Transforming the Performance of Airline Industry Through Sentiment Analysis.

MSc Research Project
MSc Artificial Intelligence for Business (MSCAIBUS)

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MSc Project Submission Sheet

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Transforming the Performance of Airline Industry Through Sentiment Analysis.

[Airline Industry]

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Abstract:

The rapid growth in technology-oriented businesses have encouraged different industries to adopt modern approaches such as sentiment analysis for better understanding of their customers to help gauge their feelings regarding the provided service. This research paper focuses on gathering meaningful insights from airline company customers through sentiment analysis which can help transform the overall performance within the airline industry. This research employs machine learning techniques such as Random Forest and Naïve Bayes to critically assess customer sentiments based on airline company's dataset sourced through Kaggle. The used dataset in this research focuses on several aspects of airline services offered throughout the journey and provides customer ratings on its key factors.

The models were evaluated through metrics such as accuracy, precision, recall, ROC curve and AUC score. Random Forest outperformed Naïve Bayes with an accuracy of 89.1% and an AUC of 95.1% compared to 79.3% accuracy rate and 89.3% AUC of Naïve Bayes. Correlation through weights highlighted the key factors that airline industry must focus on to transform the performance and enhance user experience. In-flight entertainment, ease of online booking and online customer support were the key factors that derive most customer satisfaction. This research highlighted actionable insights for the airline industry through the effective deployment of machine learning techniques in sentiment analysis. These insights can help airline companies in enhancing user experience, retaining customer loyalty and create a competitive advantage to capture market share and overall transform the performance of their business.

Keywords: Sentiment Analysis, Machine Learning, Airlines Industry, Random Forest, Naïve Bayes, Social Media.

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1. Introduction

The need to evolve with the evolution of technology is a necessity for every individual or business entity to adapt technological measures in everyday operations. This allows businesses to enhance business performance and understand their customers in a much more effective way. Use of technology allows businesses to critically assess human sentiments and provide them with valuable insight. In recent times, the competition has significantly increased within the Airlines Industry. Each organization tries to identify gaps and gather market share through assessment of customer sentiments. (Noviantoro and Huang, 2022). Due to this excessive opposition, the Airline industry had previously adapted conventional approaches in identifying customer sentiments but with rapid technological advancements, sentiment analysis through Machine Learning (ML) models have helped organizations in accurately gathering customer insights. Sentiment analysis remain one of the important tools adapted by various industries to understand and assess customer's feedback and address their challenges head on to retain their interest towards the business offerings or before the competitors capitalize on the matter. (Georgescu & Bogoslov, 2019) highlights how customer feedback is valuable in providing businesses an opportunity to understand the current gaps in customer's experiences and how this information can be utilized for further enhancement. Customer feedback can be gathered through in-flight feedback forms or social media channels, but it has become vital for businesses to adapt sentiment analysis approach to encounter the challenges and enhance the experience provided via their services.

During the last two decades, the growing competition amongst the airlines industry is witnessed by each customer. This cut-throat battle amongst Airline companies has led a space for the utilisation of customer insights to own a competitive advantage over one another. This data helps organizations in conducting a sentiment analysis as Airlines try to understand through bits and pieces of customer sentiments on how they can improve their service (Khan et al., 2021). It is a traditional approach for both customers and businesses to gather insights about one another through previous user reviews by people who use their services regularly. Airline companies can understand through customer sentiments whether the provided service to users justifies the prices they charge for airfare. In our current digital age, people have become exceedingly vocal about their experiences as they believe in appreciating and highlighting the good and bad aspects of the service to help future users. These reviews help transformer customer opinions and help companies gain more market share. Hence, the need for sentiment analysis for airline companies has increased quite significantly and different approaches have been used to gather essential insights about customer experiences.

Kumawat et al. (2021) explained in her research paper that sentiment analysis refers to gathering valuable insights from customers feelings about the service and classifying those feelings into positive, negative or neutral sentiments. It has become very critical for airline businesses to understand and evaluate their current image in the minds of customers as it can help in enhancing the user experience and creating a competitive edge. Sentiment Analysis through ML techniques will help in enhancing user experience for airline industry.

ML Techniques have initiated the way for businesses to understand and critically analyse customer sentiments and gather useful insights that can help in meeting customer challenges. Commonly used ML models for Sentiment analysis that have shown promising results are Random Forest (RF), Logistic Regression, and Naïve Bayes (NB) with RF standing with better results.

