increase communication, simplify data exchange, and boost coordination. This game-changing strategy is in line with recent developments in multiple sclerosis, the expanding role of ML in healthcare, and the rising awareness of the significance of human-technology partnerships in times of crisis. The incorporation of ML into ambulances signifies a progressive approach to launching a new phase of intelligent and responsive emergency medical treatment.

2. LITERATURE REVIEW

A gadget that can detect the wearer's core temperature and heart rate. Once sensing is complete, the microcontroller will get the corresponding data from the sensors. The data is then sent from the microcontroller to the raspberry-pi, which establishes a connection to the internet or an IoT cloud. The driver will utilize Google Maps and its accident-avoidance

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algorithms to get to their destination on time and keep people safe. A system consisting of a sensor node to monitor patients' vitals as they engage in various activities was suggested by Timothy Malche et.al. [6] in 2022. The suggested sensor node gathers patient data using the nRF5340 Development Kit's (DK) associated sensors. A temperature sensor, pulse oximeter, microphone, and accelerometer are all part of the networked sensors. Various bodily activities, including as walking, sleeping, exercising, and running, may be tracked by the accelerometer. The doctor may prescribe medication or provide advice by analyzing the vitals while the patient is engaged in various activities. Using the electrocardiogram (ECG) and thoracic impedance (TI) data, a novel approach to pulse identification during out-of-hospital cardiac arrest is described in research [7]. A support vector machine (SVM) classifier based on features extracted from the ECG and the circulatory-related component of the TI, the impedance circulation component (ICC), is used to distinguish between pulseless electrical activity (PEA) and the PR interval in this method [1]. A proposal for an EDCNN, or enhanced deep convolutional neural network, for the early diagnosis and detection of cardiac illness was made in [8]. This study aims to increase diagnostic accuracy by developing EDCNN-based prediction models for the detection of cardiac abnormalities in patients. Mathematical calculations have been made to forecast the likelihood of heart disease based on patient data. Creation of an Ambulance System via the Application of Human-Computer Interaction A research work on distributive functions is Section A of 180 Eur. Chem. Bull. 2023,12(Special Issue 9), 177–188. Exercising, resting, and working heart rates have all been studied [2]. The suggested approach in [9] makes use of ANN for classification, PCA for dimensionality reduction, and the Decision Tree algorithm for feature selection. An analytical method known as principal component analysis (PCA) may be used to transform a collection of data points representing potentially correlated variables into a fresh collection of data points representing linearly uncorrelated variables [3]. In this study, we gathered data, cleaned it up, extracted features, reduced dimensions, classified it, and then analyzed the results.

3. PROPOSED SYSTEMS

3.1 Overview

In light of these difficulties. The core of the machine learning-driven method is to train these models using surface-specific datasets that have been painstakingly labelled. The training method allows the models to learn on their own how to extract useful characteristics from sensor data, which in turn improves the robot's surface detection and classification capabilities.

This Python script uses Tkinter to build a GUI application for a surface identification project that uses data collected by robots. The application's processes are described in full here:

First Stage: Gathering and Preprocessing Data

The patient's vitals (heart rate, blood pressure, temperature, etc.), medical history, and other pertinent health characteristics are some of the data sources that must be gathered for this purpose. In order to ensure that the model performs as expected, the dataset has to be cleaned and preprocessed to eliminate any anomalies, missing data, or inconsistent entries.

The second step is to split the data and build the features.

To assess the efficacy of the ML models, the dataset is partitioned into training and testing subsets. A key part of feature engineering is choosing the right input features and then converting them into a format that training models can use. The accuracy of the models' predictions is enhanced by this procedure.

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Thirdly, train the models using RFC, DT, and K-Nearest Neighbors.

The preprocessed data is used to train three machine learning models. During training, models are able to absorb patterns in the dataset, which improves their predictive abilities.

Fourth Step: Coordinating Hospital Care and Predicting Patients' Conditions in Real Time

Using data collected from ambulances, the trained models can provide real-time predictions about a patient's health state. The hospital server receives the forecasted circumstances so that the right medical care may be provided.

Fifth Step: Assessing Results and Contrasting with Conventional Methods

Accuracy, precision, recall, and F1 score are some of the performance measures used to assess the models after they have been trained and predicted. The outcomes are contrasted with conventional methods used in emergency medical systems for making decisions.

