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IMPROVING HEALTHCARE SYSTEM EFFICIENCY USING MACHINE LEARNING TO PREDICT PATIENT STAY DURATION

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ABSTRACT

Healthcare demand is rapidly growing both in Australia and globally. In Australia, the healthcare system is a blend of public and private organizations, including hospitals, clinics, and aged care facilities. The system is relatively affordable and accessible, with around 68% of the expenditure funded by the government. In 2015-16, healthcare expenditure amounted to AUD 170.4 billion, representing 10% of the country's GDP. However, rising healthcare costs and increasing demand for services are straining the sustainability of the government-funded healthcare system. To maintain sustainability, it is essential to improve the efficiency of healthcare service delivery.

One way to achieve this is by optimizing the scheduling of care delivery processes, which can enhance system efficiency when the demand for services is accurately predicted. However, the inherent randomness in healthcare demand introduces inefficiencies, particularly in resource allocation. Addressing this challenge requires better prediction of patient resource needs. By classifying patients into groups with similar resource usage patterns, we can reduce uncertainty and improve resource management.

Traditional machine learning methods like Random Forest and k-Nearest Neighbors (KNN) have shown poor performance in classifying patients and predicting resource needs. Our approach aims to overcome these limitations, offering a more accurate classification of patients based on their resource requirements, ultimately contributing to a more efficient healthcare system.

Keywords: Healthcare, Machine Learning, KNN, Random Forest, Resource Management, Patient Classification.

1. INTRODUCTION

1.1 History

The history of healthcare delivery has been marked by a constant struggle to optimize resource utilization while ensuring quality care for patients. Over the years, healthcare systems worldwide have faced challenges related to rising costs, growing demand, and the need for efficiency. In Australia, a country with a mixed healthcare system comprising both public and private entities, these challenges have been particularly pronounced.

In Australia, the healthcare landscape has evolved significantly, driven by factors such as population growth, aging demographics, and advances in medical technology. As a result, healthcare expenditure has steadily increased, reaching substantial proportions relative to the country's GDP. For instance, in 2015-16, healthcare expenditure accounted for 10.0% of Australia's GDP, amounting to AUD 170.4 billion. Despite the substantial government funding, there has been increasing pressure on the sustainability of the healthcare system due to rising costs and growing demand.

Traditionally, healthcare delivery processes have been characterized by uncertainties, particularly concerning resource requirements for patient care. The unpredictability of patient stays and resource utilization poses challenges for effectively scheduling and allocating healthcare resources. Conventional methods for predicting patient stays, such as random forest and k-nearest neighbor (KNN) algorithms, have exhibited limitations in accurately classifying patients and predicting resource needs.

1.2 Research Motivation

The motivation for the research stems from the imperative to address the inefficiencies prevalent in healthcare delivery systems, particularly in the context of escalating costs and increasing demand. As healthcare expenditure continues to rise, there is a pressing need to optimize resource allocation and improve the efficiency of care delivery processes.

Efforts to enhance efficiency in healthcare provision are crucial for ensuring the sustainability of healthcare systems, particularly those predominantly funded by the government, as in the case of Australia. By gaining insights into patient resource requirements and predicting their length of stay more accurately, healthcare providers can better plan and allocate resources, thereby reducing inefficiencies and enhancing overall system performance.

Moreover, by leveraging machine learning techniques, such as the two-stage approach proposed in the research, there is an opportunity to harness the vast amount of electronic patient records data to derive meaningful insights. This approach offers the potential to classify patients into distinct resource utilization groups, thereby reducing uncertainty and improving the accuracy of resource planning.

1.3 Problem Statement

The core problem addressed by the research is the uncertainty surrounding patient resource requirements, particularly their length of stay within healthcare facilities. The unpredictable nature of patient stays poses challenges for efficient resource allocation, leading to potential bottlenecks and inefficiencies in care delivery processes.

Conventional methods for predicting patient stays, including random forest and k-nearest neighbor algorithms, have exhibited limited accuracy and predictive performance. This limitation underscores the need for more sophisticated approaches that can effectively leverage electronic patient records data to classify patients into resource utilization groups and predict their length of stay more accurately.

The research aims to overcome these challenges by proposing a two-stage approach driven by machine learning techniques. By employing a novel methodology for classifying patients and predicting their length of stay, the research seeks to reduce uncertainty and improve the efficiency of healthcare resource allocation.

2. LITERATURE SURVEY

Kadri, et al. [1] proposed a deep learning-driven approach for predicting the patient LOS in ED using a generative adversarial network (GAN) model. The GAN-driven approach flexibly learned relevant information from linear and nonlinear processes without prior assumptions on data distribution and significantly enhanced the prediction accuracy. Furthermore, they classified the predicted patients' LOS according to time spent at the pediatric emergency department (PED) to further help decision-making and prevent overcrowding.

