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Investigating airline passenger satisfaction: Data mining method

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A R T I C L E I N F O

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A B S T R A C T

In the current competitive environment, winning excellent services in the aviation industry can gain competitive advantages. Aviation companies should understand how their services satisfy customers' needs and want to achieve passenger satisfaction. This study examines airline passenger satisfaction using a data mining method. As for service attributes, we conclude that: (1) online/mobile boarding, (2) inflight wi-fi service, (3) baggage handling, and (4) inflight entertainment is the top 4 crucial service to be improved by the airline to gain passenger satisfaction.

1. Introduction

The aviation competition is growing as airlines attempt to acquire and retain customers. The change in airline passengers' behaviour following the pandemic crisis, travel restrictions, the ensuing economic crisis, market liberalisation, high technology, and reorganisation has resulted in airline services. Airlines can quickly and effectively adapt and change the market in such a competitive environment, which is crucial to the highly competitive aviation industry's success.

In reducing expenditure, the aviation sector has become aggressive. Price is first used as the main competitive instrument. Airlines will soon realise, however, that price competition alone in the longer term would not win the competitive situation because airlines respond relatively efficiently to changes in prices by their competitors' price (Chang & Yeh, 2002). According to Jou, Lam, Hensher, Chen, and Kuo (2008), the passenger not only considers the price but also the quality of the service when choosing an airline service. In the digital era, all of the airlines began to make several services: online reservations, online check-in, e-ticketing and apex fare. The airline's competitive advantages are the service quality sensate by the passengers in a highly competitive environment.

This paper will focus on the full services airline business model on passenger satisfaction rather than the low-cost carrier business model. For passenger of full-service airlines, the quality of services is very important and affect the perception and satisfaction that results in the purchase of airline services. Meanwhile, the needs and expectations of low-cost carriers' passengers could be different.

Many previous research studies identify that winning excellent services in the aviation industry can gain competitive advantages. Passengers compare the airline to other airlines and to many industries and factors. Airlines thus need to provide an excellent service and facility for their passengers (Leon & Martín, 2020). Passengers in airlines have raised their service quality expectations. Satisfied passengers will benefit the long-term survival of the airline (Gudmundsson & Rhoades, 2001). An airline's capacity to distinguish its services enables customers to become a key strategy rather than an operational instrument (Dolnicar, Grabler, Grün, & Kulnig, 2011).

The aviation industry also should evolve from transport to hospitality and services. By offering passengers a quality service with a pleasant experience, greater customer satisfaction and loyalty will be rewarded. Quality of services is essential for airlines to survive and strengthen their competitiveness, thus ensuring profitability (Martín, Román, & Espino, 2008). Aviation companies should understand how their services satisfy customers' needs and want to achieve passenger satisfaction.

Several previous studies mentioned airline service qualities as a significant driver of passenger satisfaction (Jiang, 2013; Namukasa, 2013; J. W. Park, Robertson, & Wu, 2006), passengers' loyalty (Dolnicar et al., 2011; Etemad-Sajadi, Way, & Bohrer, 2016; Jiang & Zhang, 2016; Namukasa, 2013), and the choice airline (Adeola & Adebiyi, 2014; Ariffin Mohd, Yajid, & Johar, 2020; Chen, Huang, Chen, Zhong, & Cheng, 2017; Suzuki, 2004). Therefore, high-quality services' delivery becomes a marketing availability for the aviation industry as a market rivalry (Hapsari, Clemes, & Dean, 2017). If an airline offers high-quality services concerning its competition, it will lead the market. For the airlines to understand their relatively competitive benefits in terms of service quality is therefore strategically important.

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Transactions on an airline industry have even recorded hundreds or almost thousands of transactions in one day. To analyse this large, complex, and flexible empirical data, advanced methods are needed to find useful information as evaluation materials (Mrzic & Zaimovic, 2020). The data mining approach for big data can be a solution to complex data processing by offering better methods to produce more accurate predictions.

This study examines airline passenger satisfaction using a data mining method, especially what kind of service is desired most by airline passengers using feature selection. To get better predictive results and compare, we use several classifiers rather than only a single classifier. Some of the classification algorithms employed for this research include decision tree, random forest, gradient boosted tree, k-NN, Naïve Bayes, rule induction, logistic regression, neural net, deep learning and support vector machine.

This study aims to investigate airline passenger satisfaction so that it can be used as a reference in strategies to help airline management understand how airline passenger views their airline services using a customer-driven service assessment approach.

This study offers a guideline to airlines that provide adequate service levels to respond to customer needs. This study will contribute to the improvement of better airlines management as their competitive advantages and improve the quality of certain services compared to their competitors.

2. Literature review

Service quality and passenger satisfaction are two variables that are sometimes used in many previous kinds of research interchangeably because both are measurement variables linked to the attitudes of passengers regarding service expectation and perception. This literature review will talk about airline service quality and airline passenger satisfaction as important according to previous research as the important variable or research.

2.1. Airline service quality

Only the customer can define service quality in the passenger airline industry. Therefore, several investigations on service quality have been carried out on the notion that customer perception and evaluation of service quality. As perceived by customers, service quality can be measured using evaluation analyses that are based on a comparison of customer expectations and experiences.

Due to its heterogeneity, intangibility, and uniqueness, airline service quality is difficult to describe and measure (Laming & Mason, 2014). Nevertheless, several conceptual and empirical studies were carried out to explore the quality of service problems in the aviation industry. Many schemes have been proposed in the context of passengers for defining dimensions or attributes of service quality (Etemad-Sajadi et al., 2016). Improve service enhanced profit by increasing the market share by making new and more loyal passenger choice decisions.

Previous studies elaborate service quality in the airlines' industry as an important issue related to several conceptual frameworks and methods. Chen (2008) examine relationships for air passengers between service quality, perceived value, and satisfaction using a structural equation model (SEM). While some papers apply SERQUAL methods to investigate the airline's service quality, such as Chou, Liu, Huang, Yih, and Han (2011) in comparison of expectation value and perceived value with Taiwanese airlines study case. Also, Hussain, Al Nasser, and Hussain (2015) identify airline service quality analysed by service provider image, passenger expectation, perceived value, passenger satisfaction and brand loyalty with Dubai-based airlines study case.

Some other studies employ VIKOR method modification approach to evaluate airline service quality to reduce the gaps for the aspired level. The empirical study from Kuo (2011), investigate airline service quality between China-Taiwan route airlines to understand the gaps, strengths, and weaknesses to improve airline service quality using customers survey. Another VIKOR method modification study by Liou et al. (2011a) investigates service quality among Taiwanese domestics airlines to know the priorities gaps to improve customer satisfaction needs.

A comparison study among China domestic airlines conducted by Jiang and Zhang (2016) explain service quality is a significant factor to influence airlines passenger satisfaction levels and customer loyalty. Quantitative research conducted by Lim and Tkaczynski (2017) examine among more than 500 international students in Australia found that airline service quality is an important expectation factor to choose an airline for touristic and non-touristic reasons.

Furthermore, Wu and Cheng (2013) propose airline service quality development in four dimensions: interaction quality, physical environment quality, outcome quality and access quality which represent passenger perception.

