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Non-linear Analysis of Airline Customer Experience: Logistic Regression vs Artificial Neural Network

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Abstract

Purpose of the study: This study aims to explore the best machine learning (ML) classification algorithm for curve analysis of customer experience survey data.

Methodology: The study employed a multi-method study to extract the best alternative algorithms. This study used logistic regression and artificial neural networks (ANN) to analyze data. This study used 6000 airline passenger survey datasets. To analyze the quantitative data using XLMINER software.

Findings: The findings suggest an artificial neural network (ANN) is the best alternative classification algorithm for customer experience analysis. This study also recommends using logistic regression alternatively for simple and comprehensive modeling to analyze customer experience.

Implications: Practically, this study highlights the benefit of using artificial neural networks to classify customer satisfaction.

Limitations and Future Direction: The first limitation of this study is that uses cross-sectional data, future studies should use longitudinal data. Secondly, matric reports are very close in both studies. This author refers to future studies that may include another dataset to find the clear superiority of the model.

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1. Introduction

In the competitive world of online industries, understanding customer opinion and experience is a critical matrix for a business (Asghar et al., 2020). Rapidly changing trends in globalization have impacted the transformation of diverse sectors, including transportation. Adopting globalization philosophy puts community pressure on development agents to make proper adjustments to these expected changes. In this history, transportation modes and their uses have changed since the beginning of globalization. As a faster transportation mode for passengers and cargo air mode is the most popular and expensive. However, it operates hostile and in cumbersome situations like other transportation means. Through the historical evaluation of the airline industry in the present world, this industry has been working with business and environmental challenges. However, this industry has suffered from operating cost challenges and political-economic factors for the last fifteen (15) years. It is empirically known that after the 9/11 attack, the airline industry was affected, and most North American airlines were suffering more compared to Asia Pacific operators. However, this tremendous unfortunate 2008 recession and the 2019 pandemic made it more critical and challenging. Besides these, geo-political unrest, and fast changes in industry market structure also push competitive force to the airline companies.

Today, many airline companies compete on the same routes with different facilities. So, competing with market players is challenging, particularly in capturing customers and making them loyal to a brand. In this digital era, customers are more powerful and quickly compare the relative benefits offered by other operators on the same routes and same time. Airlines companies offer the best customer service and features to maximize customer satisfaction (Amalia et al., 2022) and loyal to the brand (Saut & Song, 2022). Airline passengers are educated/ informed and more technology-friendly than other types of passengers. They choose to rank or rate airlines as per given service and passenger satisfaction (Saut & Song, 2022). Kumar and Zymbler (2019) explained customer satisfaction is a key metric of loyalty and re-purchase of values. It helps to retain customers and minimize customer attraction costs. Customer feedback is beneficial, as it provides a strategic way of unveiling customer appeals (Asghar et al., 2020). Therefore, customers' expectations from airline operators have been increasing, and it is challenging for service providers to satisfy the target customers. Meanwhile, airline operators have a scarcity of resources in terms of finance and human. However, within their limitations, they committed to providing maximum benefits to customers with an optimum allocation of scarce resources. As a result, airline operators need to classify satisfied and dissatisfied passengers and set a list of priorities in the investment decision. Under this prevailing situation, marketers now focus on classifying satisfied customers and developing a generalized model.

Under this situation, it is a concern for airline operators to identify the most potent factors that make customers satisfied and loyal to a brand. In this category, operators focus on two tasks; first, classify the satisfied and dissatisfied customers to concentrate on their expectations. Second, to develop a generalized machine learning-based model for predicting maximum customer satisfaction. Empirical studies conducted research and applied machine learning algorithms on the airline's passenger data. These studies enrich marketing research wisdom and provide evidence of the extended use of machine learning algorithms in customer satisfaction research. For example, Kumar and Zymbler (2019) applied a Support Vector Machine (SVM), Artificial Neural Network (ANN), and Convolutional Neural Network (CNN). Also, Asghar et al. (2020) used hybridized Fuzzy and Deep Neural Networks to predict customer satisfaction. However, these models have concentrated on complex classification methods. However, these studies did not emphasize linear classifiers like logistic regression, which is very similar to other methods but easy to implement and generalize. On the other side, these studies used object-oriented languages to train and validate the model. Their contributions are generalized and universal in this domain of research but the use and comprehensibility of object-oriented language in marketing professionals is limited to extended use and solves the complexity of the model before and after the trained model. The author intends to introduce XLMINER (Excel-based data mining tool) to minimize the limitation of using object-oriented language and to induce business professionals to make model-driven decisions. In addition, this study contains a comparative analysis of Logistic Regression (logit) and Artificial Neural Network (ANN) classification algorithms under the data mining phases.

This study used a machine learning-based classification method to develop models to find the influential factors that contribute to satisfying airline passengers. The principal research question (RQ) is: What is the best customer satisfaction model based on the classification method? The study intends to determine the most potent factors of customer satisfaction in the airline industry and the best classification model. Finally, this study makes a comparative review of the most popular and simple classifier algorithms' (Logistic Regression and Artificial Neural Network) performances in the airline customer dataset. This paper is structured with related studies, study methods, analysis, summary, and conclusion.