Zou, et al. [2] proposed utilizing a modified deep neural network (DNN) for LOS range prediction, incorporating various methodologies for error estimation and probability distribution analysis. The overall sample error was evaluated using the root mean square error (RMSE) method, while the estimated sample error was assessed through the ERRpred method. Additionally, they explored probability distributions with different loss functions, namely Dispred_Loss1, Dispred_Loss2, and Dispred_Loss3 methods. To validate these methods, they utilized the Medical Information Mart for Intensive Care III (MIMIC-III) database.

Saadatmand, et al. [3] proposed that in this pursuit, the outcome variables were in three separate models predicted by five different ML algorithms: eXtreme Gradient Boosting (XGB), K-Nearest Neighbor (KNN), Random Forest (RF), bagged-CART (b-CART), and LogitBoost (LB). With the exception of KNN, the studied models showed good predictive capabilities when evaluating relevant accuracy scores, such as area under the curve. By implementing an ensemble stacking approach (either a Neural Net or a General Linear Model) on top of the aforementioned ML algorithms, the performance was further boosted. Ultimately, for the prediction of admission to the ICU, the ensemble stacking via a Neural Net achieved the best result with an accuracy of over 95%.

Moya-Carvajal, et al. [4] proposed that the results of their case study demonstrated an increase in the accuracy of the predictions using raw text with a minimum preprocessing. The precision increased by up to 2% in the classification of the patient's post-care destination and by up to 8% in the prediction of LoS in the hospital. This evidence encouraged practitioners to use available text to anticipate the patient's need for hospitalization more accurately at the earliest stage of the care process.

Goltz, et al. [5] proposed a multicenter retrospective review of 5410 anatomic (52%) and reverse (48%) total shoulder arthroplasties performed at 2 large, tertiary referral health systems. The primary outcome was extended inpatient LOS of at least 3 days, and over 40 preoperative sociodemographic and comorbidity factors were tested for their predictive ability in a multivariable logistic regression model based on the patient cohort from institution 1 (derivation, N = 1773). External validation was performed using the patient cohort from institution 2 (validation, N = 3637), including area under the receiver operator characteristic curve (AUC), sensitivity, specificity, and positive and negative predictive values.

Hansen, et al. [6] proposed a novel approach for predicting LOS by modeling patient information as sequences of events. Specifically, they presented a transformer-based model, termed Medic-BERT (M-BERT), for LOS prediction using the unique features describing patients' medical event sequences. They conducted empirical experiments on a cohort of more than 45k emergency care patients from a large Danish hospital. Experimental results showed that M-BERT could achieve high accuracy on a variety of LOS problems and outperformed traditional non-sequence-based machine learning approaches.

Wang, et al. [7] analyzed the data of 1694 patients with LEAD from a retrospective cohort study conducted between January 2014 and November 2021. Nine variables were selected, and a prediction model was created using the least absolute shrinkage and selection operator (LASSO) regression model after dividing the dataset into training and test sets in a 7:3 ratio. The performance of the prediction model was evaluated by calibration, discrimination, and the Hosmer-Lemeshow test. The effectiveness of clinical utility was estimated using decision curve analysis.

Goltz, et al. [8] conducted a retrospective review of 37,406 primary total hip (17,134, 46%) and knee (20,272, 54%) arthroplasties performed at two high-volume, geographically diverse, tertiary health systems during the study period. Patients were stratified by 3 binary outcomes for extended inpatient length of stay: 72 + hours (29%), 4 + days (11%), or 5 + days (5%). The predictive ability of over 50 sociodemographic/comorbidity variables was tested. Multivariable logistic regression models were created using institution #1 (derivation), with accuracy tested using the cohort from institution #2 (validation).

An, et al. [9] analyzed and predicted LOS of all inpatients hospitalized in medical institutions within South Korea for obtaining the universality, as well as to identified important features that affected LOS. They thus compared the prediction performance using machine learning techniques that were known to perform well including XGBoost (eXtreme Gradient Boost), Decision Tree (DT), Random Forest (RF), and Support Vector Machine (SVM). Having identified which features affected LOS, they intended to improve model explainability and provide information about which features were important when it came to securing patient data in the future. Therefore, they used 2016 to 2019 health checkup cohort DB data provided by Korean National Health Insurance Service (NHIS). For the features used for LOS analysis, they referred to previous studies to select ones available in the cohort DB in which they were able to analyze the prediction performance and the features that had an important effect on LOS.

Arora, et al. [10] divided patients into three stratified cohorts: cervical degenerative, lumbar degenerative, and adult spinal deformity groups. Predictive variables included demographics, body mass index, surgical region, surgical invasiveness, surgical approach, and comorbidities. Regression, classification trees, and least absolute shrinkage and selection operator (LASSO) were used to build predictive models. Validation of the models was conducted on 16% of patients (N=587), using area under the receiver operator curve (AUROC), sensitivity, specificity, and correlation. Patient data were manually entered into the ACS NSQIP online risk calculator to compare performance.

