Analysis of Outpatient Visit Pattern and Outpatient Waiting Time Prediction for Selected Government Health Clinic in the State of Selangor

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Analysis of Outpatient Visit Pattern and Waiting Time Prediction for Selected Public Health Clinics in Selangor

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Abstract. Public clinics are the preferred choice for health treatment worldwide. This preference results in many outpatients seeking remedies at public clinics and is the leading factor in patients' long waiting time. The definition for waiting time is when a patient has to remain at the clinic for treatment. The waiting time starts with the registration process until consultation with the physician. Lengthy waiting time is the leading cause of patient dissatisfaction. The discontent is especially so when there is no convenient waiting facility. The objective of this study is to analyze outpatient visits patterns to public outpatient clinics. The recognized patterns will form the basis to recommend which public outpatient clinics are the best to visit at a specific time to minimize waiting time. The waiting time is also predicted based on the arrival time. Fifteen public outpatient clinics in Selangor that use an electronic medical record system provided this study's data. The data analysis shows a correlation between patient waiting time, day, the month of visit, patient age, and consultation time. Past research shows that classification of machine learning methods can predict the waiting time. This study has demonstrated that Linear Discriminant Analysis creates the best classification model for Puchong and Batu 9 Cheras datasets. Support Vector Machine (SVM) is the best classifier for the Anika dataset.

Keywords: Waiting time, public outpatient clinic, arrival time, SVM, LDA.

1 Introduction

The life expectancy statistics of the Malaysian population increases every year. Individuals born in 2018 may live 2.8 years longer until they reach 75 years compared to 72.2 years for individuals born in 2000 [1]. The longer life expectancy in the nation is related to the increased demand for health services in public outpatient clinics. Outpatients clinics in public hospitals are often overcrowded. Overcrowding significantly contributes to poor patient experience with physician services [2]. This paper has five sections starting with section 1 for Introduction and Background, section 2 for Problem

Statement, Section 3 for Research Methodology, section 4 for Data Analysis, and the last section is for Conclusion.

1.1 Background

[3] defined the waiting time as when the patient has to wait from registration until consultation with the medical officer. The global issue of long waiting time in hospitals has spurred research in this domain. [4] proposed a Patient Treatment Time Prediction or PTTP algorithm predict the required time for each treatment task for a patient and subsequently developed a Hospital Queuing-Recommendation (HQR) system. An improved Random Forest (RF) algorithm is the basis for PTTP. The PTTP and HQR have undergone extensive experiments and shown high precision and performance.

Easing congestion in emergency departments is an active research area [5]. Research in this area works on various aspects, such as the length of patients' stay [6]. Closer to home, the Ministry of Health Malaysia has implemented multiple initiatives such as the Teleprimary Care System (TPC) since 2004. TPC is an electronic system used in healthcare to facilitate the workflow in a healthcare organization and improve patient care quality [7]. The system is an electronic medical record system that records outpatients' activities from check-in to service completion. TPC is the primary source of data for the work reported in this paper.

[8] investigated several machine learning algorithms such as neural network, random forest, support vector machine, elastic net, multivariate adaptive regression splines, k-nearest neighbours and others to find the most accurate methods to predict waiting times. They concluded that the elastic net model is the best model to predict waiting time or delay time.

[9] compared several machine learning algorithms, including random forests, elastic net, gradient boosting algorithm, support vector machine and multiple linear regression, to find the most accurate model for predicting waiting time in pediatric ophthalmology outpatient clinics. Their work concluded that supervised machine learning models could accurately predict wait time and identify the most significant contributing factors.

2 Problem Statement

Public outpatient clinics are the first choice for health treatment in a community. The preference for outpatient clinics causes long waiting periods and subsequently leads to overcrowding. A long waiting time with no available comfortable waiting space is a significant cause of public outpatient clinics' complaints. Uncertainty of expected waiting time for treatment is one of the possible reasons for dissatisfaction in outpatients. Sickly outpatients who are waiting their turn also have the potential to spread the disease to other outpatients. If the clinic can estimate the waiting period during the initial registration to the patient, the outpatient can wait at various locations or return home whilst waiting for their turn. However, possible waiting times are difficult to be predicted as the waiting period depends on the type of treatment for each outpatient, the procedures to be followed for individual ailments and the doctor's consultation or diagnosis style [10].

The waiting time is when the patient has to wait from registration or check-in until consultation with the medical officer [3]. In Malaysia, the average waiting time is between 1 to 2 hours [10]. According to [11], long waiting time is the main reason for patient dissatisfaction compared to other reasons such as clinic facilities and staff attitude. Informing the estimated waiting time to the patient earlier can minimize the patient's dissatisfaction. However, it is difficult to predict the patients' waiting time since the waiting time depends on the type of treatment, procedures of the previous patient and the doctor consultation or diagnosis style [4].

