Analyzing and Implementing Feature Selection Method for Predicting Patient Waiting Times in Clinic

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ABSTRACT

Patient waiting time is a common issue in healthcare services that can affect patient satisfaction and clinic efficiency. This study aims to identify the most relevant features for predicting patient waiting times using feature selection techniques and machine learning models. Three feature selection methods, namely Correlation-based Feature Selection (CFS), Recursive Feature Elimination (RFE), and Sequential Feature Selection (SFS), were implemented and evaluated. The selected features were then validated using Decision Tree and Logistic Regression models based on accuracy, precision, recall, and F1-score. The results showed that SFS achieved the best performance among the evaluated methods, with training and testing accuracies of 92.99% and 87.69%, respectively. In addition, SFS successfully reduced the predictor set from 11 predictor variables to 4 selected predictor variables while retaining important predictive information. Validation results indicated that the Decision Tree model achieved the highest prediction accuracy, whereas Logistic Regression demonstrated more stable performance between the training and testing datasets. Based on these findings, a web-based patient waiting time prediction application was developed using the SFS feature subset and the Decision Tree model. The developed application enables real-time waiting time prediction through a simple user interface. Overall, the findings suggest that SFS is an effective feature selection method for reducing dataset dimensionality while maintaining satisfactory predictive performance for patient waiting time prediction.

Keywords: Feature Selection, Prediction Model, Sequential Feature Selection, Decision Tree

INTRODUCTION

Patient waiting time remains one of the most important indicators of healthcare service quality and operational efficiency. Excessive waiting times may negatively affect patient satisfaction, reduce service accessibility, and increase the burden on healthcare providers. In outpatient and primary healthcare settings, waiting times are often influenced by various factors, including patient arrival patterns, consultation duration, appointment scheduling, and resource availability. Therefore, healthcare organisations continuously seek effective approaches to improve service delivery and minimise patient waiting times.

Al-Mousa et al. [1] proposed a machine learning-based approach for estimating waiting times in healthcare facilities and demonstrated that predictive models can provide more accurate waiting time estimates than conventional estimation methods. Their study highlighted the potential of machine learning techniques in improving operational efficiency and patient flow management within healthcare environments. Similarly,

Shin et al. [2] developed an interpretable machine learning framework for outpatient waiting time prediction and reported that accurate waiting time prediction plays an important role in improving patient satisfaction and supporting healthcare decision-making. Their findings further emphasised the importance of balancing prediction accuracy and model interpretability in healthcare applications.

The increasing availability of electronic healthcare records has accelerated the adoption of machine learning techniques in healthcare. An et al. [3] reviewed various machine learning applications in the healthcare industry and highlighted their effectiveness in supporting prediction, classification, diagnosis, and clinical decision-making tasks. The authors reported that machine learning algorithms can identify meaningful patterns from healthcare data and contribute to improved healthcare service quality and efficiency.

Several machine learning algorithms have been applied to patient waiting time prediction. Joseph et al. [4] compared multiple machine learning algorithms for predicting consultation waiting times in outpatient clinics and found that tree-based models achieved superior predictive performance compared with several alternative techniques. Their findings demonstrated the suitability of machine learning approaches for modelling waiting time prediction problems using patient and operational data.

Despite the promising performance of machine learning models, their effectiveness largely depends on the quality and relevance of the input variables used during model development. The inclusion of irrelevant or redundant variables may increase model complexity, reduce interpretability, and negatively affect predictive performance. Consequently, feature selection has become an important preprocessing stage in machine learning applications. Noroozi et al. [5] investigated the impact of feature selection methods on machine learning algorithms and reported that appropriate feature selection can improve predictive performance, reduce redundant information, and enhance model efficiency. Their findings demonstrated that selecting relevant features plays a significant role in improving the effectiveness of machine learning models. Likewise, Kushagra et al. [6] reported that feature selection contributes to improved model interpretability, reduced computational complexity, and enhanced classification performance through the selection of relevant attributes from the original dataset. Their review highlighted the growing importance of feature selection techniques in healthcare-related machine learning applications.

Although previous studies have demonstrated the effectiveness of machine learning and feature selection techniques in healthcare prediction tasks, limited attention has been given to comparing different feature selection methods for patient waiting time prediction in dental clinic settings. Most existing studies focus primarily on prediction model development, while comparatively less attention has been given to evaluating the effectiveness of feature selection methods in identifying the most relevant predictors of patient waiting time.