Kumar, et al. [11] predicted the healthcare analysis using the Novel Deep Belief Network algorithm and found 90.25% accuracy. Therefore, the study needed to find better accuracy for health prediction with the Convolutional Neural Network algorithm in machine learning. This research study found 87.11% accuracy for healthcare analysis using the Convolutional Neural Network algorithm, with a significant value of two-tailed tests being 0.045 ($p<0.05$) with a 95% confidence interval. The study concluded that the Novel Deep Belief Network algorithm for patient healthcare analysis was significantly better than the Convolutional Neural Network algorithm.

Yang, et al. [12] retrieved the medical records of patients who had received acute ischemic stroke diagnoses and were treated at a stroke center between January 2016 and June 2020, and a retrospective analysis of these data was performed. Prolonged length of stay was defined as a hospital stay longer than the median number of days. They applied artificial neural networks to derive prediction models using parameters associated with the length of stay that were collected at admission, and a sensitivity analysis was performed to assess the effect of each predictor. They applied 5-fold cross-validation and used the validation set to evaluate the classification performance of the artificial neural network models.

Hansen, et al. [13] performed empirical experiments on a cohort of 48k emergency care patients from a large Danish hospital. Experimental results showed that M-BERT could achieve high accuracy on a variety of LOS problems and outperformed traditional non-sequence-based machine learning approaches.

Sitar, et al. [14] conducted an analysis of the accuracy of prediction models for predicting patients' LOS in a rural community hospital in the Northwest United States of America. Data were collected from 181 patients for hip, knee, and shoulder surgeries. A decision tree (DT) prediction model was compared with the National Surgical Quality Improvement Program (NSQIP) calculator for predicting LOS of TJA. The DT model (RMSE = 0.67) provided a more accurate LOS prediction than the NSQIP calculator (RMSE = 1.18). Furthermore, a greater level of interpretability of the decision-making process made the DT model very applicable in “high stakes” environments like healthcare. They identified primary unilateral TKAs (n = 9,064) and THAs (n = 8,649) performed for primary osteoarthritis at their institution from 2018 to 2021 (excluding March to June 2020) using a prospectively maintained institutional registry.

Le Brun, et al. [15] used the Medical Information Mart for Intensive Care (MIMIC III) dataset and applied four different machine learning algorithms: decision tree classifier, random forest, Artificial Neural Network (ANN), and logistic regression. First, they performed data pre-processing to clean up the dataset. In the next step, they performed function selection using the Select Best algorithm with an evaluation function of chi2 to perform hot coding. They then performed a split between training and testing and applied a machine learning algorithm. The metric used for comparison was accuracy.

3. PROPOSED METHOD

Overview

This project has a to-stage algorithm called CART (classification and regression tree) to predict patient hospital stay after surgery. Now-a-days it's become difficult for patients and hospital to maintain inflows of the patient as if patient stay for longer duration due to miscalculation after surgery then it will raise bill amount for the patient and hospital resources like rooms and other articles will be wasted and cannot be used for other patients. To overcome from this problem, we are introducing two stage algorithm which will predict hospital stay by using classification in STAGE 1 and then further enhance this classification output by adding STAGE 2 technique called clustering and both this stages will run by using algorithm called CART. CART will split or partition data into cluster which help in getting accurate classification result as similar data will be in same cluster. To implement this project, we have collected real patient and hospital dataset and not publish this dataset on internet so we have patient LENGTH OF STAY (LOS) dataset from internet. Propose algorithm will apply strategic technique (such as classification, regression and clustering by partition data into tree cluster) to predict patient LOS so its prediction output will be better. Existing algorithms such as Random Forest will not use any strategic technique so its prediction will not better and its error will be low compare to propose CART algorithm as its not applying any strategic technique.

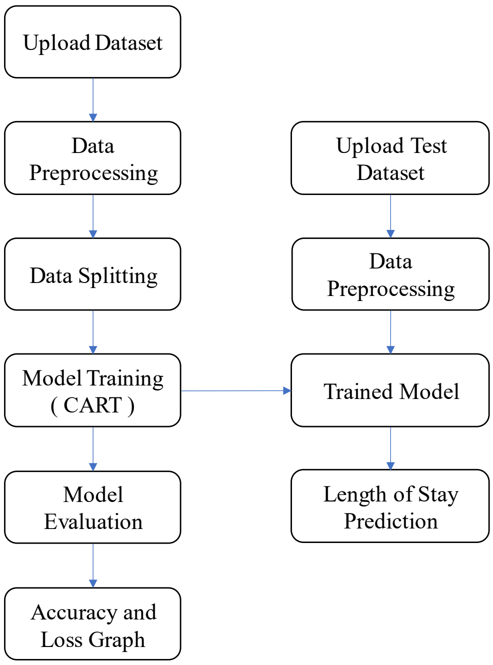


Figure: Block Diagram

Cart Algorithm

CART (Classification And Regression Trees) is a variation of the decision tree algorithm. It can handle both classification and regression tasks. Scikit-Learn uses the Classification And Regression Tree (CART) algorithm to train Decision Trees (also called "growing" trees). CART was first produced by Leo Breiman, Jerome Friedman, Richard Olshen, and Charles Stone in 1984.