The patient's historical record of visits to the clinics is a potential source of data containing hidden past visits. Based on the TPC data set, there are different peak hours between various public outpatient clinics in the same district. Analyzing these records may unearth hidden patterns unique to the patient's visits. The results from these analyses are potentially helpful. Possible uses are to suggest the time to visit a particular clinic since this will minimize waiting time. Another benefit is to predict the waiting time based on patient arrival time.

3 Research Methodology

Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology formed this study's basis (Fig. 1). The study started with a business understanding phase, data understanding phase, and data preparation phase in line with the CRISP-DM method. The following two steps are the attribute selection phase and the modelling phase. The data source is obtained from the TPC records from 15 outpatient clinics in Selangor from January to December 2018. The raw data contained more than a million lines of records (1320459 records) in Microsoft Excel format.

The data understanding phase consists of several activities, namely data acquisition, descriptive analysis and data visualization. Then, the data goes through the data preparation phase, which aims to produce the final dataset to be analyzed by the machine learning algorithms. Activities in this phase are data cleaning, generating new attributes, integrating data sets, and data transformation into a format that is compatible with machine learning algorithms. The first task in data preparation is data cleaning to remove attributes that are not relevant to the study. For example, PatientName, PositionConsultation, Module dan PerformByConsultation. The study eliminated any records that contain the attribute TimeWaiting with negative values. Since the public outpatient clinics start their operation at 7.30 am, the study removed any records that contain the attribute ArrivalTime with value before 7.30. Although outpatient clinics are open on weekends by appointment, this study is only focusing on weekdays. Therefore, the study did not consider weekend records.

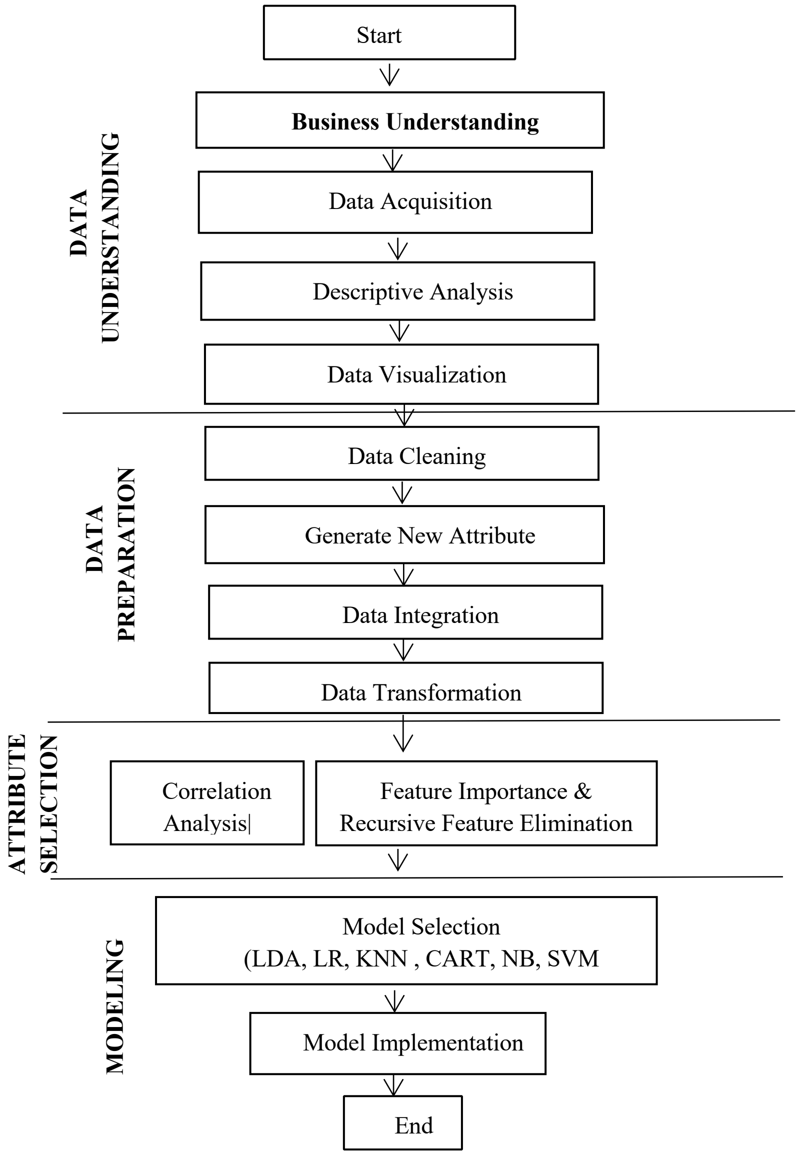

Fig. 1. Research Methodology

The next activity is generating new attributes. The original data set has no available detail for medical officer consultation time length. To generate the new attribute ConsultationLength, this formula is; attribute ConsultationTime minus attribute ArrivalTime. The study separated the ArrivalTime attribute into two parts: hour and minute, without deleting the original feature. The new attributes are named ArrivalHour and ArrivalMinute. Then, the data set is integrated with other data set containing the day of the week, day of the month and month.