In many studies, survey methods have been used to measure airline service quality. Most of these studies have been presented to be examined in the context of service quality index (Waguespack & Rhoades, 2014), passenger satisfaction survey (Bellizzi, Eboli, & Mazzulla, 2020) as well as airlines' service quality perception (Suki, 2014). Some studies assess the quality of airline service included on-time performance, handling baggage, food quality, seat comfort, check-in, and in-flight service (Bellizzi et al., 2020).

2.2. Airline passenger satisfaction

Passenger satisfaction in the airline industry is a complex customer knowledge and experience and can be defined as an assessment that passengers have encountered (Tahanisaz, & shokuhyar, S., 2020). Understanding passengers' expectations in an airline service industry are essential since passengers compare their performance with their expectations. Research from Hu and Hsiao (2016) using Kano model in quality risk assessment for Taiwanese airlines case study mention poor airline service quality cause passenger dissatisfaction. Chen (2008) explains airlines passenger satisfaction is indirectly affected by airlines perceived service quality performance moderated by perceived value.

An empirical study using Kano model by Tahanisaz, and shokuhyar, S. (2020) explain that capability of airline to satisfy the passenger in various services considering pre-purchase expectation increases the degree of passenger satisfaction. Otherwise, Leon and Martín (2020) use the Fuzzy segmentation method for technical quality and functional quality in the US airline industry to determine airline passenger satisfaction.

Many studies have been done to assess the service quality of airlines and airline passenger satisfaction levels using traditional statistical testing while others have used multiple-criteria methods to accomplish the same goals. In the field of machine learning method, the study of airline passenger satisfaction is usually measured using sentiment analysis (Khan & Urolagin, 2018; Kumar & Zymbler, 2019; Lucini, Tonetto, Fogliatto, & Anzanello, 2020), which is analyze text, tweet or comment to detect positive or negative satisfaction. Then this study aims to investigate the airline passenger satisfaction using more advanced methods of big data machine learning approach from complex surveys to detect the priority aspect of airlines service as the gap of this study.

3. Methodology

3.1. Feature selection

Features selection is an essential pre-processing data management technique for processing data sets (García et al., 2015). The feature selection process is defined as selecting the optimal minimum features to select more representative characteristics with more significant discrimination for the original dataset (Du, Rong, Michalska, Wang, & Zhang, 2019).

Feature selection is an essential tool when dealing with high dimensional data (V. Kumar, 2014). Data processing with several input features is very problematic in machine learning data processing, especially for large data sizes or noisy data or redundant information. In a dataset, hundreds and thousands of inputs are often contained to predict a target class in some fields. Some features may be needed, but others may not be appropriate for the target class prediction. It is intended to filter out non-representative features of the complete data set because certain variables will affect the prediction results because of feature noise. Therefore, feature selection is a problem solver that selects a small sub-set of appropriate features without losing any prediction against all datasets.

Feature selection can be divided into two main approaches (Solorio-Fernández, Carrasco-Ochoa, & Martínez-Trinidad, 2016) as a filtering method wrapper method. The filter-based approach evaluates and picks a sub-set from features based on a given dataset's general characteristics. The wrapper-based approach is based on a specific classification algorithm used in research, and the output performance is used as an evaluation criterion.

The wrapper-based method is shown in Fig. 1. Each data set is initially divided into training and test sets. Each training set is further examined to train the methods of function selection. First, each training subset generates functional selection models. After designing the model, the validation subset is used to determine its accuracy. Each machine learning will investigate the performance of models built through a training subset. To replace the existing subset, range, cross-over and variations are added. So, the selection process is completed until the desired condition is met. With maximum precision in the validation subset, the selected training subset features are performed. Finally, the test set is used to test the prediction model output with the same features chosen.

This research applies the forward selection form of the wrapper selection method for selecting sub-set evaluation criteria for the machine learning algorithm. The wrapper approach selects the optimum combination of selected assessment features ideally suited to the machine learning algorithms' performance measurement model. This approach generally enhances its efficiency. However, this method takes a longer time than other methods in terms of time calculation effort.

3.2. *The supervised machine learning algorithm*

Classification is an essential issue in the data mining field. In classification, we use a machine-learning algorithm to train and test the dataset's attributes to predict a categorical attribute, called the class label, which indicates the class target. This process evaluates the performance of model supervised machine learning algorithms by accurate predicting.

Supervised machine learning algorithms (or classifiers) learn from a labelled training dataset to uncover insights, patterns and connections. The satisfaction status in this study is the dataset label feature. The supervised machine learning algorithm learned how the characteristics of features correspond to the label feature during the training.

This study will examine and compare several classifiers. The purpose is to get the best prediction for the given dataset. Eight classifiers will be applying as decision tree, random forest, gradient boosted tree, k-NN, Naïve Bayes, rule induction, logistic regression, neural net, deep learning and support vector machine.

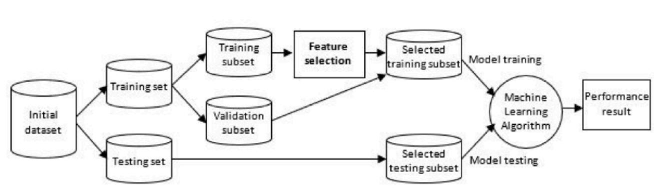

Fig. 1. Flow chart process of data mining of this study: feature selection, machine learning algorithm, and performance model.

3.2.1. *Decision tree*

The decision tree algorithm is one of the most popular and common classification methods because humans easily interpret it because of its simplicity and clarity. A decision tree is a prediction model algorithm that uses a hierarchical structure or tree structure to collect nodes intended to decide values' affiliation to classes or numeric target values (Wahyono et al., 2019).

The decision tree is a predictive model that identifies an item's observations (represented in a branch) to a conclusion about the item's target value (represented in a leaf). Compared to an upside-down tree structure, and root represent the initial dataset, branches represent feature relationships that point to that class label, and leaves represent the class labels shown in Fig. 2.

3.2.2. *Random forest*

Random Forest is a learning algorithm that belongs to the category of supervised learning. Random Forest is useful both for classification and regression problems in machine learning. Ensemble learning is based on the concept of "learning from data." Random forest algorithm has the central concept to build a lot of many decision trees (Svetnik et al., 2003).

Random Forest works by combining many trees and making predictions with each decision tree shown in Fig. 3. The development process can be described as follow: first, select random points from the training set, then build decision trees from the data (second step), choosing the number of the decision trees, then repeat steps 1 and 2, the last one is building a decision tree for all of the input data. Random forest works with each decision tree to predict the final decision based on majority votes. The final results can be consistent but not predict all the cases. Together, all trees predicted the correct expected output. Random forest generally results in a comprehensive better model (Pavlov, 2019).

3.2.3. *Gradient boosting tree*

A gradient boosted tree model is a supervised machine learning algorithm in classification models, which boosting methods with gradually improved estimates to achieve predictive results. Gradient boosting trees use a flexible nonlinear regression method that improves trees' accuracy. A sequence of decision trees that produce weak prediction models is created by applying weak algorithms to the increasingly changed data. Gradient boosting is a modification of decision trees by improves the quality to avoid overfitting. The method of gradient boosting tree generally boosts the tree to minimise these overfitting problems.