CART (Classification And Regression Tree) for Decision Tree

CART is a predictive algorithm used in Machine learning and it explains how the target variable's values can be predicted based on other matters. It is a decision tree where each fork is split into a predictor variable and each node has a prediction for the target variable at the end.

The term CART serves as a generic term for the following categories of decision trees:

Classification Trees: The tree is used to determine which "class" the target variable is most likely to fall into when it is continuous.

Regression trees: These are used to predict a continuous variable's value.

In the decision tree, nodes are split into sub-nodes based on a threshold value of an attribute. The root node is taken as the training set and is split into two by considering the best attribute and threshold value. Further, the subsets are also split using the same logic. This continues till the last pure sub-set is found in the tree or the maximum number of leaves possible in that growing tree.

CART Algorithm

Classification and Regression Trees (CART) is a decision tree algorithm that is used for both classification and regression tasks. It is a supervised learning algorithm that learns from labelled data to predict unseen data.

- **Tree structure:** CART builds a tree-like structure consisting of nodes and branches. The nodes represent different decision points, and the branches represent the possible outcomes of those decisions. The leaf nodes in the tree contain a predicted class label or value for the target variable.
- **Splitting criteria:** CART uses a greedy approach to split the data at each node. It evaluates all possible splits and selects the one that best reduces the impurity of the resulting subsets. For classification tasks, CART uses Gini impurity as the splitting criterion. The lower the Gini impurity, the more pure the subset is. For regression tasks, CART uses residual reduction as the splitting criterion. The lower the residual reduction, the better the fit of the model to the data.
- **Pruning:** To prevent overfitting of the data, pruning is a technique used to remove the nodes that contribute little to the model accuracy. Cost complexity pruning and information gain pruning are two popular pruning techniques. Cost complexity pruning involves calculating the cost of each node and removing nodes that have a negative cost. Information gain pruning involves calculating the information gain of each node and removing nodes that have a low information gain.

How does CART algorithm works?

The CART algorithm works via the following process:

- The best-split point of each input is obtained.
- Based on the best-split points of each input in Step 1, the new "best" split point is identified.
- Split the chosen input according to the "best" split point.
- Continue splitting until a stopping rule is satisfied or no further desirable splitting is available.

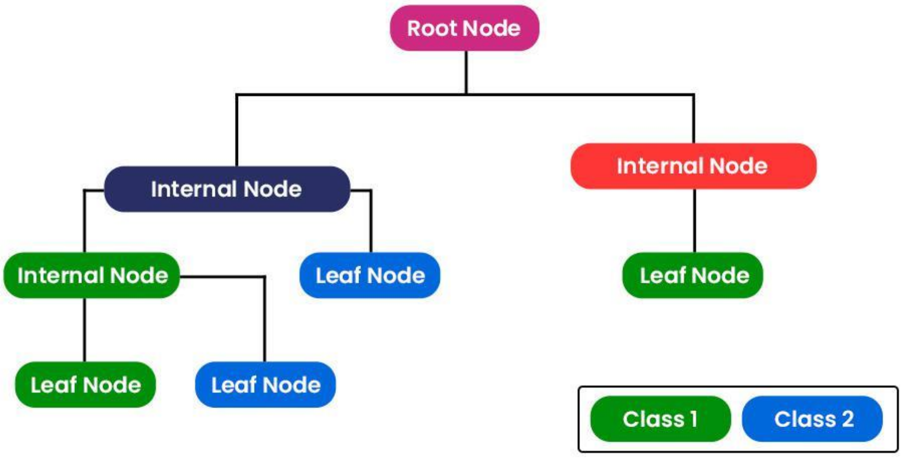


Figure: CART

CART algorithm uses Gini Impurity to split the dataset into a decision tree. It does that by searching for the best homogeneity for the sub nodes, with the help of the Gini index criterion.

Gini index/Gini impurity

The Gini index is a metric for the classification tasks in CART. It stores the sum of squared probabilities of each class. It computes the degree of probability of a specific variable that is wrongly being classified when chosen randomly and a variation of the Gini coefficient. It works on categorical variables, provides outcomes either "successful" or "failure" and hence conducts binary splitting only.

The degree of the Gini index varies from 0 to 1,

Where 0 depicts that all the elements are allied to a certain class, or only one class exists there.

The Gini index of value 1 signifies that all the elements are randomly distributed across various

A value of 0.5 denotes the elements are uniformly distributed into some classes.

CART for Classification

A classification tree is an algorithm where the target variable is categorical. The algorithm is then used to identify the "Class" within which the target variable is most likely to fall. Classification trees are used when the dataset needs to be split into classes that belong to the response variable(like yes or no)

For classification in decision tree learning algorithm that creates a tree-like structure to predict class labels. The tree consists of nodes, which represent different decision points, and branches, which represent the possible result of those decisions. Predicted class labels are present at each leaf node of the tree.