Therefore, this study evaluates three feature selection methods, namely Correlation-Based Feature Selection (CFS), Recursive Feature Elimination (RFE), and Sequential Feature Selection (SFS), to identify the most relevant predictor variables for patient waiting time prediction. The selected features are subsequently validated using Decision Tree and Logistic Regression models. The findings are expected to provide useful insights into the effectiveness of feature selection methods for reducing dimensionality while maintaining predictive performance in patient waiting time prediction.

METHODOLOGY

This section describes the development of the feature selection and prediction models using machine learning techniques.

Data Preprocessing

The dataset used in this study was obtained from a public dental clinic in Melaka and was originally recorded in Microsoft Excel. The dataset consisted of 15,835 instances containing patient- and treatment-related information, including registration number, appointment time, gender, patient type, referring doctor, treatment information, payment details, and patient arrival and departure times. These records were used to determine the

waiting time experienced by patients before receiving treatment. The waiting time was subsequently analysed based on the patient and service-related factors available in the dataset, with the objective of identifying the variables that contribute to variations in patient waiting time.

Before conducting feature selection, data preprocessing was performed to convert the raw dataset into a suitable format for machine learning analysis. This stage is important because inconsistencies, duplicate records, irrelevant attributes, incomplete information, and abnormal observations in the raw dataset may introduce noise and negatively affect the learning process. Therefore, the preprocessing procedure involved data cleaning and data transformation.

The original dataset contained records from multiple doctors. The number of records varied across doctors, and the dataset contained duplicate and incomplete records. Data cleaning was performed manually using Microsoft Excel. Duplicate records and incomplete records were removed before proceeding with the selection of records for prediction modelling. After data cleaning, the records were filtered by doctor using the filtering function in Microsoft Excel. A single doctor with the largest number of available records and the most complete data was selected for this study to provide a sufficiently large dataset for prediction modelling. Following these data cleaning and selection procedures, 1,000 instances were retained for subsequent analysis.

The original 84 columns were reviewed to identify relevant attributes for the prediction task. Columns representing different categories of the same attribute were consolidated into a single feature using numerical category codes, as illustrated in Table 1. Columns containing no data were also excluded. Following these procedures, the final dataset consisted of 1,000 instances and 12 variables, comprising 11 predictor variables and one target variable. The target variable in this study was the Waiting Period Class, while the remaining 11 variables were treated as predictor variables. The waiting period values were transformed into three categorical classes according to predefined waiting-time ranges. Class 1 represented short waiting times, Class 2 represented moderate waiting times, and Class 3 represented long waiting times. This categorisation was performed to convert the prediction task into a multiclass classification problem suitable for machine learning modelling.

Table 1: Description of Dataset Attributes

Attributes	Conditions
Frequency	New patient (1)
	Repeat patient (0)
Ethnicity	Malay (1)
	Chinese (2)
	India (3)
Gender	Female (1)
	Male (2)
Category Of Patients	Toddle (0-4 Years Old) (1)
	Pre-School (2)
	Primary School (3)
	Secondary School (4)
	Person with Disabilities (OKU) (5)
	Maternity (6)
	Adult (7)
	Senior Citizen (8)
Officer	Pensioners (1)
	Government Personnel (2)
	Community College And Others (3)
Fast Lane	<60 Years Old (Female) (1)

	<60 Years Old (Male) (2)
	>60 Years Old (Female) (3)
	>60 Years Old (Male) (4)
Yield	Outpatient (1)
	Denture (2)
Treatment	Tooth Extracting (1)
	Scaling (2)
	Tooth Extraction (3)
	App Fs (4)
	Fluoride Vanish (5)
	Endo Anterior (6)
	Endo Posterior (7)
	Other Surgical (8)
	Denture Case (9)
Blood Pressure	140 And Below (1)
	140 And Above (2)
Family History	Yes (1)
	No (2)
Number Of Patients Waiting	Less Than 30 Patients (1)
	More Than 30 Patients (2)
Waiting Period (Target)	0-30 Minutes (Class 1)
	30-60 Minutes (Class 2)
	60-90 Minutes (Class 3)

To evaluate the predictive performance objectively and minimise the risk of overly optimistic results, the dataset was divided into training and testing subsets using a 70:30 ratio. The training dataset was used for feature selection and model development, while the testing dataset was reserved exclusively for final model evaluation. The selected features obtained from each feature selection method were subsequently used to train the prediction models. Model performance was then assessed using the unseen testing dataset to provide an unbiased evaluation of predictive capability.