3.2.4. *K-NN Classifier*

The k-nearest neighbour algorithm is a supervised learning algorithm that compares new data with the nearest neighbours' previous

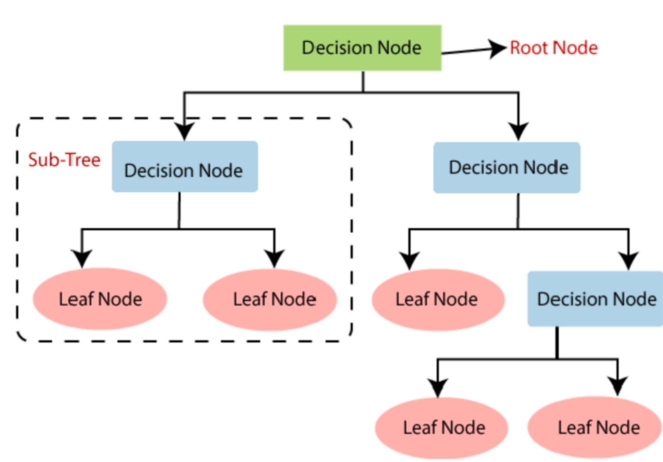

Fig. 2. Diagram of the decision tree.

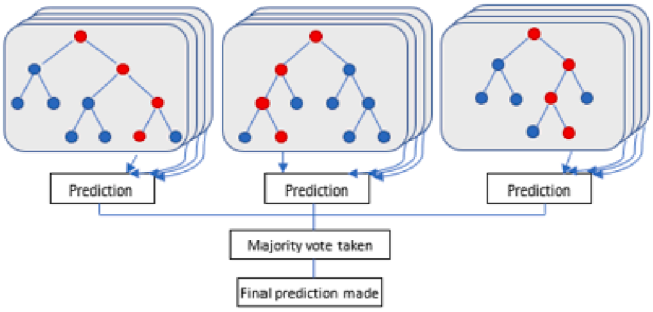

Fig. 3. Information travel of random forest.

training data sample. k-nearest neighbour is a simple algorithm that extracts and classifies all available cases based on a similarity behaviour (e.g., distance functions). K-nearest neighbour was already used as a non-parametric technique in statistical estimation and pattern recognition. A non-parametric model is a model that does not assume anything about the distribution of instances in the dataset. The advantage is that the model's class decision line can be very flexible and non-linear.

The k-nearest neighbour is an algorithm that categorizes a data point according to the classification of its neighbours. As shown in Fig. 4, this indicates that if there are four green dots and two red dots surrounding a data point, the majority vote will suggest that the data point maybe green. The parameter k in k-nearest neighbours is the nearest counting neighbour in the majority vote.

The k-nearest neighbour is also called a lazy learning algorithm. Despite its simplicity, many of the problems of classification and regression were successful for the k-nearest neighbour.

3.2.5. Naïve Bayes

Naïve Bayes is a straightforward supervised machine learning algorithm. Naïve Bayes classifier is a classification derived from the Bayesian probability theorem. The classification method uses statistical and probability methods that predict future opportunities based on previous experience. This classifier's main characteristic is the naïve assumption of independence for any event or condition (Ketjie, Christanti Mawardi, & Jaya Perdana, 2020). While the assumption is naïve, experiences indicate Naïve Bayes' classification also works well.

The Naïve Bayes equation for classification is given the equation:

$$p(C_k|x_1,\dots,x_n)$$

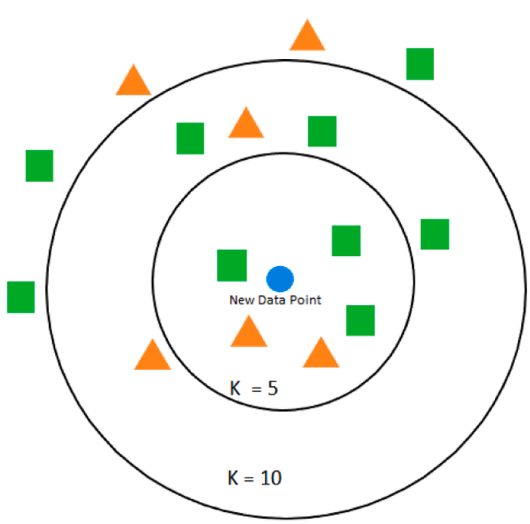

Fig. 4. k-nearest neighbour surrounding data point.

$$p(C_k|x) = \frac{p(C_k)p(x|C_k)}{p(x)}$$

$$y\,(C_k) = p(C_k)\prod_{i=1}^{n} p(x_1|C_k)$$

C_k = a class label.
x = the feature.
n = the number of features.

The method forecasts a class based on the likelihood of the function value in that class. It first measures the probability of a vector categorized into one class based on how its probability fits the class. Then it normalizes the probability of all classes to obtain the probability of a class assignment. Finally, the outcome is the highest probability of selecting the class.

Naïve Bayes is a simple technique with generating models that assign class labels to problem instances, defined as vectors of functional meaning, in which a specific set includes class labels. Naïve Bayes advantage is that only a small number of training data are needed to calculate classification parameters.

3.2.6. Rule Induction

Rule induction is machine learning methods that create useful "if-else-then" type rules which emphasise an induction relationship between the attributes and class labels based on statistical significance (Fernández et al., 2010). In the rule induction algorithm, a series of observations derive formal rule extracted. The algorithm for rule induction takes training data as the input and generates rules through cluster analysis of the table. It uses information theory calculations to choose the input (and their values) variables most important to the output variables values. The benefit of rule induction algorithm is easy to understand and can be readily applied to previous first-order logic experience.

3.2.7. Logistics regression

Logistic regression is a supervised learning algorithm using the core of the logistic function method, the logistic curve shown in Fig. 5. Logistic regression is a sufficient regression analysis for the class label (binary). Logistic regression evaluates the relationship between the dependent variable and one or more independent variables by estimating the probability using a logistic function. Thus, it uses similar methods to deal with the same number of problems with linear regression, with the latter using a cumulative normal distribution curve instead.

Logistic regression uses equations as a representation, very similar to linear regression transformed using logistic formula. Logistic regression mathematically estimates an output logistic regression function defined as:

$$logistics\ (p) = \frac{1}{1+e^{-p}}$$

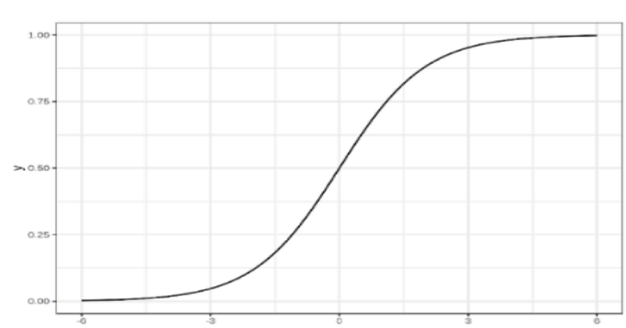

Fig. 5. Logistics regression curve.

$$p = \beta_0 + \beta_1 x_1 + \ldots + \beta_i x_i$$

$$L(\beta_0, \beta) = \prod_{i=1}^{n} p(x_1)^{y} \left(1 - p(x_i)^{1-y}\right)$$

logistics(p) = output between 0 and 1 (probability estimate).

p = input to the function (formula prediction).

e = base of natural log.