How Does CART for Classification Work?

CART for classification works by recursively splitting the training data into smaller and smaller subsets based on certain criteria. The goal is to split the data in a way that minimizes the impurity within each subset. Impurity is a measure of how mixed up the data is in a particular subset. For classification tasks, CART uses Gini impurity

- **Gini Impurity-** Gini impurity measures the probability of misclassifying a random instance from a subset labeled according to the majority class. Lower Gini impurity means more purity of the subset.

- **Splitting Criteria-** The CART algorithm evaluates all potential splits at every node and chooses the one that best decreases the Gini impurity of the resultant subsets. This process continues until a stopping criterion is reached, like a maximum tree depth or a minimum number of instances in a leaf node.

CART for Regression

A Regression tree is an algorithm where the target variable is continuous and the tree is used to predict its value. Regression trees are used when the response variable is continuous. For example, if the response variable is the temperature of the day.

CART for regression is a decision tree learning method that creates a tree-like structure to predict continuous target variables. The tree consists of nodes that represent different decision points and branches that represent the possible outcomes of those decisions. Predicted values for the target variable are stored in each leaf node of the tree.

How Does CART works for Regression?

Regression CART works by splitting the training data recursively into smaller subsets based on specific criteria. The objective is to split the data in a way that minimizes the residual reduction in each subset.

- **Residual Reduction-** Residual reduction is a measure of how much the average squared difference between the predicted values and the actual values for the target variable is reduced by splitting the subset. The lower the residual reduction, the better the model fits the data.
- **Splitting Criteria-** CART evaluates every possible split at each node and selects the one that results in the greatest reduction of residual error in the resulting subsets. This process is repeated until a stopping criterion is met, such as reaching the maximum tree depth or having too fe w instances in a leaf node.

CART model representation

CART models are formed by picking input variables and evaluating split points on those variables until an appropriate tree is produced.

Steps to create a Decision Tree using the CART algorithm:

- **Greedy algorithm**: In this the input space is divided using the Greedy method which is known as a recursive binary spitting. This is a numerical method within which all of the values are aligned and several other split points are tried and assessed using a cost function.
- **Stopping Criterion:** As it works its way down the tree with the training data, the recursive binary splitting method described above must know when to stop splitting. The most frequent halting method is to utilize a minimum amount of training data allocated to every leaf node. If the count is smaller than the specified threshold, the split is rejected and also the node is considered the last leaf node.
- **Tree pruning:** Decision tree's complexity is defined as the number of splits in the tree. Trees with fewer branches are recommended as they are simple to grasp and less prone to cluster the data. Working through each leaf node in the tree and evaluating the effect of deleting it using a hold-out test set is the quickest and simplest pruning approach.
- **Data preparation for the CART:** No special data preparation is required for the CART algorithm.

4. RESULTS AND DESCRIPTION

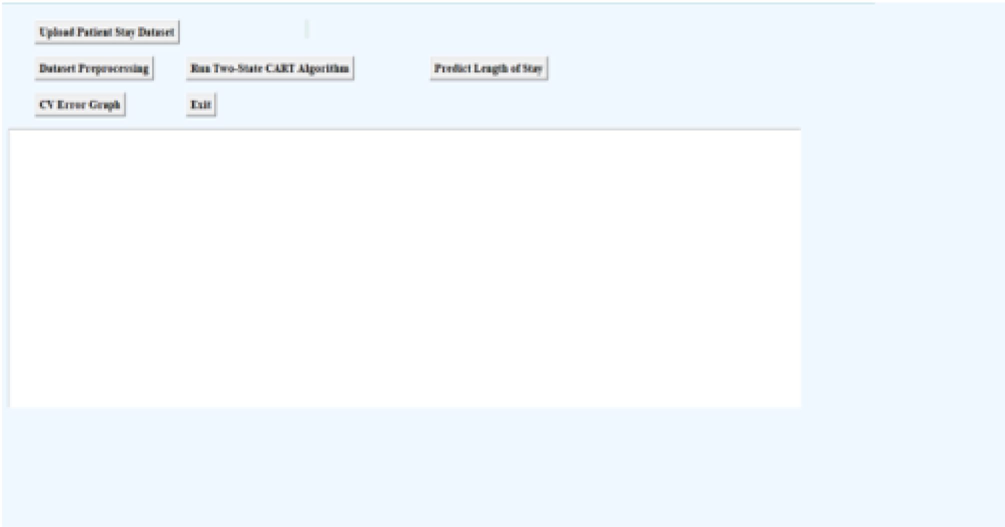


Figure 1: Upload Patient Stay Dataset in GUI.