Feature Selection Method

After preprocessing, the dataset was defined by 11 input features related to patient waiting time. The relevance of these features was evaluated using feature selection techniques to determine which variables should be retained for subsequent prediction modelling. Three feature selection methods were considered in this study: Correlation-based Feature Selection (CFS), Recursive Feature Elimination (RFE), and Sequential Feature Selection (SFS).

Feature selection was applied to reduce the number of input variables while retaining the features that provide useful information for predicting patient waiting time. Irrelevant or redundant features can introduce unnecessary information into the learning process and may increase model complexity. Therefore, the selection of an appropriate feature subset can help the prediction model focus on variables that have stronger relationships with the target variable.

For each method, the 11 input features were evaluated, and a subset of features was selected based on the criteria of the respective feature selection technique. The selected features were subsequently used as inputs to the prediction models. The performance obtained from the different feature subsets was then compared to determine which feature selection method produced the most suitable feature combination for patient waiting

time prediction. This process enables the identification of a suitable subset of input features for subsequent prediction modelling, while reducing the number of input variables from the original dataset.

Correlation-based Feature Selection

Correlation-Based Feature Selection (CFS) was applied to identify the features that have the strongest relationships with the target variable, namely patient waiting time. The method evaluates the correlation between the input features and the target variable to determine the relevance of each feature. CFS was implemented in Jupyter Notebook by applying Pearson correlation to measure linear relationships among features. Duplicate values were masked using an upper triangular matrix, and absolute correlation values were computed to emphasize the strength of associations regardless of direction. The resulting correlations were sorted in descending order, and the output was restricted to the ten strongest feature pairs. The parameter settings are summarized in Table 2.

Table 2: Parameter settings for CFS

Parameter	Setting	Description
Correlation method	Pearson (default in pandas.corr())	Measures linear correlation between features.
Duplicate masking	Upper triangular mask (np.triu)	Removes redundant correlation values by masking duplicates.
Correlation values	Absolute (.abs())	Considers only the strength of correlation, ignoring direction (positive/negative).
Sorting order	Descending (sort_values (ascending=False))	Ranks feature pairs from strongest to weakest correlation.
Output limit	Top 10 pairs ([:10])	Displays only the 10 most highly correlated feature pairs.

Recursive Feature Elimination

Recursive Feature Elimination (RFE) was applied to identify the most relevant features in the dataset. The process iteratively removes the least significant features and builds models with the remaining ones until the desired number of features is obtained. SelectKBest was used to extract the top features based on regression scoring, while Gradient Boosting Classifier served as the estimator within the RFE framework. To enhance robustness, Repeated Stratified K-Fold cross-validation was employed. A pipeline structure was implemented to ensure consistency, reproducibility, and systematic sequencing of preprocessing, feature elimination, and model training. Finally, features were ranked according to importance, and the least significant ones were eliminated until the target number of features was achieved. The parameter settings are presented in Table 3.

Table 3: Parameter settings for RFE

Parameter	Setting	Description
Estimator	Gradient Boosting Classifier	Combines weak learners to form a strong predictive model.
Number of features to select	6	Desired number of features retained after elimination.
Feature scoring method	f_regression (SelectKBest)	Evaluates features based on regression scoring function.
Cross-validation strategy	Repeated Stratified K-Fold (10 splits, 5 repeats, random state = 240)	Ensures robustness and reduces bias in performance estimation.
Feature ranking output	RFECV ranking and grid scores	Provides ordered importance of features and performance scores.

Sequential Feature Selection

Sequential Feature Selection (SFS) was applied to iteratively add or remove features from the dataset using a greedy search strategy. Features were evaluated based on their contribution to predictive accuracy, and only the most relevant attributes were retained. StandardScaler was employed to normalize the dataset by subtracting the mean and scaling to unit variance. The parameter settings are outlined in Table 4.