L = likelihood function for logistic regression.

In order to minimize the misclassification rate, the prediction should y = 1 when $p \geq 0.5$ and y = 0 when $p < 0.5$. It means β_0 + β_1 x_1 + ⋯ + β_i x_(i) is non-negative. The model fit is another significant consideration when choosing the model for the logistic regression analysis. The logistic regression algorithm's coefficient was estimated from the training data performed using the maximum likelihood estimate (Heinze & Schemper, 2002).

Compared to other classification techniques, logistic regression is relatively quick but is sufficiently accurate. The problem is also the same as the linear regression since both approaches are too generalized for complex relations between variables.

3.2.8. Neural net

A neural net algorithm is a computational model or mathematical model influenced by human biological neural networks' functional aspects and structure. Neural net adopts the brain ability, which can supply variations stimulation, carry out process information and set output (Günther & Fritsch, 2010).

The neural net algorithm works excellent to generate complex relationships between inputs and outputs and works excellent when finding patterns in the data. Neural networks can be applied in memory simulation, prediction, recognition, classification and many other tasks.

The neural net algorithm has three different layers of consciousness processing functions: input layer, hidden layer and output layer, where the system decides what to do based on the dataset. In this network, information travels from the input nodes to the output nodes in only one direction, through the hidden node without loops of information travel signal, as shown in Fig. 6.

3.2.9. Deep learning

Deep learning is a machine learning algorithm that uses sequential sets of neuron layers instead of a single set layer. A multi-layered feedforward of a neural network is trained using the stochastic gradient descent method by the back-propagation technique (Guo et al., 2016).

In deep learning, there are several layers of neural networks involved in the deep learning algorithm process. There are an input layer, many hidden layers and an output layer. In the first layer of the neural network, raw data from the input are received by the first layer and passed to the second layer. The network can be made up of several hidden layers. Information is further processed by adding additional information and passing it to the next level. This process works through until the desired result is obtained. The pattern is shown in Fig. 7 to understand how the computation process works.

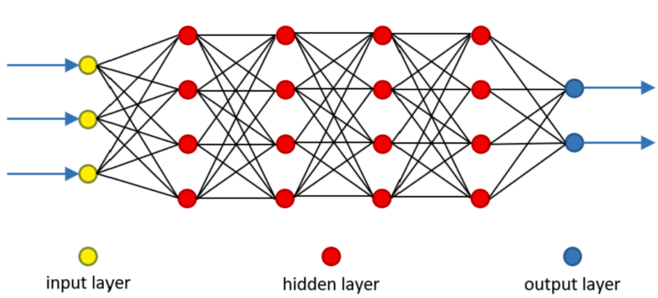

Fig. 6. Information travel of Neural Network.

3.2.10. Support vector machine

Support Vector Machines (SVM) was first developed by Cortess and Vapnik (1995) from structural risk minimization research. The idea is to obtain the optimal separatory hyperplane in the two distances by optimizing the difference between the closest distance's values, as shown in Fig. 8. SVM discovers the hyperplane using a support vector and a margin (Hsu & Lin, 2002; Salcedo-Sanz, Rojo-Álvarez, Martínez-Ramón, & Camps-Valls, 2014).

A support vector machine constructs hyperplane in a high-dimensional or infinite space, which can be used for regression, classification, or other tasks. SVM can control capacity and transformability in preparing implementation decisions to make it very useful and widely functioning in machine learning (Cortess & Vapnik, 1995).

4. Research methods

This study builds on a data mining approach that provides data source, data preparation by cleansing data as necessary, modelling the data by feature selection modelling, selecting algorithm, building a predictive model, and performing performance evaluation by verifying the final model.

4.1. Data source

In this research, the dataset was obtained from the Kaggle Dataset of The U.S. Airline Passenger Satisfaction Dataset describes passenger satisfaction by conduct a survey at the airport after arriving in 2015 with collected data 129.880 passenger samples that using full-service airline carriers. The dataset details each customer's information as it relates to age, gender, type of travel, flight distance, class type, departure and arrival delay.

The dataset also contains 14 airline services of customer satisfaction levels ranging from values 0–5. The airline services for measured satisfaction level categories such: inflight wi-fi service, departure/arrival time convenience, ease of online booking, gate location, food and drink, online boarding, seat comfort, inflight entertainment, on-board service, leg-room service, baggage handling, check-in service, inflight service, and cleanliness.

In conclusion, the airline passenger gives their final opinion either dissatisfied, neutral or satisfied. However, in this paper, we classify into the binary class, which classify 'dissatisfy' and 'neutral' into one group. The reason is to maintain high-quality service. When neutral is treated poorly, the airline passenger can be dissatisfied.

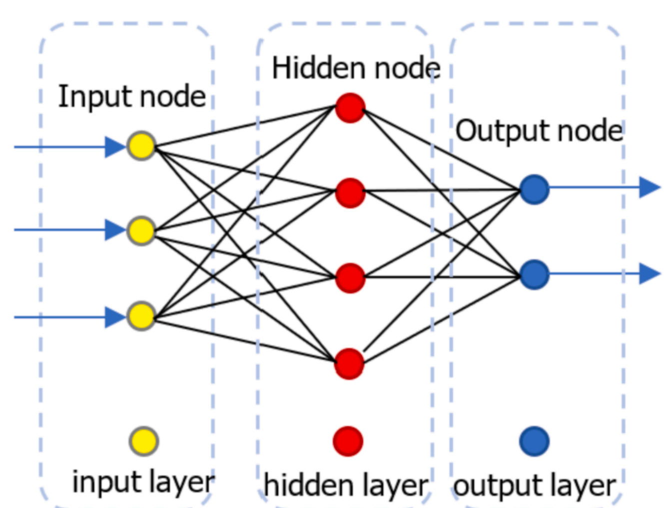

Fig. 7. Information travel of deep learning.

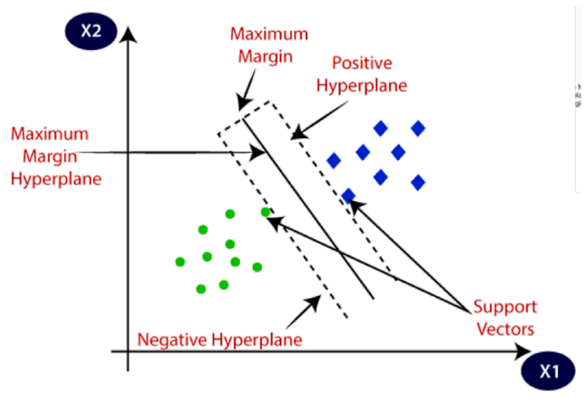

Fig. 8. Support vector machine illustration.

4.2. Data preparation

The first step in data preparation is handling data by filtering data without containing the missing value. We eliminate missing values by the final dataset as 129,487 samples.

The descriptive statistic of categorical attributes is shown in Table 1. The label attribute describes 73,225 respond neutral or dissatisfied (56.55%), and 56,262 respond satisfied (43.45%). In the gender category, men (49.26%) and women (50.74%) are almost the same percentages. For customer type, the disloyal customer is 18.31% and the loyal customer is 81.88%. In the type of customer travel, 69.08% of which is business travel, the remaining 30.92% is personal travel. In the passenger class category, 44.89% use the economy, 7.24% use economy plus, and the remaining 47.87% use business class.