Figure 1 Upload Patient Stay Dataset button to upload dataset upload a patient stay dataset, you'll first want to ensure that your dataset is properly formatted and organized. Once you have your dataset ready, you can choose a suitable platform or tool for analysis, such as Python with libraries like Pandas, R with tidyverse packages, or a cloud-based platform like Google Colab or Jupyter Notebook. Next, you'll upload your dataset using the platform's file upload interface, ensuring that it's successfully loaded into your chosen environment. After verifying the integrity of the data and addressing any missing values or inconsistencies, you can proceed with your analysis, which include exploring summary statistics, visualizing trends, or building predictive models. Finally, you'll document your analysis process and share your findings with relevant stakeholders, contributing to informed decision-making in healthcare management.

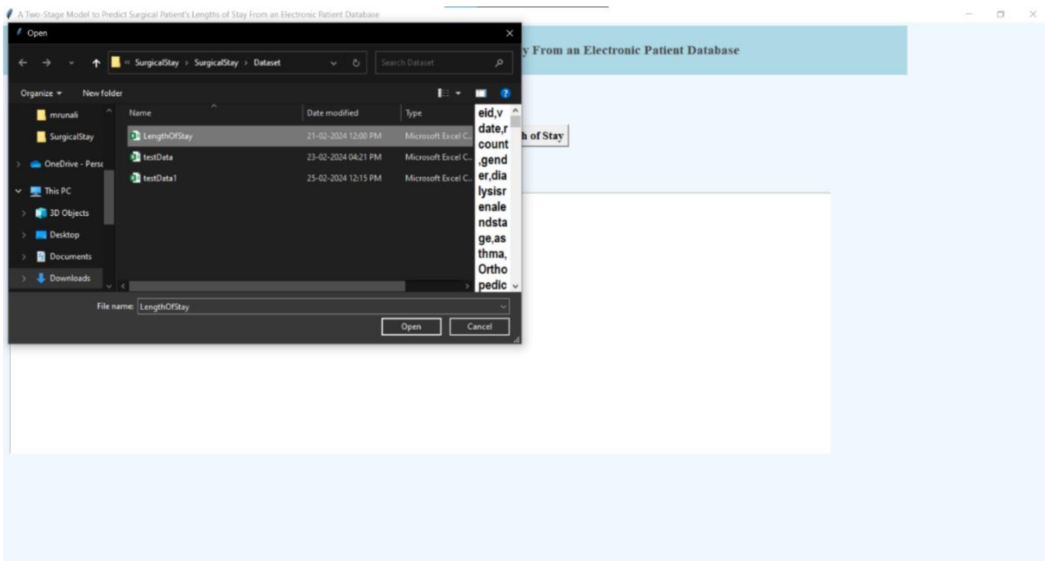


Figure 2: Upload Train dataset

Figure 2 Uploading dataset and then click on 'Open' button to get below output. To upload a training dataset for machine learning, you'll first need to ensure that your dataset is appropriately formatted and contains the necessary features and labels for training your model. Once you have your dataset ready, you can proceed to load it into your chosen programming environment, such as Python with libraries like Pandas or scikit-learn.

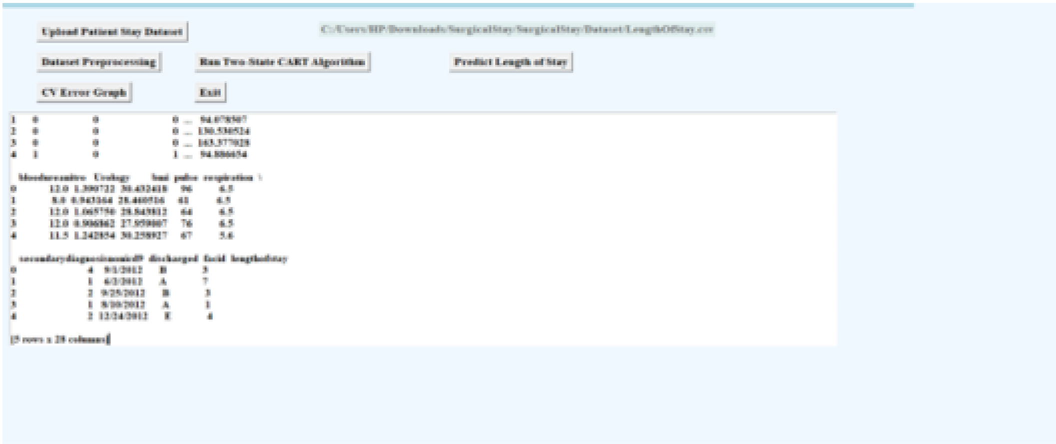


Figure 3: Output Of Train dataset

Figure 3 Shows the dataset loaded and dataset contains some non-numeric values so we need to process dataset to convert or encode non-numeric to numeric values.