Table 4: Parameter settings for SFS

Parameter	Setting	Description
Algorithm type	Greedy search	Iteratively adds or removes features based on contribution to accuracy.
Scaler applied	Standard Scaler	Normalizes features by mean subtraction and unit variance scaling.

Prediction Model

Following the identification of the most relevant features through feature selection methods, predictive models were developed to verify and evaluate the effectiveness of the selected features. Two widely used classification algorithms, Decision Tree and Logistic Regression, were employed to construct the prediction models. These models were chosen due to their interpretability, robustness, and suitability for analyzing categorical and continuous features within the dataset. The data splitting for training and testing remained consistent with a 70:30 ratio; however, the set of input features used in the models was updated according to the best-selected features obtained from the feature selection stage.

Decision Tree Model

The Decision Tree model was developed using JupyterLab notebook to evaluate the predictive capability of the selected features. The architecture was initialized as in Table 5. The maximum depth parameter controls the complexity of the tree and prevents overfitting, while the random state ensures reproducibility of results.

Table 5: Parameter settings for Decision Tree Model

Parameter	Setting	Description
Maximum depth	3	Limits the depth of the tree to prevent overfitting.
Random state	240	Ensures reproducibility of the model results.

Logistic Regression Model

Logistic Regression is a supervised machine learning algorithm commonly used for classification tasks. In this study, Logistic Regression was applied as a multiclass classification model to predict the Waiting Period Class. The model estimates the probability of each class and assigns an observation to the class with the highest predicted probability. Due to its simplicity, interpretability, and effectiveness in classification problems, Logistic Regression has been widely applied in healthcare prediction studies.

Table 6: Parameter settings for Logistic Regression Model

Parameter	Setting	Description
Solver	Default (lbfgs)	Optimization algorithm used for maximum likelihood estimation.
Penalty	L2 (default)	Regularization method to prevent overfitting.
Random state	240	Ensures reproducibility of the model results.

Development of Web Application

Upon completion of the model verification process, a web-based application was developed to implement the verified prediction model for estimating patient waiting time. The application was developed using Python and

HTML in Visual Studio Code (VS Code). The verified prediction model was saved in Pickle (.pkl) format and integrated into the web application for generating waiting time predictions based on user-provided inputs. The developed application provides a simple interface for entering the required patient and service-related parameters and displays the estimated waiting time. The application serves as the final implementation of the developed prediction approach, providing a practical and user-friendly platform for predicting patient waiting time. The interface of the developed web application is presented in Figure 1.

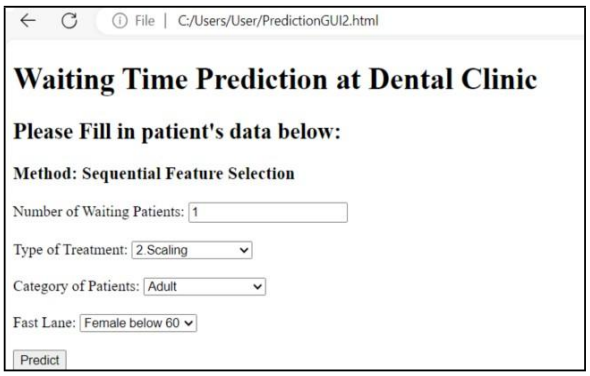


Figure 1: Web Application Interface.

RESULTS AND DISCUSSION

This section presents and discusses the performance results of feature selection and prediction models as well as the web application.

Feature Selection Model

Three feature selection methods, namely Correlation-Based Feature Selection (CFS), Recursive Feature Elimination (RFE), and Sequential Forward Selection (SFS), were applied to identify the most relevant predictor variables for classifying patient waiting periods. The final dataset consisted of 11 predictor variables, while the Waiting Period Class was designated as prediction target. The selected features obtained from each feature selection method are summarised in Table 7.