The descriptive statistics of numerical attributes shown in Table 2 contain age, flight distance, departure delay (in minutes), arrival delay (in minutes), and 14 services category of opinion survey rating range from 0 until 5. The zero-rating means no service, 1 means very bad service, 2 means poor quality, 3 means fine quality service, 4 means good quality and rating 5 means excellent service.

The correlation matrix among attributes is shown in Table 3. Between age and customer type correlated 0.28. Between the type of travel and customer type correlated 0.31. Therefore, departure delay and arrival delay are highly correlated as 0.97.

The histogram and kernel density estimation plot for each attribute is shown in Fig. 9. The categorical attribute is visually by decomposition according to the label ('dissatisfied or neutral' is blue and 'satisfied' is green). The numerical attribute is visually by kernel density estimation plot decomposition by label class.

This study applies the 10-fold cross-validation strategy to split training data and testing data for each classifier and avoiding sample variability, affecting model performance and minimising the effects of bias (Kohavi & Edu, 1993) as illustrated in Fig. 10. The parameter uses a stratified sampling of 10-fold cross-validation in which partitions are selected so that the average response values are approximately the same across all partitions.

Table 1
Descriptive statistic of categorical attributes.

Categorical	N	Least		Most	
Attribute		n	value	n	value
Label	2	56,262	satisfied	73,225	neutral or dissatisfied
Gender	2	63,784	male	65,703	female
Customer type	2	23,714	disloyal customer	105,773	loyal customer
Type of travel	2	40,042	personal travel	89,445	business travel
Class	3	9380	eco plus	61,990	business

Table 2
Descriptive statistic of numerical attributes.

Numerical attribute	min	average	max	SD
Age	7	39.43	85	15.12
Flight distance	31	1190.21	4983	997.56
Inflight wi-fi service	0	2.73	5	1.33
Departure/arrival time convenient	0	3.06	5	1.53
Ease of online booking	0	2.76	5	1.40
Gate location	0	2.98	5	1.28
Food and drink	0	3.21	5	1.33
Online boarding	0	3.25	5	1.35
Seat comfort	0	3.44	5	1.32
Inflight entertainment	0	3.36	5	1.33
On-board service	0	3.38	5	1.29
Leg room service	0	3.35	5	1.32
Baggage handling	0	3.63	5	1.18
Check-in service	0	3.31	5	1.27
Inflight service	0	3.64	5	1.18
Cleanliness	0	3.29	5	1.32
Departure delay in minutes	0	14.64	1592	37.94
Arrival delay in minutes	0	15.09	1584	38.47

4.3. Feature selection method

This study will use forward selection to filter out unnecessary features in the clickstream dataset for the feature selection method. The selection procedure of forwarding selection criteria is evaluated and compared with the best previous according to these criteria from the given dataset. The forward selection starts by choosing the feature with sufficient prediction ability in a subset. If the new feature subset becomes better, then the previous best feature subset is replaced with a new feature subset. This looping process stops until no more subset of features improves the model to a statistically significant extent. As an illustration, it is shown in Fig. 11 about the flow chart process of the feature selection to get the optimal features subset selected.

4.4. Supervised machine learning algorithms

This study will compare eight supervised machine learning algorithms as decision tree, random forest, gradient boosted tree, k-NN, Naïve Bayes, rule induction, logistic regression, neural net, deep learning and support vector machine methods to develop prediction models for predicting online shopper behaviour on clickstream data. These classifier algorithms mostly used techniques for prediction.

4.5. Performance evaluation metric

The performance evaluation metric of prediction accuracy and F-score is calculated to examine each supervised machine learning algorithm's prediction performance. Both evaluation metrics can be measured by the confusion matrix as shown in Table 4. The average prediction accuracy level is calculated based on how many data samples of the prediction model are correctly classified in a given testing set. As well, the F-score is a balance between precision and recall. The higher F-score shows more perfect harmony between precision and recall.

The prediction accuracy and F-score are obtained by:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$F1\ score = 2 \times \frac{Precision \times Recall}{Precision + Recall} = \frac{TP}{TP + \frac{1}{2}(FP + FN)}$$

This study also investigates the receiver operating characteristic (ROC) graphs of model classifiers in addition to these two commonly used metrics. This graphical curve is used to visualize the predictive model because the discrimination threshold varies in adjusting a score threshold.

Table 3
Correlation matrix among attributes.

value	g	ct	a	tt	c	fd	iws	dtc	eob	gl	fad	ob	sc	ie	obs	lrs	bh	cs	is	cl	ddm	adm
Gender																						
Customer type	−0.03																					
Age	−0.01	0.28																				
Type of travel	−0.01	0.31	−0.04																			
Class	0.00	0.00	0.00	0.00																		
Flight distance	0.00	0.23	0.10	−0.27	0.00																	
Inflight wi-fi service	−0.01	0.01	0.02	−0.11	0.00	0.01																
Departure/Arrival time convenient	−0.01	0.21	0.04	0.26	0.00	−0.02	0.34															
Ease of Online booking	−0.01	0.02	0.02	−0.13	0.00	0.07	0.71	0.44														
Gate location	0.00	0.00	0.00	−0.03	0.00	0.01	0.34	0.45	0.46													
Food and drink	0.00	0.06	0.02	−0.07	0.00	0.06	0.13	0.00	0.03	0.00												
Online boarding	0.05	0.19	0.21	−0.22	0.00	0.21	0.46	0.07	0.40	0.00	0.23											
Seat comfort	0.03	0.16	0.16	−0.13	0.00	0.16	0.12	0.01	0.03	0.00	0.58	0.42										
Inflight entertainment	0.00	0.11	0.07	−0.15	0.00	0.13	0.21	−0.01	0.05	0.00	0.62	0.28	0.61									
On-board service	−0.01	0.05	0.06	−0.06	0.00	0.11	0.12	0.07	0.04	−0.03	0.06	0.15	0.13	0.42								
Leg room service	−0.03	0.05	0.04	−0.14	0.00	0.13	0.16	0.01	0.11	−0.01	0.03	0.12	0.10	0.30	0.36							
Baggage handling	−0.04	−0.02	−0.05	−0.03	0.00	0.06	0.12	0.07	0.04	0.00	0.04	0.08	0.07	0.38	0.52	0.37						
Check-in service	−0.01	0.03	0.03	0.02	0.00	0.07	0.04	0.09	0.01	−0.04	0.09	0.20	0.19	0.12	0.24	0.15	0.23					
Inflight service	−0.04	−0.02	−0.05	−0.02	0.00	0.06	0.11	0.07	0.04	0.00	0.04	0.07	0.07	0.41	0.55	0.37	0.63	0.24				
Cleanliness	0.00	0.08	0.05	−0.08	0.00	0.10	0.13	0.01	0.02	−0.01	0.66	0.33	0.68	0.69	0.12	0.10	0.10	0.18	0.09			
Departure delay (in minutes)	0.00	0.00	−0.01	−0.01	0.00	0.00	−0.02	0.00	−0.01	0.01	−0.03	−0.02	−0.03	−0.03	−0.03	0.01	0.00	−0.02	−0.05	−0.01		
Arrival delay (in minutes)	0.00	0.00	−0.01	−0.01	0.00	0.00	−0.02	0.00	−0.01	0.01	−0.03	−0.02	−0.03	−0.03	−0.03	0.01	−0.01	−0.02	−0.06	−0.02	0.97	