To provide a pathway in understanding customer sentiments and assist airline industry in transforming their services, this paper provides a framework based on ML techniques to perform sentiment analysis on a dataset that is picked from Kaggle. The objective of this research is to help Airline companies in enhancing user experience of their customers and identifying useful insights about customers. Through this approach, organizations can strategize and create a competitive advantage based on the user's data from their own database.

1.1 Research Question:

Sentiment Analysis can help in the identification of customer sentiments about the services airline industry provided and give an opportunity to companies to act on the actionable insights that airline companies may not previously be aware of.

Question 1: To what extent can the Random Forest and Naïve Bayes effectively assess the sentiments of customers in airline industry and improving its performance?
Question 2: What are the specific sentiment indicators that has the most impact on customer satisfaction in the airline industry?

1.2 Research Objectives:

- Critically assess the previous literatures on use of sentiment analysis through conventional and machine learning approaches.
- Analyse customer sentiments based on the dataset of Airline Industry and provide actionable insights about customer preferences.
- Evaluate the effectiveness of Random Forest along with Naïve Bayes in transforming the performance of airline industry.

These research questions are developed in-line with addressing the most effective ML techniques to assess customer sentiments of airline company, how can they improve their customer experience and transform their business performance. The in-depth analysis through RF and NB techniques will help Airline companies in gathering meaningful insights about their customer sentiments and can evaluate the most efficient ways to transform user experience and company's performance. It will provide an opportunity to Airline industry to identify the most important factor during in-flight services for maximization of customer satisfaction.

2. Related Work

Prahabakar et al. (2021) reiterated how people prefer to express their opinions on social channels about their choices, likings and disliking very actively. One of the major platforms to do that in US is Twitter (now known as X) where customers actively talk about the services they have used, and its overall quality provided by the businesses. The increasing trend of expressing on social platforms have helped businesses in understanding customer sentiments about their products or services. Sentiment Analysis creates an opportunity for businesses to understand user sentiments and gather useful insights about their services. Customer reviews on Skytrax or Twitter about airline services help customers in finalizing their airline preferences and pick what seems to be the most recommended airline preference based on other people's past experiences. This paper focused on conducting a sentiment analysis of the best US based airline companies from Skytrax and Twitter through Adaboost approach and ML techniques such as RF, Support Vector Machine, Decision Tree. SVM turned out to be the top performing ML approach for sentiment analysis in this paper.

Rane & Kumar (2018) explained how the airline industry has been facing cutthroat competition for the last two decades. Previously, they relied on traditional approaches for data collection such as questionnaires and feedback forms however during recent times, the increasing trend of people expressing their opinions on social platforms has revolutionized the approach of identifying user sentiments about airlines companies. Traditional approaches are very tedious and time consuming as they tend to have possible biases but in contrast, social platforms have helped in gathering user data about the flight services for sentiment analysis. This research paper focused on twitter as a datahub for user sentiments about top 6 US airlines. Sentiment Analysis was being done through multiclass approach; from data pre-processing to cleaning techniques and deploying ML techniques to perform sentiment analysis. They used different ML algorithms such as Support Vector Machine, RF, NB and Adaboost to gather meaningful insights. Amongst all those approaches, RF gave outstanding results with a precision of 85.6%. Sentiment analysis through ML algorithms in this paper highlights the importance of using AI techniques to understand customer feedback about your respective airline service and use those actionable insights to in creating a competitive advantage.

Hasib et al. (2021) research paper focuses on the use of traditional approaches in airlines industry to understand customer feedback. Those techniques are very tiresome, time consuming and monotonous. Sentiment analysis plays a crucial role in understanding and identifying the pain points of the services in airline's business and what could be done to improve customer's experience. This research paper proposed a Deep learning approach to run sentiment analysis on dataset based on twitter users for airline service. They deployed a multi-class sentiment analysis after data processing to understand and gather actionable customer insights about the airline from social platform, twitter. Sentiment classification was done through CNN approach, and it explains the reliability of the robust method rather than relying on the traditional approaches.

Homaid et al. (2022) in his research paper identifies the key indicators which leads to customer satisfaction in the airlines industry. One of the many indicators is the quality of service provided at the airport. This, in addition, highlights the traditional approaches used by airlines to understand the customer sentiments about the services they provide. However, in the last few years, sentiment analysis has been done through ML techniques as this gathered the attention of the airline industry. This paper explained that using ML techniques such as Logistic Regression (LR) and Vader Sentiments (VS) to address the classification issue in sentiment analysis. LR outperformed VS in this paper with more precision, accuracy, and F1 score.