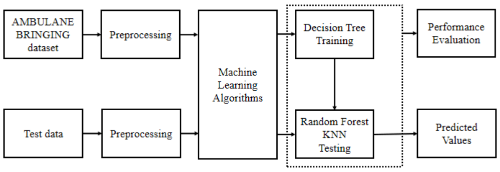

Figure1: Architecture diagram of Intelligent Ambulance

3.2 Data Preprocessing

In order to train models using clean, trustworthy, and machine learning-ready data, data preparation is essential. Included in the preprocessing procedures are:

The First Step: Choosing Columns and Cleaning the Data

At this stage, any columns that are not relevant or needed are eliminated from the dataset. One way to deal with rows that have missing data is to remove them, while another is to impute missing values using the median, mode, or mean. The reliability of the dataset for training models is assured by data cleaning.

The second step is to normalize and scale the features.

For example, the units of measurement for heart rate and age may be in beats per minute and years, respectively, in the dataset. Data is scaled using methods like Standardization (Z-score normalization) or Min-Max scaling to make sure that no characteristic is more prominent than the others. The result is a more consistent and effective procedure for training the model.

Third Step: Rearranging Data

Before dividing the dataset into training and test sets, it is shuffled to ensure that the model does not learn the data's order. In this way, we check that the data order is not causing the model to overfit.

Step 4: Output Text for Preprocessing Verification

The system updates the user interface with the current preprocessing progress in real-time to provide feedback. Users, such as engineers or medical specialists, may track how far along the data preparation and cleaning process is.

3.3 Exploratory Data Analysis (EDA)

Using EDA, one may better grasp the dataset's fundamental trends, patterns, and linkages. It is also useful for finding trends or outliers that might affect the model's accuracy. Important phases of EDA comprise:

First Step: Analyzing the Distribution of Patient Conditions

Examining the frequency of normal and atypical patient states is part of this process. This is useful for finding dataset imbalances that can need oversampling or under sampling strategies.

Section 2: Patterns in Vital Signs

The distribution of vital signs, including heart rate and blood pressure, across individuals with varied illnesses is examined in this stage.

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Insight into the differences between typical and exceptional cases is aided by this.

Third Step: Analyzing Disease Prevalence

Examining the dataset's illness distribution, including the prevalence of heart disease, hypertension, and other prevalent ailments seen in emergency scenarios.

Investigation of Feature Correlations (Step 4)

To find out whether any one factor (such age or blood pressure) is strongly associated with the patient's condition, we look at the correlations between several features. When training a model, this helps in selecting features.

Fifth Step: Distributions Based on Statistics

In order to comprehend the behavior of each characteristic across many classes, distributions such as histograms or box plots are shown. To find patterns and outliers, it is a must-do.

Step 6: Visualizing Features using Kernel Density Estimation (KDE)

To see how the dataset's characteristics are distributed probabilistically, KDE is utilised. The distribution of continuous variables, such as age, heart rate, etc., may be better understood using this.

3.3.2 Splitting the Dataset

Machine learning models are trained and tested on subsets of cleaned and preprocessed data:

First Step: Choosing Features for Training the Model

A feature's applicability to the dependent variable (patient condition) dictates its selection. This entails getting rid of elements that aren't useful for making predictions, such as those that are redundant or useless.

Second Step: Predicting Patient Condition Using Target Variables

The patient's status, often expressed as a binary value between normal (0) and abnormal (1), serves as the goal variable. When training and evaluating the model, this variable is used.

Third Step: Additional Segmentation for Multi-Class Forecasting

To make a multi-class classification job out of a dataset that has numerous conditions (like various illnesses), further splitting could be necessary. Part of this process is making many buckets out of the target variable.

Fourth Step: Showing Dataset Shapes for Validation

To double-check that the data has been appropriately divided, the training and testing datasets' shapes are shown after splitting. Typically, 80% of the data is used for training and 20% for testing.

4. Construction of ML Models

3.4.1 Current Methodology: Knowledge-Based Neural Network (KNN) Classifier Definition and Data

When it comes to supervised machine learning algorithms, one that is useful for both classification and regression is K-Nearest Neighbors (KNN). It sorts information into categories according to how similar each data item is to its neighbors in the feature space. KNN is based on the idea that comparable items tend to be located near one other in a dataset. A lazy learning algorithm, it uses the full training dataset to generate predictions rather than developing an explicit model. The simplicity and efficacy of KNN make it a popular choice for medical diagnosis, recommendation systems, and pattern recognition.

Using distance metrics like Minkowski, Manhattan, or Euclidean, the KNN algorithm finds the distance between new and old data points. The number of neighbors, or K, is a parameter that specifies how many points are considered nearest to the classifier. In classification, the k-nearest neighboring classes are employed as a majority voting process to allocate new data points to the most frequent class.

An Overview of KNN

1. After loading the dataset, split it in half to create a training set and a test set.
2. Set K (the number of neighbors) to a value.
3. Number three: find the distance between each training sample and a new test instance.