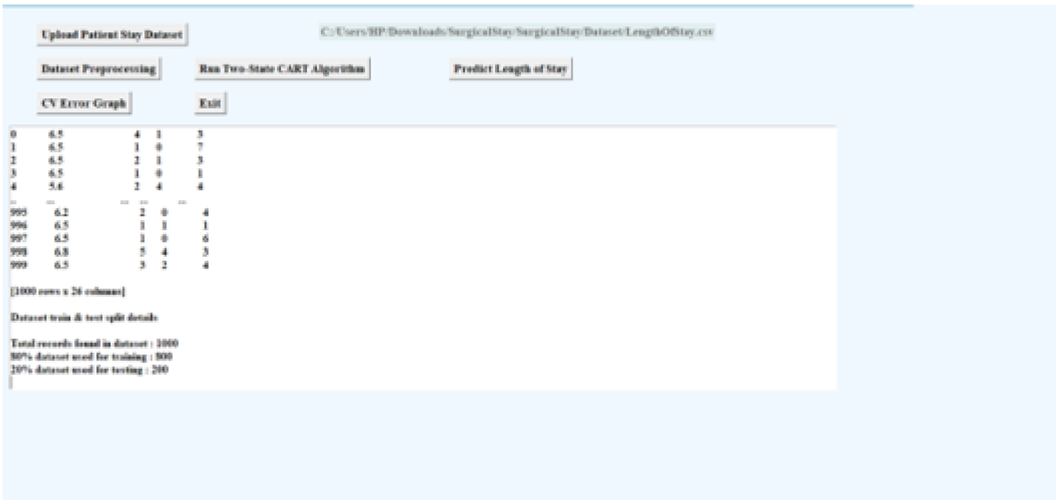
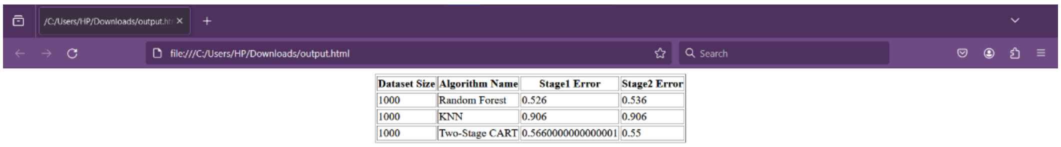


Figure 4: Preprocess Dataset

Figure 4 shows all dataset values converted to numeric and we can see dataset contains 1000 records and 800 using for training and 200 for testing.



Dataset Size	Algorithm Name	Stage1 Error	Stage2 Error
1000	Random Forest	0.526	0.536
1000	KNN	0.906	0.906
1000	Two-Stage CART	0.5660000000000001	0.55

Figure 5: Performance Table

Figure 5 the misclassification error rate for each algorithm in stage 1 and 2 and in above screen we can see Random Forest error rate is less compare to propose CART but CART using strategic techniques and Random Forest not applying and in below PAPER output also we can see Random Forest error is less compare to CART

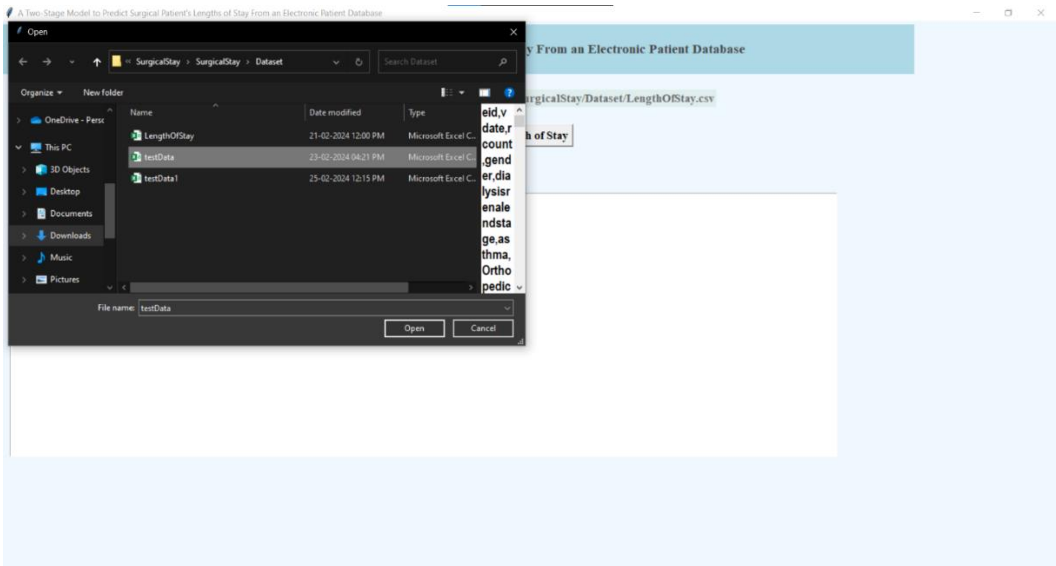


Figure 6: Upload Test dataset

Figure 6 above screen selecting and uploading testData.csv file to test the proposed model.