The values of CreatedDate and ReportDate are transformed from date format to number format using the Microsoft Excel datevalue function. The ArrivalTime, ConsultationTime and ConsultationEndTime attributes are converted from time to number format using the Microsoft Excel timevalue function. The TimeWaiting attribute is discretized form continuous integer to three categorical value, namely 60P, 120P and 160P (Table 1).

Table 1. Discretised wait time values

Discretised Value	Value Range
60P	0 to 53 minutes
120P	54 to 106 minutes
160P	107 to 160 minutes

In Attribute Selection, the study used correlation analysis with the prepared data to find attributes that correlate with TimeWaiting. Further modelling will use these most correlated attributes. The Python functions for attribute selection, such as Feature Importance (FI) and Recursive Feature Elimination (RFE) functions, were utilized for attribute selection. The final attributes selected for the study is the combination of outputs from the FI and RFE functions (Table 2). The choice of these attributes aims to reduce the experiment's processing time and ensure better accuracy.

Table 2. Selected attributes

No.	Feature Importance
1.	ArrivalTime
2.	ConsultationTime
3.	ConsultationEndTime
4.	AgeFinal
5.	Month
6.	DayOfWeek

3.1 Data Modelling

For Data Modelling, the TimeWaiting attribute is discretized into three types of categorical values of "60P", "120P", and "160P. These categorical values are class attributes. The data set is divided into two parts, training data sets that contain seventy per cent (70%) of the data and the remaining thirty per cent (30%) of the data set as test data sets. Modelling uses the 10-fold cross-validation approach to evaluate the accuracy using training data sets. The training data set is used with classifications machine learning algorithms. Later, the test data will test the performance of the best models derived from the experiments. Descriptive analysis showed that the data set is skewed to the right with a small number of records. This skewed data record is an example of noisy data. Therefore, the study removed TimeWaiting records with a value greater than 160 (representing the noisy data).

The classification algorithms are LDA (Linear Discriminant Analysis), LR

(Logistic Regression), KNN (Nearest Neighbors), CART (Decision Tree), NB (Gaussian Naive Bayes) and SVM (Support Vector Machine). The modelling phase used the top three most correlated data sets: Puchong clinic, Anika clinic, and Batu 9 Cheras clinic. The three classification algorithm's model's accuracy with the highest score for each clinic is in Table 3,4 and 5.

Table 3: Results of Classification Puchong dataset

No	Algorithm	Accuracy
1.	LDA	79.21%
2.	CART	15.99%
3.	NB	1.79%

Table 4: Results of Classification on Anika dataset

No	Algorithm	Accuracy
1.	SVM	95.84%
2.	KNN	95.16%
3.	LDA	93.67%

Table 5: Results of Classification on Batu 9 Cheras dataset

No	Algorithm	Accuracy
1.	LDA	99.02%
2.	CART	98.62%
3.	LR	79.06%

For the Puchong dataset, the LDA algorithm gives the best results with a model accuracy of 79.21%. The second-best model is CART, with a model accuracy of 15.99%. The NB model scored a very low accuracy of less than 2%. For the Anika dataset, the SVM model gives the best result of 95.84%, followed by KNN with a score of 95.16% and lastly, LDA with a score of 93.67%. The LDA model scored the best classification accuracy with a value of 99.02% for the Batu 9 Cheras data set. The CART model also provides good accuracy of 98.62%. The model produced by the LR scored lower accuracy of 79.06%.

4 Data Analysis

As described previously, the study separated the data set into 70% for the training data set, and the remaining 30% is for testing. The study uses the best model produced during the modelling phase with the test data. The results for testing are described further in this section.

4.1 EVALUATION USING TEST SET

Table 3,4, and 5 show the LDA as the best performing classifier for Puchong and Batu 9 Cheras training data set, and SVM is the best performing classifier for Anika. Therefore, the study chose LDA as the best classifier for evaluation using the Puchong and Batu 9 Cheras clinics' test data. Meanwhile, the study also chose SVM as the best classifier for the Anika test data set.