In this research paper (Tiwari et al., 2018) highlighted how Airline industry has witnessed excessive competition over the last few years. It explains the importance of understanding what your customer thinks about your airlines as people like to express themselves over different social platforms like Twitter about the services they undergo. Traditional approaches are restricted with narrow parameters and the responses often lean towards biases however executing a sentiment analysis test on tweets for airlines industry can help them understand the raw emotions of customers and the challenges they face. This will allow them to enhance customer experience. Manually understanding customer sentiments is nearly impossible in current times because of the data size based on number of customers airlines catered in a single day. The deployment of AI algorithms to assess and gather actionable insights about customer's feedback through sentiment analysis can be profitable for airline's business. This paper deployed a deep learning method to understand sentiments of the users through an open-source data platform; Kaggle. Various ML approaches can be executed for sentiment analysis however this paper focused on using neural network to assess the sentiments.

Similarly, Al-Qahtaniand & Abdul Rahman (2021) explained the use of different ML techniques to conduct sentiment analysis for the Airlines industry. They deployed AI algorithms to predict and understand customer sentiments by leveraging the US Airline Industry Data. ML techniques that were used in this research paper were RF, LR, NB and Deep Learning Methods. LR with RF having the most accurate results in terms of gathering meaningful and actionable insights from US Airlines Dataset.

Hakh et al. (2017) highlighted the impact of power that social media has on people. It has greatly affected people's opinion as they tend to rely on other people's past experiences before making any purchases or consuming any service for their own self. Recently, it has become a norm for users to assess social media to research reviews about the business before making any purchase. Similar story applies in the case of Air travel as people tend to evaluate and finalize their choices based on pre-existing reviews. This paper picked SMOTE technique to critically assess and understand user sentiments and classify into segments like positive, negative and neutral for US Airlines. It was done through feature selection and extraction on the dataset to nurture accurate results. RF was executed as another approach to extract results apart from other ML techniques and it outperformed the other ML techniques.

Vlachos & Lin (2014) talked about key drivers that create positive sentiments for the Airline Business. Customers tend to remain loyal when those key factors are not affected for them. Those key factors were divided in three aspects. One of them is operational factor which includes service, punctuality, safety and attractive factors included food and beverages and the staff services. Third key factor is competitiveness which includes loyalty flyer program, ticket prices, and schedule. If any of those factors are not looked after properly for customers, they tend to develop a negative sentiment towards the airline and airlines would need to improve in that task. This, furthermore, signifies the potential of sentiment analysis as it would allow airline companies to assess where they are lacking and how they can enhance customer experience.

Kang et al. (2021) discusses the sentiment analysis of Malaysian Airlines through BERT Approach. This paper explains the importance of using Sentiment Analysis for businesses to understand the key insight for the Airlines Business. In the airline industry, millions of users rely on social platforms to express their views about the airlines and how it can be improved. Those platform insights help in enhancing the services they offer. Social Platforms are platforms consisting of wide parameters that allow businesses to understand what the user feels about your service and various ML techniques were executed during this research to have the most accurate results in sentiment analysis. The authors used RF, Decision Tree, NB and BERT Model, with latter having the most accurate results.

Kumar & Zymbler (2019) explains how customer satisfaction remains a major gap for Airlines industry. It can define the integrity of your business or break your customer platform if their concerns are not properly and timely addressed. Airlines face severe competition as people have multiple options and alternatives available at their disposal. This paper emphasised Twitter as being the key platform where people express their positive and negative views about services they consume. This paper relies on using ML techniques to do sentiment analysis through multiple approaches. Models that were used to extract results are LR, RF, SVM, and Artificial Neural Network to critically analyse the sentiments of people regarding the Airline. The results gathered actionable insights for businesses to work with and enhance overall experience of the airline users.

This research paper by (Gitto & Mancuso, 2017) highlights the potential of sentiment analysis to assess customer sentiments on airport services. Gitto's objective in this research paper was to identify the relevant insights that define customer satisfaction. Businesses are actively acknowledging customer needs rather than solely improving operational efficiency. It is crucial for airline businesses to understand customer sentiments to bring onboard more customers and lower the chances of losing customers. Data in this research was collected through SKYTRAX website which featured the performance of European airports such as Amsterdam, Paris, Frankfurt and Madrid. Sentiment analysis was performed through open-source tools such as KNIME and Semantria and they were able to identify key insights from their research.

Amrani et al. (2018) discussed the importance of sentiment analysis and the growing use of it across different industries. His research paper focused on leveraging RF and support vector machine as a hybrid model to run sentiment analysis. The objective of his research was to enhance the accuracy of the models being deployed and strengthen the accuracy of results derived from execution. The dataset was based on amazon product reviews and classification models like SVM and RF were utilized. They were executed separately as well as through hybrid and collective approach. Individual classifiers lacked accuracy, however hybrid models outperformed individual models. It highlighted the importance of combining multiple ML techniques to derive better results.