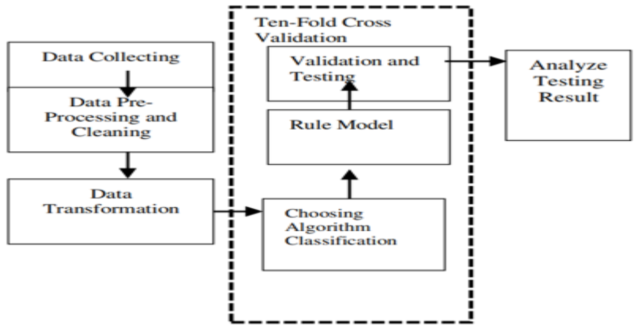

Figure 1: Research Method Source: *Amalia et al.(2022)*

2. Literature Review

Through an extensive literature review, it has been generalized that the uses of machine learning algorithms in business models have grown in the last decades. In the domain of marketing application classifier algorithms are satisfactory by the concern of time. In supervised learning, classification algorithms are mostly used in the marketing field due to categorical data patterns and pattern determination. In addition, earlier studies focused on the comparative evaluation of different classification algorithms to measure the performance of algorithms in real-time industrial big data. For example, Kumar and Zymbler (2019) applied a Support Vector Machine (SVM), Artificial Neural Network (ANN), and Convolutional Neural Network (CNN). Also, Asghar et al. (2020) used hybridized Fuzzy and Deep Neural Networks to predict customer satisfaction. Zhang et al.(2019) used Logistic Regression and CART decision tree algorithms in the imbalance dataset to measure prediction accuracy. Finally, they found that logistic regression is more precise on datasets with fewer attributes and balanced data distribution. In addition, Khemphila and Boonjing (2010) employed logistic regression, decision trees, and artificial neural networks to forecast the risk of heart disease. Finally, they found that ANN had higher accuracy and lower error rates than logistic regression and decision trees.

In addition, Adarsh and Ravikumar (2018) focused on determining sentiments, the researchers adopted a method that involved scoring each tweet based on the presence of positive and negative words based on customer tweets. This score computation enabled them to categorize sentiments as positive, negative, or neutral. Notably, they observed a distinct trend among the airlines. Specifically, Emirates Airlines stood out for having a higher number of positive sentiments compared to Indigo Airlines and Qatar Airlines. Conversely, Indigo Airlines garnered more negative sentiments, while Qatar Airlines received a higher proportion of neutral sentiment tweets. Furthermore, Al-Qahtani and bint Abdulrahman (2021) applied Machine Learning (ML) and Four Deep Learning (DL) methods to predict customer sentiment from US airlines based on tweets.

The above empirical studies and their outcomes acknowledged the present wisdom of a comparative review of machine learning algorithms' performance in the diverse group of real-time industrial data and social media data. In the field of marketing, supervised and unsupervised learning applications are popular to understand data patterns and predict future trends. However, the uses of machine learning (ML) and deep learning (DL) algorithms are not mature enough due to technical and methodological skills. Finally, these extensive studies confined usability diverse classifiers to train the best feasible model and found a generalized model for predicting airline customer satisfaction.

3. Materials and Methods

3.1 Data Source and Data Preparation

This study is based on secondary data. The author selected the online data source Kaggle.com (www.kaggle.com) data set on airline customer satisfaction. It was a survey data and open access for academic use. This data set was prepared as extensive, including 1,29,000 sample responses. Nevertheless, in this data set, many missing values were found. First, the collected data was clean and prepared for analysis by checking the missing data; finally, these values were inputted through the XLMINER rules. This study proudly used XLMINER to prepare and analyze data. The author declared a detailed research method in Figure 1 to enhance the comprehensibility of the research method. Under the KDD process, data collecting, data preparation and cleaning, Data Transformation, data mining, and interpretation were detailed by the research method as per the recommendation of (Amalia et al., 2022).

3.1.1 Sample Size Requirements: According to existing wisdom, larger samples are more used and recommended for testing ML algorithms. However, these rules are categorically applicable to complex algorithms. Furthermore, a sample size is also based on the number of events, and the event per variable method is wieldy used to determine sample size.

Therefore, through an extensive review of the data set and following the sample size requirement for a classification method, this study used 6,000 responses as a sample of this study. According to the assumption of the logistic regression model, a large sample size is required, and recommended to use a large sample size to validate any model. This study determines the sample size based on the EPV (Events per variable) concept.

Table 1: Variables Details

Variables Codes	Variables Names	Variable Types	Scale of Variables	Types of Factors
SAT	Satisfaction	Logit	Dissatisfied=0, Satisfied=1	Personal Factor
GEN	Gender	X1	Female=0, Male=1	Personal Factor
AGE	Age	X2	Number	Personal Factor
CLASS	Class	X3	Economy=0, Economy Plus=1, Business=2	Service Factor
FL_DS	Flight Distance	X4	Number	Service Factor
ON_SU	Online support	X5	Likert Scale (1= strongly Disagree, 5= Strongly agree)	Service Factor
EA_ON-BK	Ease of Online booking	X6	DO	Service Factor
ON_BO_SE	On-board service	X7	DO	Service Factor
BA_HA	Baggage handling	X8	DO	Service Factor
CH_SE	Check-in service	X9	DO	Service Factor
CLEAN	Cleanliness	X10	DO	Service Factor
ON_BOAD	Online boarding	X11	DO	Service Factor
DE_DEL	Departure Delay in Minutes	X12	Number	Service Factor
ARR_DEL	Arrival Delay in Minutes	X13	Number	Service Factor