PUCHONG TEST DATA SET

The LDA classification model scored an accuracy of 98.53% model on the test data (Table 6a). Based on the confusion matrix in Table 6a, LDA can correctly classify class for 60P. The class 60P represents TimeWaiting with a waiting time interval from 0 minutes to 53 minutes. Table 6b shows that this model has the lowest performance in predicting the class of 160P. The possible reasons are that the Puchong test data set contained a small fraction of sample data with a class value of 160P compared to class 60P.

Table 6a: Confusion Matrix for Puchong test data set (LDA)

	120P	**160P**	**60P**
120P	3327	55	66
160P	17	794	0
60P	21	0	6526

Table 6b: Accuracy, Sensitivity, F1 score and Support for the LDA model for Puchong data set

	Accuracy	**Sensitivity**	**F1 score**	**Support**
120P	0.99	0.96	0.98	3,448
160P	0.94	0.98	0.96	811
60P	0.99	1.00	0.99	6547
Average / Total	0.99	0.99	0.99	10,806

ANIKA TEST DATA SET

The SVM model produced an accuracy of 95.86% on the Anika Test data set. The confusion matrix in Table 7a shows that the SVM model can classify class attributes with a record value of 120P for TimeWaiting with an estimated waiting time interval from 19 minutes to 89 minutes very well. Based on Table 7b, the test data set does not have comprehensive sample data for class 160P. Hence the model is not able to test that particular class.

Table 7a: Confusion Matrix Anika test data set (SVM)

	120P	**160P**	**60P**
120P	17,117	0	7
160P	429	0	1
60P	839	0	12,490

Table 7b: Accuracy, Sensitivity, F1 score and Support for the SVM model for Anika data set

	Accuracy	**Sensitivity**	**F1 score**	**Support**
120P	0.93	1.00	0.96	17,124
160P	0	0	0	430
60P	1.00	0.94	0.97	13,329
Average / Total	0.95	0.96	0.95	30,883

Batu 9 Cheras Test Data Set

The LDA model performed satisfactorily on the Batu Cheras test data set with an accuracy of 99.07%. The model is very consistent in classifying all test data for all classes Table 8a. As shown in Table 8b, the LDA classification algorithm's model is the best compared to Puchong and Anika's models. Apart from the high percentage of accuracy, this model can also predict all classes consistently.

Table 8a: Confusion Matrix for Batu 9 Cheras test data set (LDA)

	120P	**160P**	**60P**
120P	5506	51	111
160P	1	1340	0
60P	8	0	11420

Table 8b: Accuracy, Sensitivity, F1 score and Support for the LDA model for Batu 9 Cheras data set

	Accuracy	**Sensitivity**	**F1 score**	**Support**
120P	1.00	0.97	0.98	5,668
160P	0.96	1.00	0.98	1,341
60P	0.99	1.00	0.99	11,428
Average / Total	0.99	0.99	0.99	18437

From the experimental results, we conclude that although each health clinic has similar data features, each clinic has its distinct characteristic and behaviour. Hence, other clinics cannot utilize the models generated from a different clinic. This behaviour is likely due to different organization culture among clinics. The developed machine learning model is unique only to the specific clinic and does not apply to other clinics. The discretization of the TimeWaiting values into three categories produced better classification results. However, there is a downside when using discretized wait time since the estimated wait time for the TimeWaiting attribute can be only estimated in a limited range (Table 1).

The Anika clinic test data set is unbalanced in term of its classes, specifically by the number of records in the 160P class. Model accuracy test on TimeWaiting attribute with the class of 160P was not possible due to a lack of records in that class. The study gained further insights from data analysis that may help avoid unnecessarily long waiting time for outpatients. Outpatients should come early to the clinics in densely-populated areas as these clinics will eventually be overcrowded by the public after 7.45 am. Based on the correlation analysis, the Puchong clinic is senior citizen-friendly since senior citizens' waiting time is shorter. All of the clinics are busiest on Mondays and Thursdays. The most active months are January and July, except for the Petaling district, where most patients frequented the clinics in July, August, October, November and December. A recommendation to avoid a long wait is that patients should arrive in the early morning before 7.30 am or in the afternoon around 4:00 pm.

5 Conclusion

This study can be used as initial input for the Ministry of Health to develop an online waiting time prediction system, especially for Puchong clinic, Anika clinic and Batu 9 Cheras clinic. Outpatient visit patterns are unique based on arrival time, day and month. The total number of medical officer consultations reaches its maximum of only one to two hours each day. An investigation into this area may identify the reason and make further corrective actions on working hours and scheduling of medical officer duty roster. For every district, there are less visited clinics. The less-visited clinics can loan or share their resources such as unused equipment or workforce owned to busier clinics. Several tasks can continue the current study; for example, to record all start and end time for each procedure that a patient has undergone. If pharmaceutical records are available, the clinic can predict the drugs needed by patients. If the weather information is for the period of illness is available, further study can perform the correlation analysis between illness and weather.

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