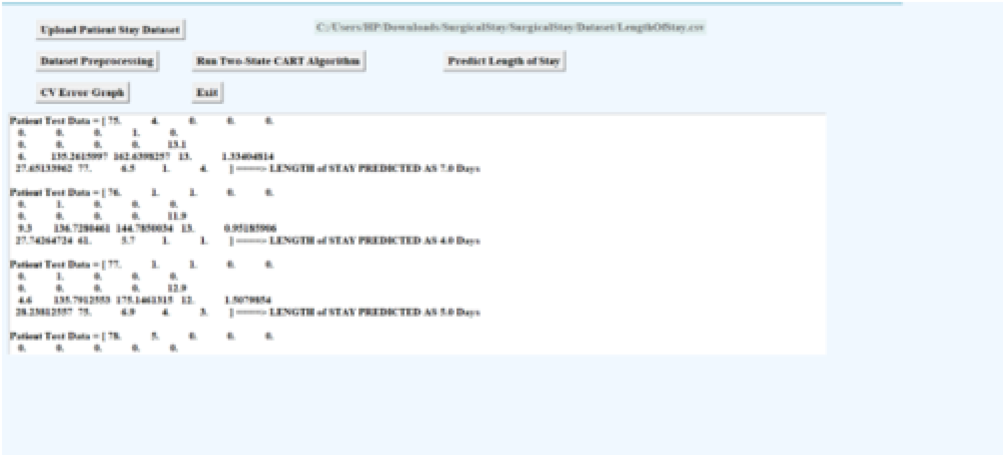


Figure 7: Model Prediction of test data.

In figure 7 square bracket can see the patient test data and after arrow symbol you can see length of stay as 7 days and similarly for each test record you can see predicted length of days.

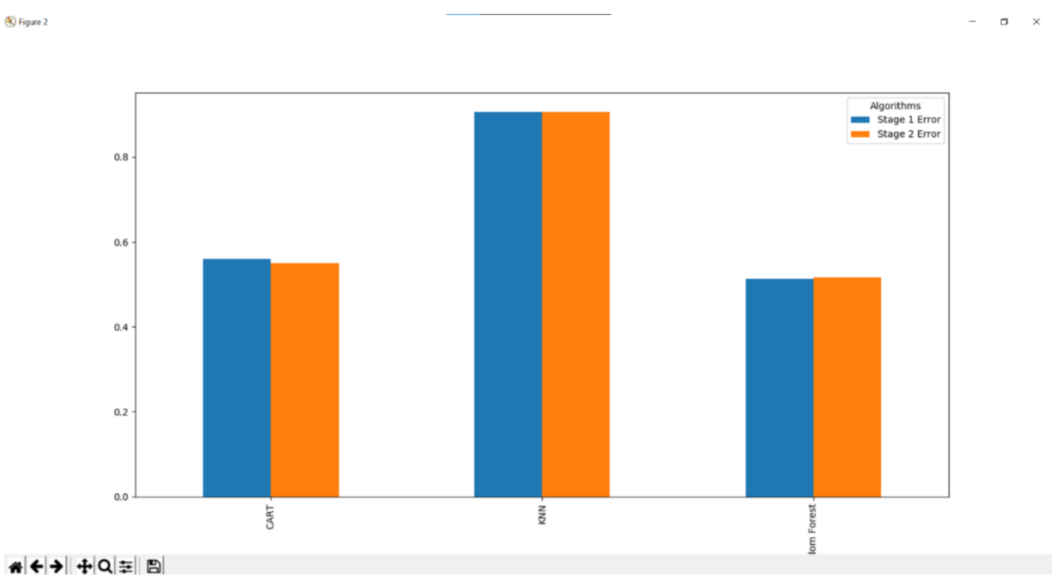


Figure 8: CV Error Graph

Figure 8 Present the x-axis represents algorithm name and y-axis represents error rate for each stage 1 and 2 and in all 3 algorithms random forest error rate is less.

5. CONCLUSION

The project presents a two-stage model for predicting surgical patients' lengths of stay using an electronic patient database, facilitated by a Tkinter-based graphical user interface (GUI). The first stage involves training various algorithms such as Random Forest, K-Nearest Neighbors (KNN), and Decision Trees to predict lengths of stay, followed by refining predictions using regression techniques in the second stage. Data preprocessing entails handling missing values, dropping irrelevant columns, and encoding categorical variables. The GUI allows users to upload datasets, preprocess data, run the two-stage CART algorithm, visualize cross-validation error graphs, predict lengths of stay for new patient data, and exit the application, offering a comprehensive tool for healthcare professionals to analyze and predict lengths of stay, potentially enhancing resource allocation and patient management strategies.

Through the application, users gain insights into algorithm performance at both stages, comparing Random Forest, KNN, and CART algorithms via cross-validation error graphs. By leveraging the trained model, healthcare professionals can predict lengths of stay for new patient data, thereby aiding in strategic decision-making. Overall, the project provides a valuable resource for healthcare professionals seeking to analyze and forecast surgical patients' lengths of stay, with potential implications for optimizing resource allocation and enhancing patient care strategies.

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