Sources: Author Compiled from Data Bank

This study applied EPV >= 10 and a sample size with a 0.10 expected probability according to Smeden et al. (2018). As per subject expertise, this study primarily selected 13 explanatory variables and the sample size was required (13*10/0.10) 1300. Meanwhile, in some other research Steyerberg et al. (2000) recommended EPV > = 50 for stepwise model selection. According to Steyerberg et al. (2000) view, the sample size would be 6500. However, in this study, the author selected between 1300 and 6500, i.e., 6000, nearest to an optimum value. Among the 119,611 useable samples, the author randomly selected 6,000 samples to evaluate the performances of classifier algorithms in the field of customer experience data. Why does the author intend to use a medium-sized sample to measure the performances of algorithms? The answer, this paper intends to explore an economic and simple classification algorithm for predicting customer satisfaction for customer survey data. In real-time research data collection is more expensive and time-consuming, and most organizations do not afford large survey samples for their business decision that are needed very early. Table 1 details the nature and types of data and the scale.

3.2 Classification Algorithms

This sub-section deals with algorithms and techniques that are applied to predict passenger satisfaction. This study used Logistic Regression and Artificial Neural Network (ANN) algorithms to analyze passenger experience data. As an intent to validate the model with medium sample size, logistic regression, and Second order ANN is the best algorithm.

3.2.1 Logistic Regression

In the machine learning classification method, logistic regression is the most popular and used method. On the other hand, in the empirical view, logistic regression is logit analysis, and binary logistic regression modeling is a frequently used method. This model helps to predict a model based on the data set and its size used to develop a model. In the general structure of logistic regression: Y is called Odds/logit, which labels values "0" and "1", p can take any value in the interval [0,1]. Thus, it can be expressed that p is the linear function of q predictors in the form:

$$p = \beta0 + \beta1x1 + \beta2x2 + \beta3x3 + \text{------} + \beta kxk \text{ -- (i)}$$

it is not guaranteed that the right-hand side will lead to values within the interval [0,1]. The solution is to use a nonlinear function of the predictors in the form.

$$= \frac{1}{1+e-(\beta0 + \beta1x1 + \beta2x2 + \beta3x3 + ---+ \beta qxq\ )} \text{ --(ii)}$$

This is called the logistic response function. For any values of x1 - - - -xq, the right-hand side will always lead to values in the interval [0,1]. However, when the Odds of belonging to class 1 (y=1) are defined as the ratio of the probability of belonging to class 1 to the probability of belonging to class 0:

$$\text{Odds}(Y=1) = p/1\text{-}p \text{ ---(iii)}$$

It also can calculate the reverse calculation: Given the Odds of the event, we can compute its probability by manipulating equation (10.3):

$$P = \text{Odds}/\ 1+ \text{Odds} \text{ ---(iv)}$$

Now subtracting equation (ii) from equation(iv), it can be noted that the relationship between odds and the predictors is:

$$\text{Odds } (Y = 1) = e\ (\beta0 + \beta1x1 + \beta2x2 + \beta3x3 + \text{------} + \beta qxq) \text{ ------------------------------------(v)}$$

$$\text{Log(odds)} = \beta0 + \beta1x1 + \beta2x2 + \beta3x3 + \text{------} + \beta qx \text{ ---(vi)}$$

3.2.2 Artificial Neural Network (ANN)

The neural net is a model based on the biological activity in the brain. In empirical wisdom, it has been clear that the "Neural Net" has been applied to multi-disciplinary issues. Artificial neural networks (ANN) have appeared as an unconventional tool for evaluating the complicated relationships between variables (Son et al., 2022). This study also noted that ANN is more flexible, and it can be applied for classification or regression. Hence, ANN can be an impressive instrument to analyze NIR data. Among these, the Neural net is applied in the business domains. For example, Trippi and Turban (1996) reported the number of applications of neural nets in business, particularly financial applications (bankruptcy, currency market trading, picking stock and trading commodities, detecting fraud in credit cards, and customer relationship management (CRM). The neural network process is conducted based on a minimum of three layers, input, hidden layer, and output. Figure 2 depicts the entire process of neural networks and shows a comprehensive diagram to make the process easy and understandable. Therefore, empirical studies for example Zhang, Wu, & Zhu (2018); Zhang, Tino, Leonardis, & Tang (2021); Islam, Ahmed, Barua, Begum (2022) remark that computer scientists are working develop a more comprehensive ANN model in the future.

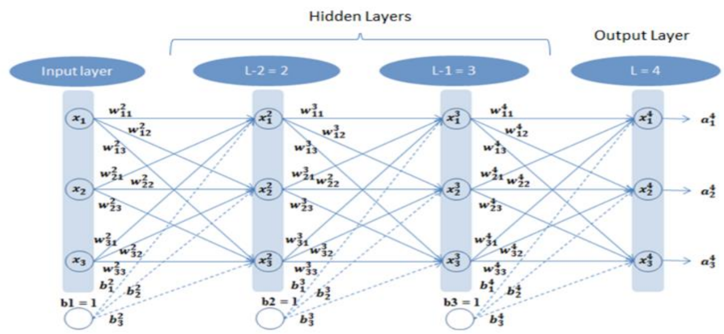

Figure 2: Multilayer Feedforward Neural Network

$$\text{Output}_j = g\left(\theta_j + \sum_{i=1}^{p} w_{ij}x_i\right) = \frac{1}{1 + e^{-(\theta_j + \sum_{i=1}^{p} w_{ij}x_i)}}.$$

Figure 3: Computing Output Nods calculation formulation

3.3 Tools of Analysis

This study used XLMINER to prepare and analyze the collected data. Finally, data were analyzed based on a research method. Secondly, this study determines the exploratory variables of customer satisfaction to analyze the descriptive features of the data. It also categorizes satisfied (1) and dissatisfied (0) customers and models powerful factors that determine customer satisfaction. Meanwhile, to find the relevant and statistically significant explanatory variables for the proposed model, the author conducted a logistic regression with 13 explanatory variables and selected only significant service and personal factors as explanatory variables to train a model with logistic algorithms and ANN.