Table 7. Features in each dataset

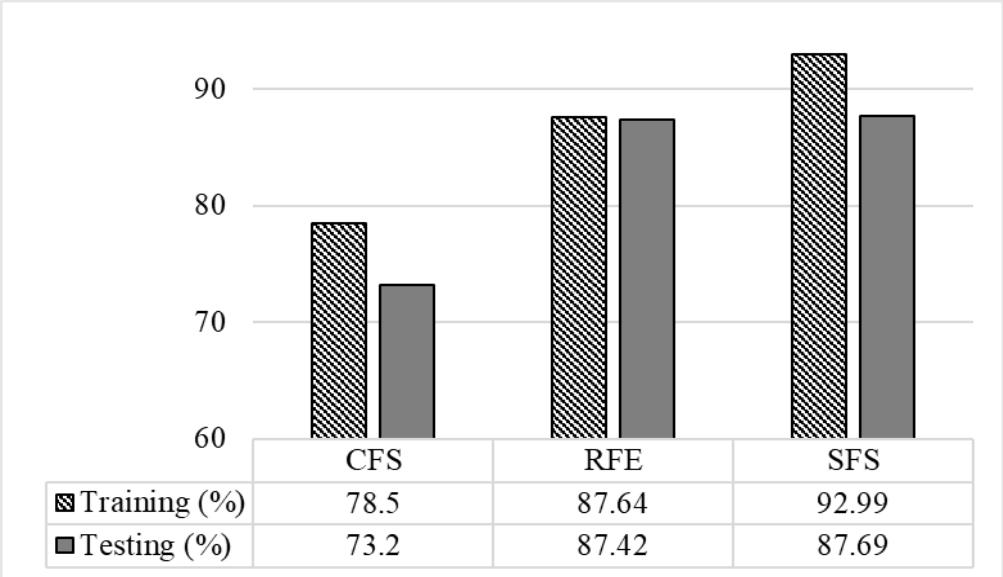
Original Dataset	Selected Features Methods		
	CFS	RFE	SFS
1. Frequency	1. Number of Patients Waiting	1. Number of Patients Waiting	1. Gender
2. Ethnicity	2. Frequency	2. Gender	2. Fast Lane
3. Gender	3. Treatment	3. Fast Lane	3. Treatment
4. Category Of Patients	4. Category of patients	4. Ethnicity	4. Category Of Patients
5. Officer		5. Treatment	
6. Fast Lane			
7. Yield			
8. Treatment			
9. Blood Pressure			
10. Family History			
11. Number Of Patients Waiting			

The CFS method selected four predictor variables, namely Number of Patients Waiting, Frequency, Treatment, and Category of Patients. In contrast, the RFE method selected Number of Patients Waiting, Gender, Fast

Lane, Ethnicity, and Treatment. Meanwhile, the SFS method identified Gender, Fast Lane, Treatment, and Category of Patients as the most relevant predictor variables for classifying patient waiting periods.

The results indicate that the three feature selection methods produced different subsets of predictor variables due to the differences in their selection strategies. Nevertheless, several variables were consistently identified across multiple methods. Treatment was selected by all three methods, suggesting that it may be an important predictor of patient waiting periods. Number of Patients Waiting was selected by both CFS and RFE, while Gender and Fast Lane were selected by both RFE and SFS. The repeated selection of these variables across different feature selection methods suggests that they may contribute to the prediction of patient waiting periods. However, the actual impact of each variable depends on the characteristics of the dataset and the classification model used.

Figure 2 presents the training and testing accuracy obtained using the feature subsets selected by CFS, RFE, and SFS. The results demonstrate noticeable differences in predictive performance among the three methods.



	CFS	RFE	SFS
Training (%)	78.5	87.64	92.99
Testing (%)	73.2	87.42	87.69

Figure 2: Training and Testing Accuracy of CFS, RFE and SFS

CFS achieved a training accuracy of 78.50% and a testing accuracy of 73.20%. These were the lowest results among the three methods when each method was evaluated using its own selected features. The relatively low testing accuracy suggests that the features selected by CFS may not capture sufficient information to achieve the same predictive performance as the other feature selection methods in this dataset.

RFE achieved a substantially higher training accuracy of 87.64% and testing accuracy of 87.42%. The difference between its training and testing accuracy was only 0.22 percentage points, indicating consistent performance across the training and testing datasets. This small difference suggests that the model generalizes well to unseen data under the current experimental conditions.