The focus of this research paper (Baid et al., 2017) was on utilizing ML techniques to conduct sentiment analysis of movie reviews. This paper focused on the application of sentiment analysis to leverage and classify sentiments expressed for movies. As the use of sentiment analysis has become very crucial, the goal of this research was to classify those reviews as positive or negative. ML techniques that were deployed in this research were RF, K-Nearest Neighbor and NB. NB outperformed all the ML techniques with 81.4% accuracy rate as it was the most efficient medium to classify textual data.

2.1 Summary of Literature Review:

Various research papers were analysed to grasp a better understanding of the topic and analyse how previous research has been conducted. Traditional approach to assess what your customers feel about the Airline service is now old-school and proper sentiment analysis through ML technique is essential for any airline company. Various ML models were deployed in existing research and each method explored a different horizon. As the competition remains cutthroat, it is vital for airline businesses to run sentiment analysis on their own datasets to gather meaningful insights and create a competitive advantage over their customers. Most Common models used in the previous research were RF, NB, LR and SVMs. Based on these literature reviews, NB and RF tends to perform effectively when there is a classification problem.

3. Research Methodology:

In this methodology section, we have discussed the data collection, description, preprocessing process, and model development techniques through RapidMiner. Following steps of methodology are explained below:

3.1 Research Procedure:

i- Dataset Collection:

Dataset was collected and sourced from Kaggle's Database. Data is based on hypothetical Airline Company 'Investico Airlines.csv" which includes customer reviews along with several different aspects which derives customer satisfaction or dissatisfaction. It covers various services provided to customers by airlines, covering before departure, in-flight experience and after departure services. This dataset was selected as it provides a comprehensive overview of different aspects that are important for customer satisfaction.

ii- Data Description:

The dataset is based on 129,881 customer entries. Each row represents a unique customer based on these features as variables:

- Age – Customer's Age,
- Gender – Customer's Gender (Male, Female),
- Travel Type – Purpose of Travel,
- Class – Economy, Business or First Class,
- Flight Distance – Distance of flight covered by customers in miles,
- Inflight WIFI Service – Rated from 0-5 by customer,
- Time Convenience of Departure and Arrival - Rated from 0-5 by customer,
- Ease of Booking Online - Rated from 0-5 by customer,
- Gate Location - Rated from 0-5 by customer,
- Comfort from Seat - Rated from 0-5 by customer,
- Inflight Entertainment Services - Rated from 0-5 by customer,
- On-Board Service - Rated from 0-5 by customer,
- Baggage Handling - Rated from 0-5 by customer,

- Check-in services - Rated from 0-5 by customer,
- Inflight Service - Rated from 0-5 by customer,
- Cleanliness - Rated from 0-5 by customer,
- Departure delay– Total minutes delayed in departures,
- Arrival delay – Total minutes delayed in arrivals,
- Satisfaction – Satisfied, dissatisfied or Neutral.

These are all the variables associated with customers which determine satisfaction levels of each customer.

iii- Data Preparation:

Dataset is prepared through RapidMiner which trains and test the data for evaluation purpose. Before deployment of the model, RapidMiner prepares the data in the following steps:

i- Data loading – Investico Airlines.csv is ingested in RapidMiner and loaded to perform further steps of preparation.

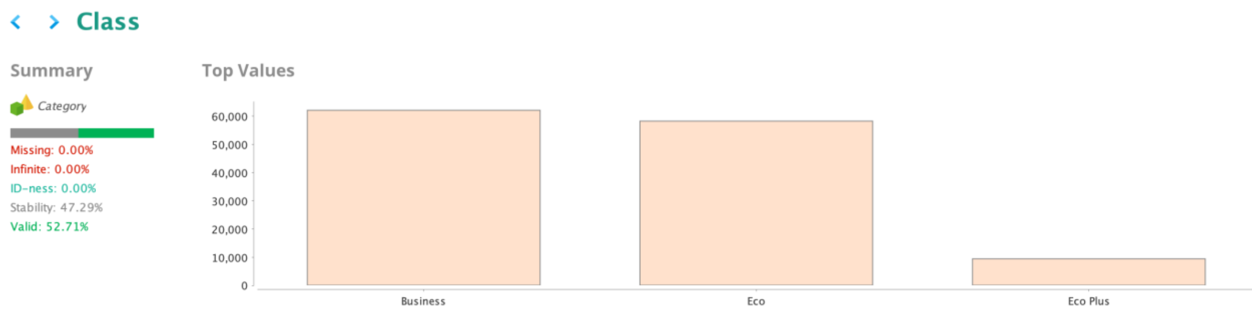
ii- Preprocessing – RapidMiner prepares data in 2 steps: Basic preprocessing and Detailed preprocessing. Basic preprocessing steps includes loading the data, creating a validation set and basic feature engineering. Moreover, detailed preprocessing in RapidMiner includes targeted encoding, handling unknown and missing values.