In addition, this study was completed with two separate studies namely study-1 and study-2. Study 1 was conducted to train the classification model through the Logistic Regression algorithm. Also, study 2 was conducted to train another classification model through Artificial Neural Network (ANN). Finally, to justify the intent of the study, the author makes a comparative evaluation of study-1 and study-2 outcomes to justify the best classifier to predict airline customer experience with a moderate sample/ statistically logical sample size. To evaluate the performance of the classifier, this study used a confusion matrix, accuracy %, Specificity, Sensitivity (Recall), Precision, and F1 Score.

4. Results and Discussions

4.1 Descriptive analysis

To check the usability of the classification test, the author conducted a descriptive analysis. This study explains the details insight of the dataset and to understand data structures and properties, which are used as an assumption of parametric test. Table 2 detailed insightful evidence about the dataset that has been used to measure and is a cornerstone of powerful analysis. Table 2 explains the mean, median, standard deviation, max, and min of 6000 sample data. The table shows that all variables are rational for further analysis and exposes these variables to build a suitable model. Therefore, there are no harmful findings regarding the sample responses and their opinions.

Table 2: Summary Statistics

Var_Codes	Mean	Standard Error	Standard Deviation	Sample Variance	Minimum	Maximum	Count
SAT	0.554	0.006	0.497	0.247	0	1	6000
GEN	0.498	0.006	0.5	0.25	0	1	6000
AGE	38.502	0.239	18.515	342.81	7	70	6000
CLASS	0.244	0.007	0.561	0.314	0	2	6000
FL_DS	1817.443	11.284	874.078	764011.9	50	6811	6000
ON_SU	3.294	0.018	1.38	1.905	1	5	6000
EA_ON-BK	2.932	0.017	1.344	1.808	1	5	6000
ON_BO_SE	3.078	0.017	1.289	1.661	1	5	6000
BA_HA	3.346	0.016	1.258	1.582	1	5	6000
CH_SE	3.358	0.016	1.247	1.554	1	5	6000
CLEAN	3.387	0.016	1.231	1.515	1	5	6000
ON_BOAD	3.192	0.017	1.344	1.806	1	5	6000
DE_DEL	14.607	0.513	39.764	1581.2	0	978	6000
ARR_DEL	14.882	0.517	39.943	1595.423	0	970	6000

Sources: Author compiled from XLMINER Print

4.2 Inferential analysis

Study-1

This study analyzed airline customer experience data through a logistic regression classifier under the support of XLMINER. In this study, the author deployed 13 selected variables to measure the passenger's experience and explored estimates and p-values that are explained in Appendix Table 1. Logistic regression is a model-used method for ML classification. It has been used for the categorical exploratory variable. In this study, customer satisfaction was measured by [0,1] dissatisfied and satisfied. In this context, ML classification, particularly binary logistics regression, is justified and logical. Appendix Table 1 depicts the coefficient tables with all reporting indices that present the model intercept and slopes. According to the values presented, five explanatory variables were found statistically significant @ p-value = 0.20 in context sample data used for developing the classification model. However, the rest of the explanatory variables are not statistically significant. Meanwhile, Appendix Table 2 describes the confusion matrix of the first logistic regression model. The confusion matrix reports model performance in the context of training classification summary. Appendix Table 2 demonstrates all reporting issues like confusion matrix, error report, and charts to validate the model's consistency and adaptability to the stakeholders. Appendix Table 2 is constructed with three desperate other sub-tables that demonstrate all necessary information required to predict the model performance. Appendix Table 2(a) depicts the confusion matrix was highlighted the 22 false positives and 385 false negative items that confused. Similarly, this confusion matrix is reported in Table 4 in the error report in the error context. This table presents 0.822% false-positive error and 11.589% false-negative error. Thus, the overall error is 6.783%. In addition, Table 4 also presents the matric-related information, including accuracy, specificity and sensitivity, precision, F1 score, and success probability. For example, the first model has identified 93.216% accuracy and 0.992 specificities and sensitivity as 0.884. Also, the precision is 0.992, the F1 score is 0.935, and the success probability is 0.5. Through extensive evaluation of model indices, this study proved that airline customer satisfaction does not depend on all 13 factors listed in Tabl-1. All parameters and confusion indices detrained that maximum significance and other model indices reported show that the model can improve. Considering this justification, this study ran the model explanatory variables (eight) that are not statistically significant by excluding all statistically insignificant @ p-value = 0.20 explanatory variables.