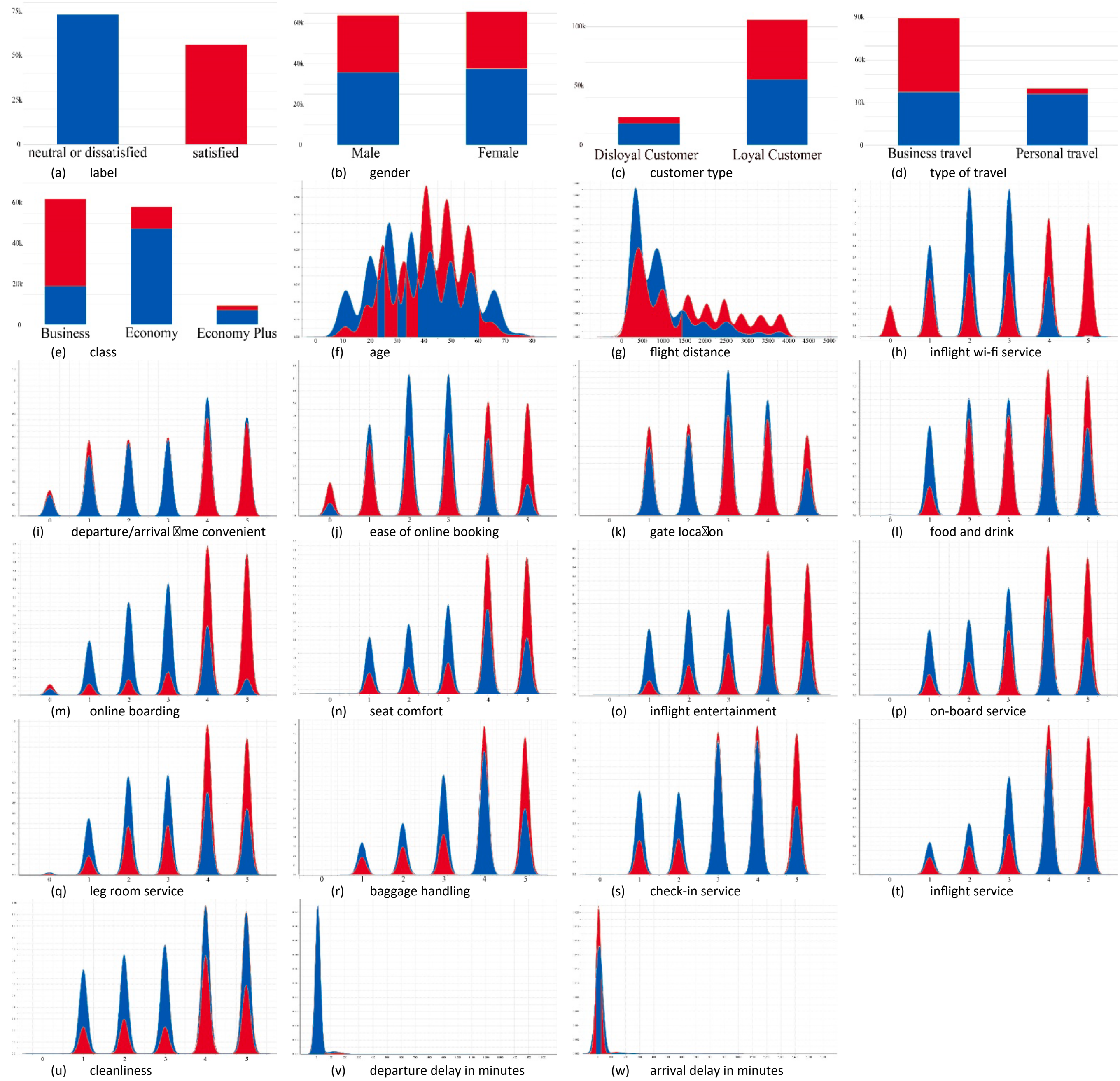

Fig. 9. The histogram and kernel density estimation plot for each attribute (blue = dissatisfied or neutral, red = satisfied). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

As shown in Fig. 12, the ROC curves are a very useful tool for organising, illustrating, and analysing prediction models based on their performance. It provides a performance graphing technique useful in the unbalanced classes appearance.

One of the advantages of the ROC curve is that it allows visualization and classifier performance regardless of the class distribution of error costs. The AUC (area under the ROC curve) is a numerical value representing the probability of the model prediction for ranking positive instances that are randomly selected higher than the negative instances.

5. Results

5.1. Results on feature selection

In Table 5, we can see the result of the selected feature subset for each different classification algorithm of feature selection. Among all validation processes of feature selection, it shows the "online boarding" attribute as the first rank by all performance measurement validation models about the airline passenger satisfaction. This is very interesting because all classifiers place online boarding as the most important service in determining airline passenger satisfaction.

Fig. 10. The 10-fold cross-validation strategy to split training data and testing data.

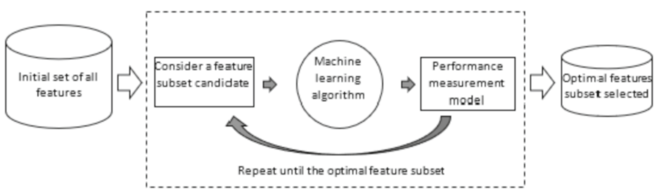

Fig. 11. Flow chart process of feature selection (wrapper methods).

Table 4
Confusion matrix.

↓Predicted\actual→	neutral or dissatisfied	satisfied
Neutral or dissatisfied	True Positive	False Positive
Satisfied	False Negative	True Negative

The second most selected feature subset is the type of travel by all classifiers except GBT. Precisely, Neutral Net and Support Vector machine as machine learning use numerical attribute choose business travel type as a priority. However, this 'type of travel' is a non-service attribute to consider airline passenger satisfaction.

The third most selected feature subset is inflight wi-fi service by all classifiers except SVM. This mean inflight wi-fi service is considered a strong feature service to determine airline passenger satisfaction. Moreover, baggage handling and inflight entertainment service are ranked as the fourth and fifth feature subset in different classifiers as we can consider these baggage handling and inflight entertainment service as other services determining airline passenger satisfaction.

5.2. *Results on performance prediction after feature selection*

In Table 6 below, we can see performance prediction results among supervised machine learning algorithms after feature selection to predict airline passenger satisfaction.

The study compared ten machine learning algorithm algorithms, as Deep Learning demonstrate the highest accuracy as 95.42% and highest F score as 95.99%, to predict airline passenger satisfaction. Neural Net follows it as accuracy 94.59% and F score 95.26%.

5.3. *Results on ROC after feature selection*

This study also compares the ROC graphs to ensure the visualisation of performance prediction among classifiers. Fig. 13 shows the ROC curve result that illustrates Deep Learning as the fittest classifier with AUC score of 0.992, followed by Random Forest (AUC score = 0.987) and Neural Net (AUC score = 0.986). This ROC result shows that Deep learning algorithm is the fittest classifier for predicting airline passenger satisfaction.