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4. Make use of distance measures such as the Minkowski, Manhattan, or Euclidean distances.
5. Fifth, using the shortest distances, determine the K closest neighbors.
6. Determine how many instances of each category there are in the K adjacent nodes.
7. Using majority vote, assign the most common class to the new instance.
8. In the case of regression, get the average of the values that are closest to each other.
9. For every test sample, repeat the procedure.
10. Use the F1-score, recall, accuracy, and precision to assess the performance.

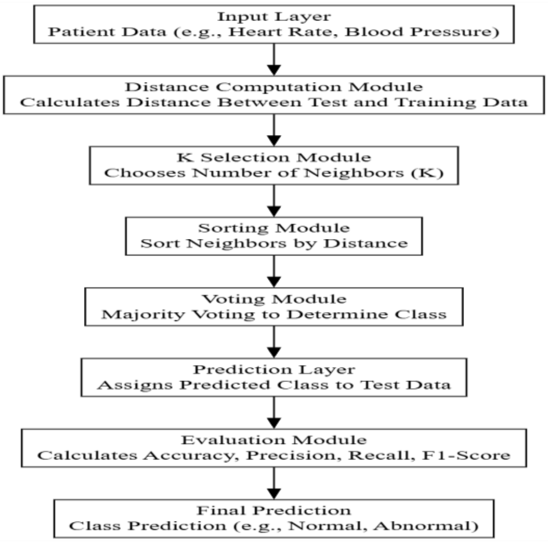

Figure 2: working algorithm of KNN

Problems with KNN

There are a number of issues with the K-Nearest Neighbours (KNN) technique that could affect how well it works, particularly with big datasets. Due to the need to calculate distances between the test data and the training samples, it is computationally costly. Furthermore, KNN is very tuned-insensitive since its performance is so tied to the selection of the K value. False classifications may also result from the algorithm being susceptible to irrelevant characteristics and noisy data. When it comes to large-scale applications, KNN could be a bit of a memory hog since it keeps all the training data.

3.5.2 Current Method: Decision Tree Classifier (DTC)

Explanation and Details

For supervised machine learning jobs like classification and regression, there's the Decision Tree Classifier (DTC). It accomplishes its goal by dividing the data into smaller groups and then using those sets to train a model to predict the target variable using feature values. Data is most effectively partitioned into similar groups according to feature values. Because it can handle both continuous and categorical data, and because it is easy to understand, DTC is used often. It finds widespread usage in fields like as risk analysis, consumer segmentation, and medical diagnostics.

Each node in a choice Tree stands for a feature-based choice, and each branch for the decision's conclusion; the structure is reminiscent of a tree. A leaf node stores the projected output, and the tree keeps splitting the data until it gets there. Depending on the job at hand, the splitting criterion might be based on measurements like entropy, variance reduction, or Gini impurity.

Architecture of an Algorithm

1. Pick out portions of the training data at random.
2. Make use of distinct subsets to generate several Decision Trees.
3. Select the optimal feature split at each node based on entropy or Gini impurity.
4. Continue to grow the trees until they reach a certain depth or until you reach pure categorization.
5. Gather predictions for a test sample from all trees.
6. Find the best tree forecast by using the majority vote.
7. Give the test sample its final class label.
8. Determine the F1-score, recall, precision, and accuracy.

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9. Maximize performance by fine-tuning hyperparameters (tree count, depth, feature selection).

10. Make real-time predictions by deploying the model that has been trained.

Rationale for RFC

By averaging the results of several decision trees, Random Forest, an effective ensemble learning approach, achieves better accuracy than individual trees while being less susceptible to overfitting. Even with noisy or missing data, it manages huge datasets effectively. It can handle numerical and categorical features equally well and helps with feature selection by highlighting key characteristics. It offers good generalizability for unseen data and is resilient to skewed datasets. Furthermore, Random Forest is frequently used in sectors like as medical diagnostics for illness prediction, and its parallelizability makes it an ideal choice for processing large-scale data.

Benefits . RFC Methodology

By minimizing overfitting, the Random Forest Classifier outperforms individual decision trees in terms of accuracy. Its performance-preserving ensemble technique allows for more rapid and accurate prediction. The approach reduces the effect of superfluous characteristics on the model's accuracy and is therefore very resilient to noisy data. In addition, RFC excels in high-demand applications like real-time emergency medical response systems because it is scalable and can effectively handle big datasets.

4. RESULTS

Figure 3: Main GUI application of proposed intelligence ambulance server side.