Best Model Selection (Variable Selection)

In addition, this study again conducted a logistic regression analysis with significant variables. From the data exploration tables (Appendix Table 1 and Table 2), some explanatory variables should be dropped from the model. In this context, the author first dropped all explanatory variables that were not statistically significant p-value of 0.20. So first, the author initiated to drop eight explanatory variables as per consideration of p-values. Secondly, check whether the lift curve and ROC curve consideration rationalize the dropped variables in this regard. Table 3 describes the model's coefficients, where all explanatory variables are statistically @ 5% level significance except variable DE_DEL. According to the subject matter expertise, departure delay is the most important variable in the customer satisfaction model. Thus, the author was generous to adopt a level of significance up to 20% which is not usual in practice, but it is not illegal in research. In addition, this model represents a significant and contributory logit model. This model depicts that gender, flight distance, departure delay, and arrival delay have a pessimistic estimate. Also, among these predictors' departure delay is significantly based on 16%.

Table 3: Coefficients Table (with explanatory variables p-value less than 0.20)

Predictor	Estimate	Confidence Interval: Lower	Confidence Interval: Upper	Odds	Standard Error	Chi2-Statistic	P-Value
Intercept	6.453	5.705	7.201	634.535	0.382	286.018	0.000
GEN	-7.765	-8.394	-7.135	0.000	0.321	584.492	0.000
FL_DS	0.0003	-0.001	0.000	1.000	0.000	19.957	0.000
CH_SE	0.107	0.023	0.192	1.113	0.043	6.190	0.013
DE_DEL	-0.009	-0.021	0.003	0.991	0.006	2.063	0.151
ARR_DEL	-0.034	-0.046	-0.021	0.967	0.007	26.722	0.000

Sources: Author compiled from XLMINER Print

It also presents that the male and female presager satisfaction difference is 0.0004 odds (negative effect, Odds value less than one means negative effect). It means that female passengers are more satisfied than male passengers. It also replicated that one unit increase in distance reduces satisfaction by 0.9997 odds or it does not affect odds=1.00. Besides this, checking service (CH_SE) has optimistic estimates, and one unit increase in the checking service increases passenger satisfaction by 1.113 odds (positive effect), respectively. In addition, increasing the departure and arrival delay unit may reduce passenger satisfaction by 0.991 and 0.967 odds (negative effect), respectively.

The model is structured:
Log (Odds) = 6.453 + -7.765(GEN) + -0.0003(FL_DS) + 0.107 (CH_SE)+ -0.009 (DE_DEL) + -0.034(ARR_DEL)

Furthermore, Table 4 describes the training classification summary of logistic regression with success possibilities of 0.5 and 0.553. This study shows that in this case, standardization did not affect the model accuracy measurements robustly. The table below shows the confusion matrix, and error report about the false positive and false negative, respectively. Also, Table 4 describes the accuracy, sensitivity, and specificity of the metrics table. This information reveals that the model is more accurate, more sensitive, and more specific than earlier models' parameters reported success probability = 0.5 and success probability =0.553. Finally, this study validates the logistic regression model with an empirical conclusion that gender, flight distance, checking service, departure time, and arrival delay influence airline passenger satisfaction. Also, the logistic regression algorithm-based model summary reported model accuracy is 93.639%, model specificity is 0.993, Recall or sensitivity is 0.890, Precision is 0.994 and F1 score is 0.939. Also, this study reported an ROC curve and an AUC value of 0.957, which is noted as satisfactory.

Table 4: Classification Summary Training Model

Logistic regression with Sus probability=0.5 (Training Classification)					Logistic regression with Sus probability =0.553_ STD (Training Classification)				
Confusion Matrix					Confusion Matrix				
Actual\Predicted		0	1		Actual\Predicted		0	1	
	0	1608	12			0	1609	11	
	1	217	1763			1	218	1762	
Error Report					Error Report				
Class		# Cases	# Errors	% Error	Class		# Cases	# Errors	% Error
	0	1620	12	0.741		0	1620	11	0.679
	1	1980	217	10.959		1	1980	218	11.010
Overall		3600	229	6.361	Overall		3600	229	6.361
Metrics					Metrics				
Metric		Value			Metric		Value		
Accuracy (#correct)		3371			Accuracy (#correct)		3371		
Accuracy (%correct)		93.639			Accuracy (%correct)		93.639		
Specificity		0.993			Specificity		0.993		
Sensitivity (Recall)		0.890			Sensitivity (Recall)		0.890		
Precision		0.993			Precision		0.994		
F1 score		0.939			F1 score		0.939		
Success Class		1			Success Class		1		
Success Probability		0.5			Success Probability		0.553		

Sources: Author Compiled from XLMINER Print

Study 2

This study analyzed airline customer satisfaction data through an artificial neural network (ANN) classifier to train a classification model under the support of XLMINER. A feed-forward neural network with three layers (an input layer, a hidden layer, and an output layer) was used in this study. To conduct a training model by ANN, the author used a single hidden layer ANN principle that is very similar to logistic regression or a less complex neural network model. A neural network is another method for ML classification. It has been used for the categorical exploratory variable. In this study, customer satisfaction was measured by [0,1] dissatisfied and satisfied. Therefore, ML classification, particularly neural networks, is justified and rational in this context. According to Wisdom, the author follows the detailed neural network process (Figure 2). First, the author conducted a general model of a neural net with a default cut-off value (probability=0.5) with partitioned data 60/40. Finally, the confusion matrix shows false positive and false negative errors, and the total error is unusual and unaccepted according to statistical wisdom.