5.4. *Results on performance prediction for selected features*

After we get results from feature selection, we try to train again using the selected top 5 feature subset for all machine learning algorithms without the feature selection process. The top 5 feature subsets as online boarding, type of travel, inflight wi-fi service, baggage handling, and inflight entertainment.

In Table 7 above, we can see performance prediction results among supervised machine learning algorithm only using selected feature attribute to predict airline passenger satisfaction.

Still, we get Deep Learning to demonstrate the highest accuracy among other algorithms as 92.08% and also highest F score as 93.03%, to predict airline passenger satisfaction.

5.5. *Results on ROC for selected features*

Again, we the ROC graphs for the top 5 selected features to ensure the visualisation of performance prediction among classifiers. Fig. 14 shows the ROC curve result that illustrates Deep Learning as the fittest classifier with AUC score of 0.977. This is confirmation that Deep learning algorithm is the most robust classifier for predicting airline passenger satisfaction.

6. Discussion of results

The top 4 crucial service findings to be improved by the airlines especially by the full-service carriers to gain passengers satisfaction are online boarding, inflight wi-fi service, baggage handling, and inflight entertainment. This section will compare findings with other literature reviews.

Comparing with Bellizzi et al. (2020) findings, passengers evaluate some aspects of services provided by airlines, which is the judgment of priorities service aspect must be convenient and level of satisfaction according to passenger priorities on each services aspect.

An online questionnaires research for experience using air transportation by Nurhadi, Ratnayake, and Fachira (2019) found that travellers felt dissatisfaction because of lack of Wi-Fi and lack of in-flight

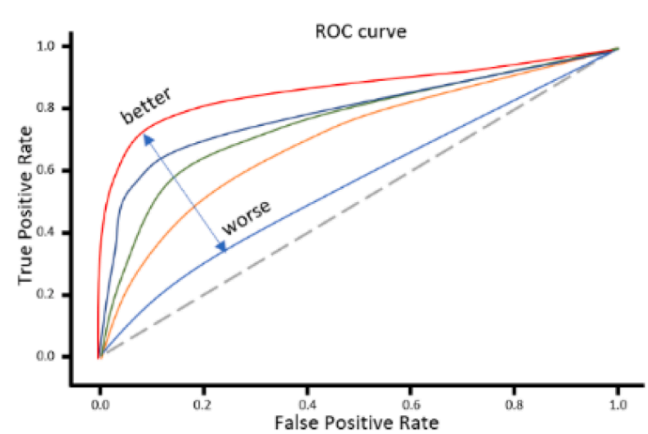

Fig. 12. The ROC curves illustration.

Table 5
Selected feature subset by feature selection process among classifiers.

	1	2	3	4	5	6	7	8	9	10
DT	Online boarding	Type of travel	Inflight wi-fi service	Baggage handling	Customer type	Check-in service	Cleanliness	Seat comfort	Gate location	Class
RF	Online boarding	Type of travel	Inflight wi-fi service	Inflight entertainment	Customer type	Class	Gate location	Check-in service	Seat comfort	Baggage handling
GBT	Online boarding	Class	Inflight wi-fi service	Type of travel	Inflight entertainment	On-board service	Customer type	Flight distance	Check-in service	Arrival delay in minutes
NN	Online boarding	Type of travel = business travel	Inflight wi-fi service	Inflight entertainment	Customer type	On-board service	Class = business	Gate location	Check-in service	Inflight entertainment
DL	Online boarding	Type of travel	Inflight wi-fi service	Gate location	Inflight service	Customer type	Class	Baggage handling		
NB	Online boarding	Type of travel	Inflight wi-fi service	Baggage handling	Customer type	Departure/ arrival time convenient	Gender		Class	Inflight entertainment
k-NN	Online boarding	Type of travel	Inflight wi-fi service	Baggage handling	Customer type	Gate location	Seat comfort	Inflight service		
LR	Online boarding	Type of travel	Inflight wi-fi service							
RI	Online boarding	Type of travel	Inflight wi-fi service	Inflight entertainment	Flight distance	Gate location	Ease of online booking			
SVM	Online boarding	Type of travel = business travel	Inflight entertainment	Check-in service	Food and drink	Gate location				

entertainment, on other hand, travellers seem to be satisfied using online booking. Nurhadi et al. findings are in line with our research.

As well as the online survey study from Park (2019) suggest online airline services and customer in-flight experiences be improved to increase customer satisfaction, as well as the intention to reuse.

Likewise, according to the multicriteria satisfaction analysis method by Tsafarakis, Kokotas, and Pantouvakis (2018) research, inflight entertainment enrichment and inflight wi-fi service to satisfy passengers themselves can improve airline passenger satisfaction from flight criterion.

Survey research by Namukasa (2013) suggests improving the quality of developing convenient reservations, ticketing systems, in-flight meals and solving service problems effectively will affect passenger satisfaction and loyalty.

A web review research study from Brochado, Rita, Oliveira, and Oliveira (2019) revealed some services related to money ratings of airline travel experiences as in-flight services, airport operations, ground staff service, type of ticket classes, seat comfort, and flight entertainment.

Significant statistical differences were found in research from Warnock-Smith, O'Connell, and Maleki (2017) with regards to the purchase of food and drink, extra baggage, priority boarding and seat assignment on a short flight.

The findings from our study are more about showing the priority of the type of service that airlines service providers need to pay attention to based on the big data of passengers on full-service airlines. By taking priority of these types of services, it is hoped that it will increase the satisfaction and loyalty of full-service airline passengers.

7. Conclusion

7.1. Implication for theory and research

Service quality is essential to winning passenger choice in the role of airline competition. The airline should improve services using a customer-driven evaluation approach of service by knowing which services most effective strategies is to win more passengers.

This study examines the data mining approach using feature selection to determine airline passenger satisfaction. The study results find that online boarding features are the most critical service for airline passengers, followed by the type of travel, a non-service attribute that is considered improved service in segmentation business class. The next service that should be improved is inflight wi-fi service as the third place. Then improvement of baggage handling and inflight entertainment services for strengthening passenger satisfaction.

As for service attribute, we can conclude that: (1) online boarding, (2) inflight wi-fi service, (3) baggage handling, and (4) inflight entertainment is the top 4 crucial services to be improved by the airline to gain passenger satisfaction.

This study examines different supervised machine learning algorithms on the airline passenger satisfaction dataset. The purpose is to identify more accurate prediction performance with several suitable classifiers. This study has run several different classification algorithms

Table 6
Prediction models of classification algorithms after feature selection.