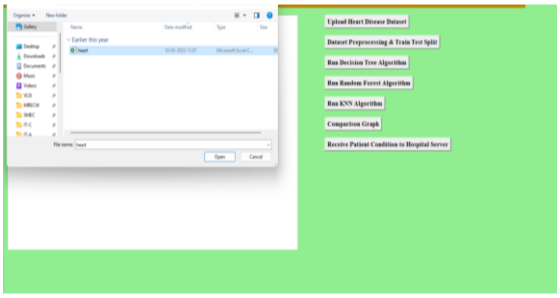

Figure 4: Selecting the dataset in the GUI application.

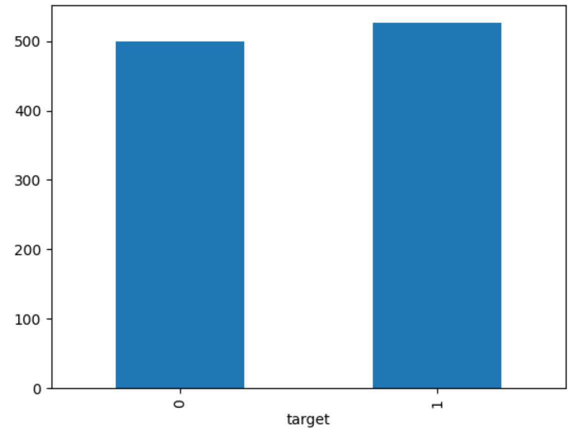

Figure 5: Displays the dataset and count plot of target columns.

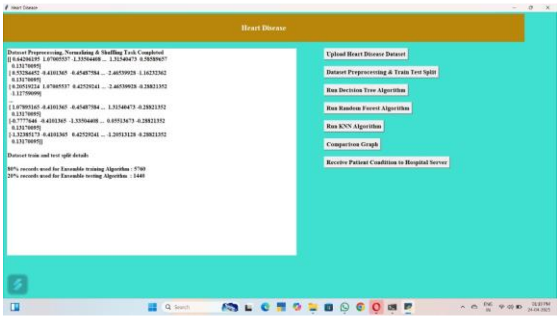

Figure 6: Presents the pre-processed data from the dataset.

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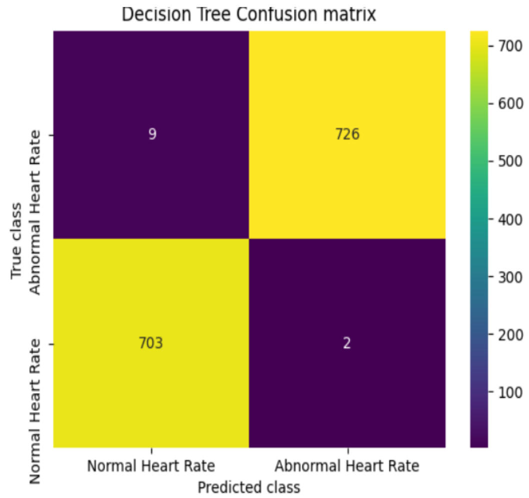

figure 7: shows the evaluation metrics

Figure 8: Main GUI application of ambulance side.

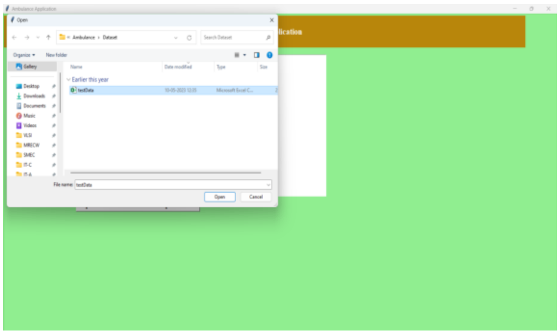

Figure 9: Selecting the test dataset and reporting to hospital server.

5. CONCLUSION

This study details the development and deployment of an AI-powered ambulance system that can monitor patients' vitals in real time and provide accurate diagnoses. Through a socket-based server-client architecture, the suggested system enables intelligent decision-making and smooth data transmission by integrating a user-friendly GUI on both the hospital and ambulance sides. K-Nearest Neighbors (KNN), Decision Tree Classifier (DTC), and Random Forest Classifier (RFC) were among the machine learning models created and tested on a cardiovascular dataset. With an impressive accuracy of 99.72%, RFC proved to be more trustworthy than KNN and DTC in all performance parameters, making it an ideal choice for crucial applications like emergency decision-making and patient triage. Reducing response time and allowing hospitals to plan in advance for incoming patients, the operational performance of emergency medical services is greatly enhanced by the combination of GUI-based interface and real-time prediction capability.

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