Finally, to again improve the model, the author used the normalization of data to improve the model with a new success probability of 0.553 (adjusted). In this journey, the author found the expected results, and it has satisfied all statistical desires and requirements. Again Table 5 describes the new reporting values in the classification summary for the training and validating model. Table 5 shows that 0.494% false-positive error, a false-negative error is 12.323%, and a total error is 7% in the training model. Also, in the validation model, the false-positive error is 1.039%, the false-negative error is 13.115 %, and the total error is 7.791% in the validation model. This table also describes that in the training model, accuracy is 93%, specificity is 0.995, sensitivity is 0.877, and precision is 0.995 and F1 score is 0.931. In addition, the same table also describes the validation model accuracy as 92.208; specificity is 0.989, sensitivity is 0.869, and precision is 0.990, respectively. Comparing both models, it has been proved that the training model is more accurate and reliable than the validated model.

Table 5: Classification Summary Training and Validation Model

Training: Classification Summary					Validation: Classification Summary				
Confusion Matrix					**Confusion Matrix**				
Actual\Predicted		0	1		Actual\Predicted		0	1	
	0	1612	8			0	1047	11	
	1	244	1736			1	176	1166	
Error Report					Error Report				
Class		# Cases	# Errors	% Error	Class		# Cases	# Errors	% Error
	0	1620	8	0.494		0	1058	11	1.040
	1	1980	244	12.323		1	1342	176	13.115
Overall		3600	252	7.000	Overall		2400	187	7.792
Metrics					**Metrics**				
Metric			Value		Metric			Value	
Accuracy (#correct)			3348		Accuracy (#correct)			2213	
Accuracy (%correct)			93		Accuracy (%correct)			92.208	
Specificity			0.995		Specificity			0.990	
Sensitivity (Recall)			0.877		Sensitivity (Recall)			0.869	
Precision			0.995		Precision			0.991	
F1 score			0.932		F1 score			0.926	
Success Class			1		Success Class			1	
Success Probability			0.553		Success Probability			0.553	

Sources: Author compiled from XLMINER Output Print

However, these differences are not more significant, and both models are found in rational and logical. This similarity proved that the model is fitted and free from overfitted problems. Thus, the evaluation of all measures and indices of the training and validating model depicts that an artificial neural network is a generalized model to classify satisfied and dissatisfied customers.

Table 6: Neurons Weights

Neuron Weights: Input Layer - Hidden Layer 1						
Neurons	GEN	FL_DS	CH_SE	DE_DEL	ARR_DEL	Bias
Neuron 1	-0.186	0.248	-1.023	0.408	0.417	-0.005
Neuron 2	0.536	-0.179	0.436	-0.142	0.674	0.005
Neuron 3	-0.781	-0.370	0.127	-0.076	-0.444	-0.003
Neuron 4	-0.026	-0.483	0.501	-0.070	-0.281	0.000
Neuron 5	0.012	0.121	-0.401	0.118	0.051	-0.026
Neuron Weights: Hidden Layer 1 - Output Layer						
Neurons	Neuron 1	Neuron 2	Neuron 3	Neuron 4	Neuron 5	Bias
0	-0.091	0.336	-1.246	0.294	0.431	-0.059
1	0.251	-0.394	0.604	-0.112	0.538	-0.142

Sources: Author compiled form XLMINIER Output Print

Initial Pass of the Network

The table below shows the weights of neurons to determine the network. This table extensively describes all relevant information about neurons' weights and their related aspects. The following table represents all the information to build a network diagram on ANN to classify passenger satisfaction from the given response data set.

Table 6 depicts details of network nodes of different layers of beta values corresponding to neurons. The neuron weights: Hidden layer 1 to the output layer represents outcomes. To effectively use the provided support information, the authors prepare a sketch of a neural network diagram under the support of neuron weights.

The following Figure 4 exhibits the comprehensive network diagram (5x5x1) that is constructed under the NN-SVG software.

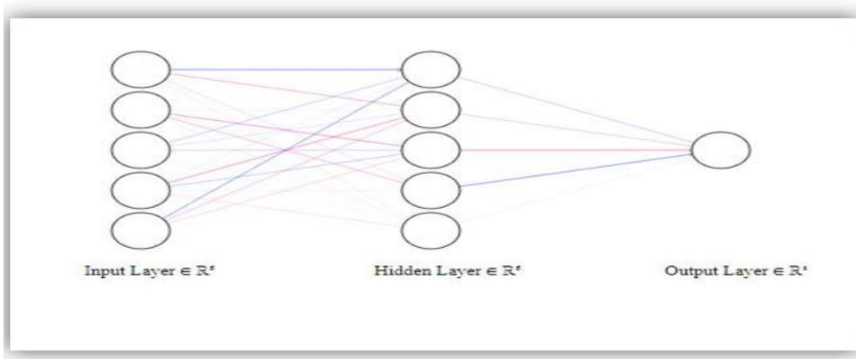

Figure 4: Neural Networks Diagram Sources: NN-SVG Output
Note: i) This diagram was drawn under the support of NN-SVG software, dedicated to NN
ii) (All inputs are standardized_ Gender, flying distance, checking service, arrival delay and departure delay, and output node is passengers' satisfaction.)

Evaluation of Logistic Regression and Artificial Neural Network Modelling

This study conducts a comprehensive review of outcomes with different methods of analysis identically ANN and logistic regression. With neural network analysis, the author, side by side, conducts different methods of analysis (logistic regression) to compare the outcomes of neural network analysis.