Machine Learning	Accuracy	Precision	Recall	F score	AUC
DT	93.46%	92.96%	95.69%	94.30%	0.974
RF	94.41%	94.37%	95.83%	95.09%	0.987
GBT	90.90%	92.78%	90.99%	91.88%	0.973
NN	94.59%	94.56%	95.97%	95.26%	0.986
DL	95.42%	94.93%	97.08%	95.99%	0.992
NB	88.60%	89.00%	90.02%	89.51%	0.930
k-NN	94.49%	94.25%	96.12%	95.17%	0.976
LR	84.73%	85.25%	88.27%	86.73%	0.881
RI	89.76%	89.75%	92.45%	91.08%	0.922
SVM	82.80%	81.54%	89.94%	85.53%	0.877

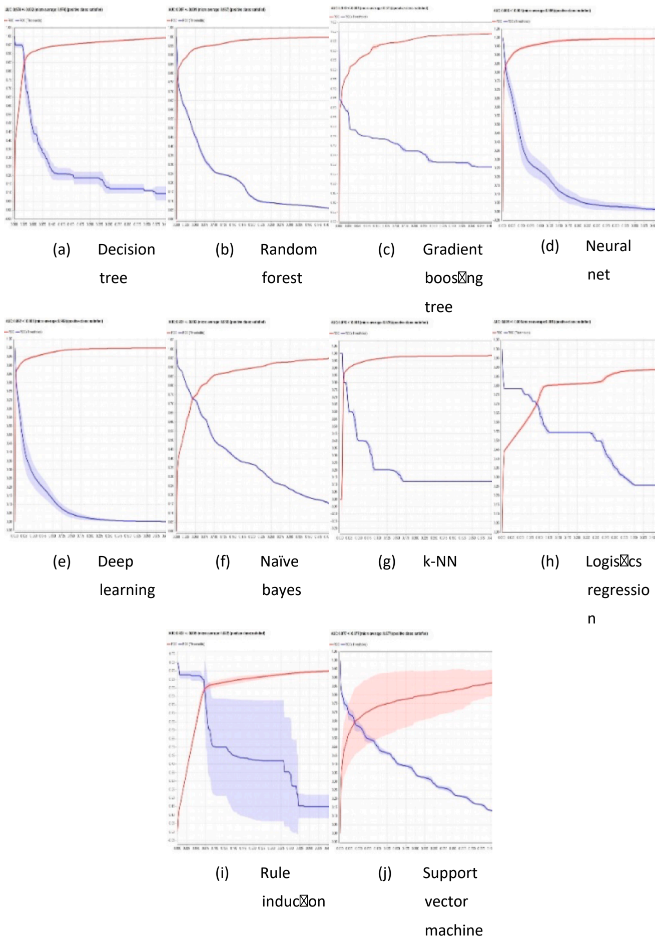

Fig. 13. The ROC curve result after feature selection among supervised machine learning algorithms.

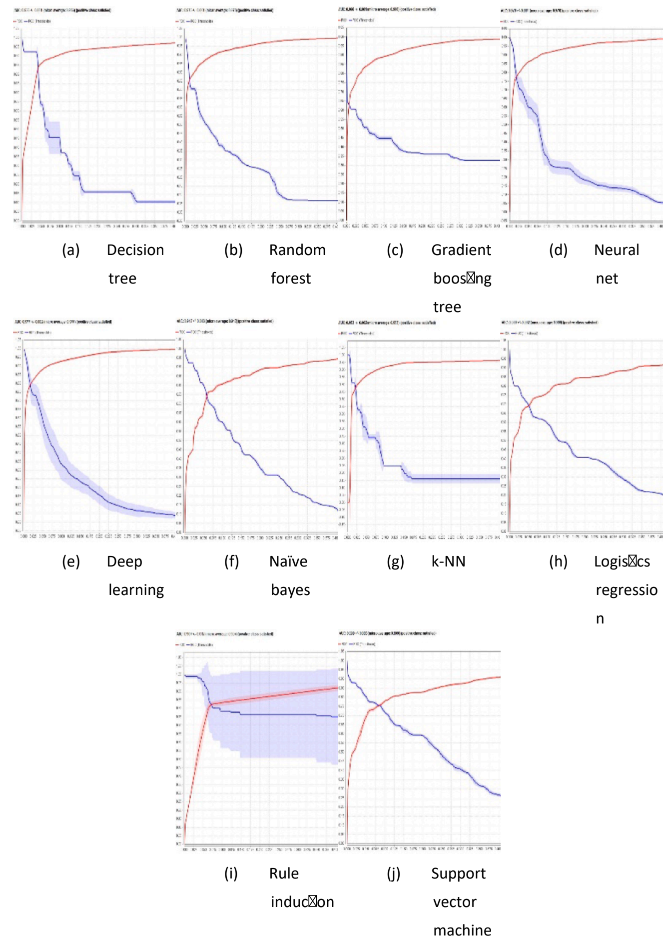

Fig. 14. The ROC curve result for selected features among supervised machine learning algorithms.

Table 7
Prediction models of classification algorithms for the top 5 selected features.

Machine Learning	Accuracy	Precision	Recall	F score	AUC
DT	91.25%	90.73%	94.14%	92.40%	0.956
RF	91.37%	90.66%	94.47%	92.53%	0.975
GBT	90.22%	90.10%	92.92%	91.49%	0.966
NN	91.05%	91.65%	92.60%	92.12%	0.970
DL	92.08%	92.62%	93.45%	93.03%	0.977
NB	85.57%	87.32%	87.14%	87.23%	0.917
k-NN	91.07%	89.33%	95.64%	92.38%	0.953
LR	84.42%	85.65%	87.03%	86.34%	0.900
RI	88.52%	87.26%	93.33%	90.19%	0.907
SVM	79.85%	87.07%	75.60%	80.93%	0.899

such as decision tree, random forest, gradient boosted tree, k-NN, Naïve Bayes, rule induction, logistic regression, neural net, deep learning and support vector machine. This study also investigates the receiver operating characteristic (ROC) graphs of model classifiers to examine prediction models' visual performance. The results show that Deep learning is the fittest machine learning algorithm in the accuracy, F score, the ROC curve as robust data mining techniques to predict airline passenger satisfaction.

7.2. Managerial implication

These four crucial services (online boarding, inflight wi-fi service, baggage handling, and inflight entertainment) should be prioritised to meet passenger satisfaction.

The most important service is online boarding, or we can say mobile boarding because the passenger can use their mobile device when getting their online boarding pass which means a paperless boarding system. Online/mobile boarding proceeded in passenger mobile devices avoids passengers' queues, saving passenger time and energy. Once the passenger gets a boarding pass, the mobile phone can scan the given barcode on the screen at airport security checkpoints. Using mobile boarding is fast and convenient for the passenger.

The strong important service that should be improved is inflight wi-fi service because nowadays the need to be connected to the internet is a necessity for passengers, especially on long-distance travel, open business email, or important passenger need. Airline service should be equipped with wi-fi service that can offer free limited access internet or reasonable wi-fi pricing to attract more passenger convenience.

Baggage handling service performance need to be improved by airline service to meet passenger satisfaction. The airline can utilize new efficient technology to create efficiencies such as Artificial Intelligence, online check-in, and self-service options at the airport.

In the top 4 services, inflight entertainment is important to modern airline passengers. Passengers are much more likely to experience an airline positively, particularly during long-haul trips, when they are entertained during their flight. Therefore, flight entertainment is a concern for airline passengers in determining their satisfaction when flying with an airline.

In addition to these services, other services deserve attention from improvement so that airline passenger satisfaction increases and the airline can win a competitive advantage in aviation.

Author statement

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All authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. We confirm that this work is original and has not been published elsewhere, nor is it currently under consideration for publication elsewhere before its appearance in the Research in Transportation Business & Management.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rtbm.2021.100726.

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