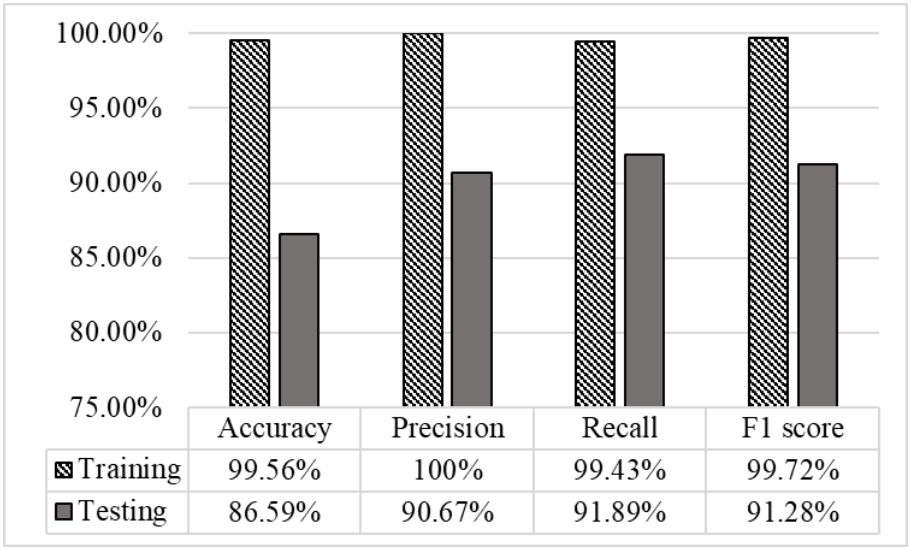
SFS produced the highest training accuracy of 92.99% and a testing accuracy of 87.69%. Compared with CFS, SFS improved training and testing accuracy by 14.49 and 14.49 percentage points, respectively. Compared with RFE, SFS improved training accuracy by 5.35 percentage points and testing accuracy by 0.27 percentage points. Although SFS achieved the highest accuracy on both datasets, the difference between its training and testing accuracy was 5.30 percentage points. This larger gap, compared with RFE, suggests that the model using SFS-selected features may exhibit a greater degree of overfitting. Nevertheless, its testing accuracy remained marginally higher than that of RFE, indicating that SFS provided the best predictive performance when each method was evaluated using its own selected feature subset.

Overall, the results indicate that SFS was the most effective feature selection method, achieving the highest training accuracy of 92.99% and testing accuracy of 87.69%. Although RFE demonstrated more consistent

performance between training and testing, SFS achieved a slightly higher testing accuracy, making it the preferred method for the subsequent prediction stage. Therefore, the feature subset selected by SFS was used to develop the prediction model, and its performance was compared with that of a model developed using the original dataset containing all 11 features. This comparison aimed to evaluate whether feature selection could maintain or improve prediction accuracy while reducing the number of input features. The results provided insights into the effectiveness of SFS in simplifying the prediction model without compromising its predictive performance.

Predictive Model

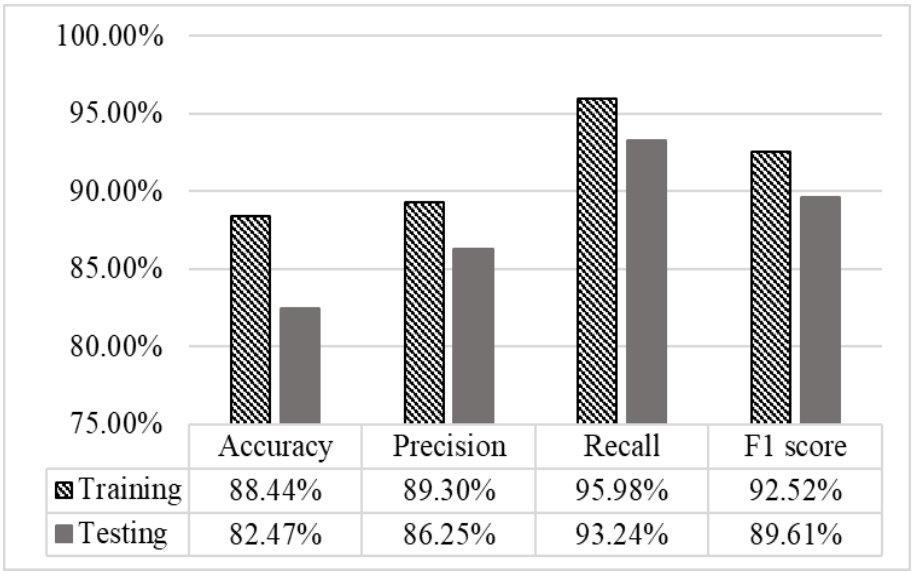
Figures 3 and 4 present the performance of the Decision Tree and Logistic Regression models using the feature subset selected through Sequential Feature Selection (SFS). The evaluation was conducted using four performance metrics, namely accuracy, precision, recall, and F1-score, on both training and testing datasets.