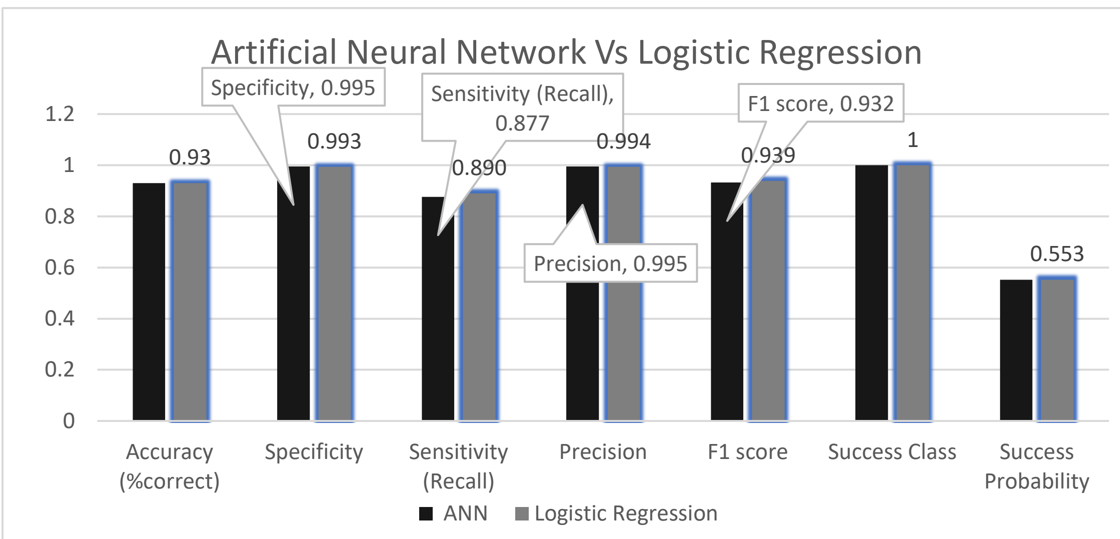

Figure 5: Comparison of ANN and Logistic Regression Classifier (@ p=0.553) based on Metric Values
Sources: Author compiled from Table 4 and Table 5

Figure 5 depicts the comparative review of logistic regression with customized values, i.e., change of success probability (0.553) and standardization of data set with a default value of probability (0.5) in logistic regression. In this context, the author used all customized values used in the final run model of ANN. First, the author noted that the change of default values in logistic regression does not make much more variation between the two models in logistic regression analysis. Secondly, the author observed that the standardized model is better in all categories, but the differences are very nominal. Finally, this study extensively compared the value changes in the final model of ANN and logistic regression and noted the two methods' outcomes are almost similar in a single expression. Nevertheless, in the categorical evaluation, in context to the error report, logistic regression is better than neural networks. Also, in context to metrics values, the neural net is better than logistic regression (in comparing the training classification summary). Finally, the author recommended using the single-layer ANN as a more applicable model for the classification of customer satisfaction in the airline industry.

4.3 Discussion

This project is conducted to classify satisfied customers. This study used 6000 samples collected from online data sources. The author used XLMINER to train a model. This study applied Artificial Neural net (ANN) and Logistic Regression to classify customers as satisfied and dissatisfied. The Main intent study was to examine the classification algorithms' performance with a medium sample size of customer survey data and make a comparative review of algorithms to select the right algorithm for non-linear customer experience analysis. To explore the research intent, the author conducted two separate studies with the same dataset with different ML classification algorithms namely logistic regression and artificial neural network. The first motivation of the research is to examine an accurate and generalized ML classification for a medium sample dataset because survey data collection is more expensive and time-consuming. To conduct study 1, the author first employed 13 explanatory variables in the model and found five variables are significant at a 20% level of significance.
Finally, a study with a partitioned dataset 60/40 and a trained logistic regression model with a success probability of 0.5 and a standardized value success probability of 0.553. Study 1 empirically proved that logistic regression is a generalized model for the classification of customer experience with 93% accuracy and other metrics evaluation. Then, to cross-check the performance of other algorithms, the author conducted study 2 on the artificial neural network model. This study selects five input variables (which variables are found significant in the logistics regression analysis). This study also used five neurons and one hidden layer. First, the author conducts a descriptive analysis to check the descriptive features of data and the association of output and input variables. Later, I conducted a neural network analysis and found a classification model that fits the standard of measure with default values. Secondly, to find the best model, the author again conducted the neural network with the adjusted values of success probability (0.553) and standardization of the data set in the partitioned data (60/40) and found the best network model in all categories of evaluation of training and validation classification model. Then this study describes all outcomes of this final model in the project report to make it compelling and understandable to the target stakeholders. In conclusion, to exhibit the neural network connections among the nodes and neurons, the author prepares the diagram of an artificial neural network under the support of the values expressed in Figure 5.
In addition, to examine the best application of logistic regression and artificial neural networks, the author has comprehensively evaluated these two methods and found them almost similar in terms of prediction and model accuracy. According to empirical wisdom, this similarity is rational and logical. Figure 5 examines the facts to evaluate two studies and many experts reported that the single-layer neural network is like logistic regression. In this study, the author follows the single-layer network to validate a simple and accurate model with a statistically logical number of samples for future researchers. Thus, these comparative outcomes are logical and valid. Thus, this study packed a takeaway for readers to use logistic regression and artificial neural networks for non-linear modeling of customer experience data. If neurons or input variables are minimal, then logistic regression is the best for predicting customer satisfaction. On the other hand, when input variables are maximal then ANN can train a model that requires a maximum number of hidden layers under the black box. This study found better accuracy in simple ANN but in complex level ANN requires a large sample size and it would not be simple to explain like single layer ANN. So, it is recommended to use multilayer feedforward ANN models for many neurons or input variables, it will be more accurate than logistic regression. However, it should be remembered that more hidden layers may be caused by overfitted problems. When ANN is used, avoiding overfitting is very important (Son, et al., 2022).

5. Implications and Limitations

Overall, this study contributes to the present research methodology about the uses of classification algorithms. Many earlier studies recommended the use of different classifiers to predict customer satisfaction, for example, Kumar and Zymbler (2019); Asghar et al. (2020); and Adarsh and Ravikumar (2018). However, these papers were focused on the large sample size used for the prediction of customer experience. One major limitation of a large sample size-based model is more expensive and time-consuming and is not affordable to all levels of companies in the industry. Hence, this study explores a classifier that is more accurate and tolerable error rate that proved as best classification model for minimal neurons or input variables. Finally, this study recommended

using logistic regression based on the specificity and sensitivity of the model, but a single-layer feedforward artificial neural network based on F1 score and precision for predicting customer satisfaction with statistically logical and medium sample size. The most important thing noted by the author is that the values of the metric used to compare the two models are very close and negligible to consider. Thus, in a nutshell, the author recommended that further study could select both classifiers as alternative tools for non-linear analysis of customer experience/ sentiment data. This study a emerge new dimension in marketing research to apply classification algorithms to train customer survey data or social media data through XLMINER. Another implication of the study is to introduce the new KDD tools for marketing data to work without object-oriented programming for machine learning algorithms. The author finally notes due to its black-box nature, ANN is less comprehensive and generalized than logistic regression. When the directness of the model is required, then logistic regression would be the best alternative machine learning classification algorithm.
Finally, the author noticed a few limitations in the study process, The first limitation of this study is that uses cross-sectional data, and future studies should use longitudinal data. Secondly, matric reports are very close in both studies. This author refers to future studies that may include another dataset to find the clear superiority of the model. Finally, this study applied XLMINER to evaluate two classifiers, future studies may consider any object-oriented programming to evaluate the best model for consumer survey data.

6. Conclusion

The central theme of this study was to explore the best-classified algorithm for medium sample-size survey data. This study evaluates the performances of logistic regression and artificial neural networks with a medium sample size with XLMINER tools. Through the logical and empirical evaluation, both algorithms are found best-performing algorithms for minimal features or input variables and medium sample size. However, through head-to-head analysis, it is found that logistic regression model specificity and sensitivity of better than ANN. Conversely, in F1 score and precision consideration, ANN is the best model, and their difference in parameters is very few and negligible to consider. Thus, the author recommended selecting both algorithms logistic regression and single-layer feedforward neural network alternatively. The author also remarks logistic regression model generalization and comprehensibility are better than artificial neural networks. Finally, the author addressed a few limitations and shared perspective guidelines for fellow mates and managers. In conclusion, the author noted that the originality of this study is to explore the best machine learning (ML)-based classification algorithm for marketing research with XLMINER. This study also expands the marketing research wisdom for the employability of machine learning (ML) algorithms in future research without object-oriented language.

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Appendices

Appendix Table-1: Coefficients Table (with 13 explanatory variables)

Predictor	Estimate	CIL	CIU	Odds	Standard Error	Chi2-Statistic	P-Value
Intercept	6.268	5.387	7.149	527.520	0.450	194.438	0.000
GEN	-7.772	-8.411	-7.133	0.000	0.326	568.620	0.000
AGE	-0.002	-0.008	0.003	0.998	0.003	0.707	0.400
CLASS	0.044	-0.143	0.231	1.045	0.096	0.216	0.642
FL_DS	0.000	-0.001	0.000	1.000	0.000	17.845	0.000
ON_SU	0.047	-0.080	0.174	1.049	0.065	0.534	0.465
EA_ON-BK	-0.090	-0.275	0.094	0.914	0.094	0.916	0.339
ON_BO_SE	0.034	-0.060	0.128	1.034	0.048	0.498	0.481
BA_HA	0.046	-0.068	0.161	1.047	0.058	0.627	0.429
CH_SE	0.077	-0.015	0.170	1.080	0.047	2.687	0.101
CLEAN	0.031	-0.089	0.151	1.031	0.061	0.251	0.617
ON_BOAD	0.034	-0.173	0.240	1.034	0.106	0.102	0.750
DE_DEL	-0.009	-0.021	0.003	0.991	0.006	1.987	0.159
ARR_DEL	-0.034	-0.046	-0.021	0.967	0.007	26.804	0.000

Sources: Author Compiled from XLMINER Output Print

Author's Biography:

Mohammad Sirajul Islam is an Assistant Professor at AIUB, and he works as a consultant in decision science and sustainability. He holds a PhD in Marketing from the University of Dhaka and an MS in Decision Science from Western Illinois University, USA. Mr. Islam specializes in Decision Science, Business Analytics, Marketing, Supply chain, and Sustainability issues. His Ph.D. was focused on 'Agricultural Marketing System for Sustainable Dairy Industry with Triple Bottom Line Framework in Bangladesh'. His research focused on decision science, applied Statistics, business analytics, marketing, and sustainable development. Mr. Islam examines his research issues for public and private organizations and is also interested in model and data- driven decision analytics in sustainability and business for future generations. He can be reached at sirajuits@gmail.com/ dr.siraj@aiub.edu