	Accuracy	Precision	Recall	F1 score
Training	99.56%	100%	99.43%	99.72%
Testing	86.59%	90.67%	91.89%	91.28%

Figure 3: Decision Tree Model

The Decision Tree model recorded the highest performance across all evaluation metrics. The model achieved a training accuracy of 99.56% and a testing accuracy of 86.59%. Similarly, high values were obtained for precision (100% training, 90.67% testing), recall (99.43% training, 91.89% testing), and F1-score (99.72% training, 91.28% testing). These results indicate that the selected features retained sufficient predictive information for the Decision Tree algorithm to accurately classify patient waiting time outcomes.



	Accuracy	Precision	Recall	F1 score
Training	88.44%	89.30%	95.98%	92.52%
Testing	82.47%	86.25%	93.24%	89.61%

Figure 4. Logistic Regression Model

In comparison, the Logistic Regression model achieved a training accuracy of 88.44% and a testing accuracy of 82.47%. The model also recorded precision values of 89.30% and 86.25%, recall values of 95.98% and 93.24%, and F1-scores of 92.52% and 89.61% for the training and testing datasets, respectively. Although these values were lower than those obtained by Decision Tree, the differences between training and testing performance were relatively small, suggesting that the model maintained a consistent level of predictive performance on unseen data.

Figure 5 compares the accuracy performance between the original dataset and the SFS dataset. The results show that Sequential Feature Selection (SFS) was able to reduce the number of input features while preserving most of the predictive information in the dataset. This can be observed from the slight increase in training accuracy for both Decision Tree and Logistic Regression after feature selection was applied.

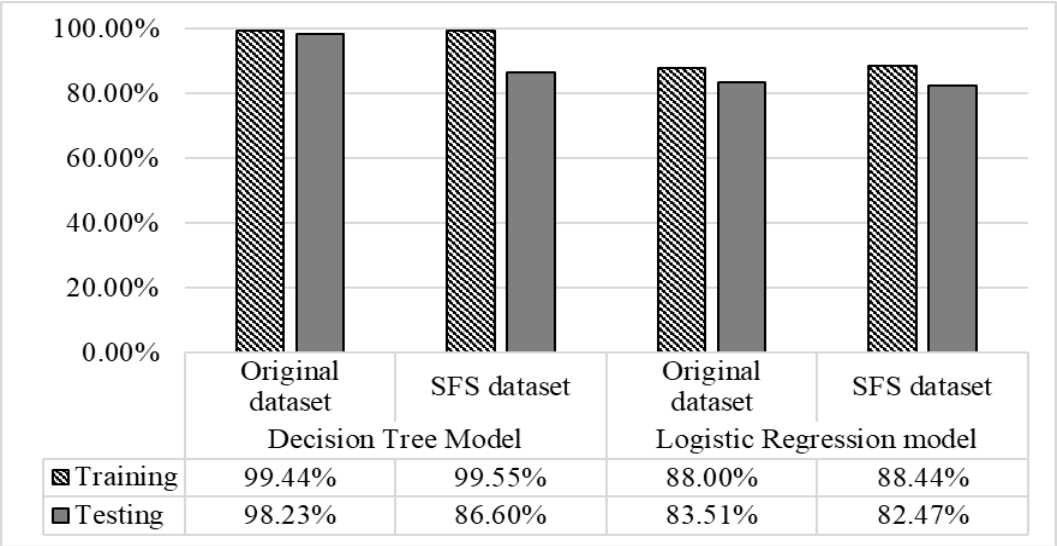


Figure 5: Accuracy performance between original dataset and the selected features dataset

However, the impact of SFS on testing performance was different for each model. For the Decision Tree model, testing accuracy decreased substantially from 98.23% to 86.60%. This suggests that some features removed during the selection process may have contributed important information for the model when making predictions on unseen data. As a result, the model became less effective in generalising beyond the training dataset.

On the other hand, Logistic Regression demonstrated more consistent performance after feature selection. Although testing accuracy decreased slightly from 83.51% to 82.47%, the difference was relatively small. This indicates that the selected feature subset still retained the key information required by the model to make accurate predictions. In addition, the reduction of unnecessary features may help simplify the model without causing a significant loss in predictive performance.

Overall, the findings indicate that the feature subset generated by SFS was effective in preserving the important information required for patient waiting time prediction. The Decision Tree model achieved superior predictive performance across all evaluation metrics, demonstrating its strong classification capability. However, Logistic Regression exhibited more consistent results between the training and testing datasets, indicating better model stability and generalisation capability when using the reduced feature set. Therefore, the selected features were considered suitable for predictive modelling, as both algorithms were able to achieve satisfactory performance despite using only four features.

Web application to predict waiting time

Figure 6 shows the web-based patient waiting time prediction system developed using the features selected through Sequential Feature Selection (SFS) and the Decision Tree model. The system enables users to input patient information and obtains an instant waiting time prediction. The successful development of the

application demonstrates that the selected features were sufficient to support the prediction process and demonstrates the potential to support patient waiting time prediction in clinical settings. However, further validation using independent datasets is required before practical deployment can be recommended.

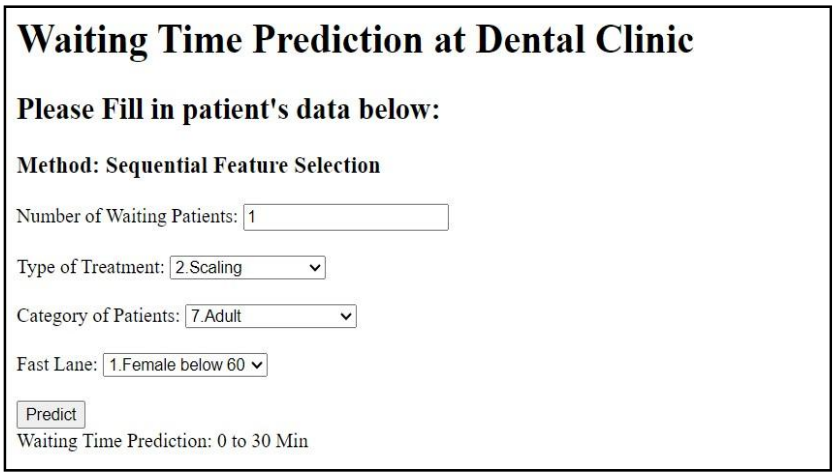


Figure 6: Web-Based Patient Waiting Time Prediction Application

CONCLUSIONS

In summary, three feature selection methods, namely Correlation-Based Feature Selection (CFS), Recursive Feature Elimination (RFE), and Sequential Feature Selection (SFS), were evaluated to identify the most suitable subset of predictor variables for patient waiting time prediction. Among the evaluated feature selection methods, SFS produced the most favourable results and was therefore selected for subsequent validation using Decision Tree and Logistic Regression models. Using this approach, the predictor set was successfully reduced from 11 predictor variables to 4 selected predictor variables, resulting in a simpler and more compact dataset while retaining important predictive information.

The selected feature subset was subsequently validated using Decision Tree and Logistic Regression models. The validation results showed that Decision Tree achieved the highest prediction accuracy, demonstrating its strong capability in predicting patient waiting times. However, Logistic Regression exhibited more consistent performance between the training and testing datasets, indicating better model stability and generalisation capability after feature reduction. Overall, the findings suggest that SFS effectively reduced the number of predictor variables while maintaining acceptable predictive performance, making it a suitable feature selection method for patient waiting time prediction. Although a reduction in prediction accuracy was observed after feature selection, SFS successfully reduced the dimensionality of the dataset from 11 predictor variables to 4 selected predictor variables while maintaining acceptable predictive performance. Nevertheless, the findings should be interpreted with caution, as the models were developed using data from a single clinic. Further validation through repeated cross-validation and independent datasets from different healthcare institutions is recommended before practical deployment in real-world clinical settings.

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