3.2 Exploratory Data Analysis:

EDA was performed to understand the structure and important features of the dataset. EDA through RapidMiner provided a statistical summary of our customers based on the gender count, type and class of travel, average age of people travelling in airline company's dataset.

Value	Count	Percentage
Female	65,899	50.74%
Male	63,981	49.26%

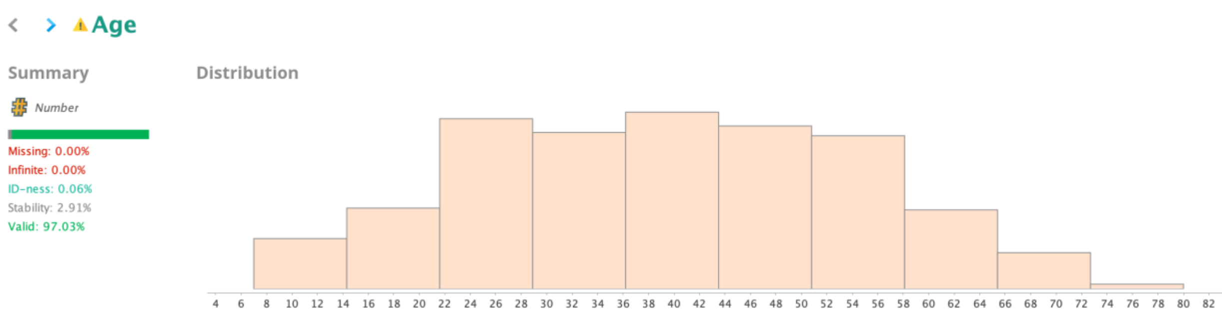
Figure 1: Statistical Insights – Gender Count.



3 Distinct Values:

Value	Count	Percentage
Business	62,160	47.86%
Eco	58,309	44.89%
Eco Plus	9,411	7.25%

Figure 2: Statistical Insights – Class of Travel.



Statistics

Name	Value
Minimum	7
Maximum	85
Average	39.428
Standard Deviation	15.119

Figure 3: Statistical Insights – Average Age of the Customers.

3.3 Statistical Procedures:

Machine learning models such as RF and NB were deployed in this research paper to assess sentiment analysis of customers of the airline company and how these models can help the airline industry in enhancing its performance. The dataset was split in 80-20 rule of model training and testing.
The evaluation of these models was based on statistical measures that would be derived from the deployment of these models in RapidMiner. Following metrics will be measured and evaluated:

1. Accuracy – This is the ratio of predicting correct instances out of total instances.
2. Precision – It refers to the ratio of correctly predicting the observations out of total observations.
3. Recall – It refers to predicting correct positive instances out of total instances.
4. F1 Score – This is a weighted average between precision and recall.

5. Confusion Matrix – It represents the summary of predictions with being correct or incorrect by the model. It's a table that defines the performance of classification algorithm.

4. Design Specification:

This section explains the implemented techniques in this research paper. Additionally, it defines the framework, key elements and proposed models along with their detailed analysis on how they are implemented.

4.1 Framework:

This framework explains how ML techniques are deployed to assess sentiment analysis and identify how airline industry can improve customer experience and enhance their business performance. The framework is divided into following sections:

1. Data Pre-Processing:
i- Basic Pre-processing:

- Load and Process Data – Dataset is uploaded into RapidMiner for initial processing. Initial Processing is based on handling missing values and categorization of the data. This step allowed in labelling data and identifying the unlabelled data.
- Create Validation: Dataset is split into training and testing data based on 80 to 20 ratio, respectively. It ensures the robustness of models when they are applied and provide accurate results.
- Basic Feature Engineering – Feature engineering includes the handling of missing values, data categorization and standardizing numerical features were incorporated for detailed pre-processing.

ii- Detailed Preprocessing Steps:

- Handling Unknown Values – All unknown values were processed to ensure that model is accurately trained and there are no unknown values during the training process.
- Replace Missing Values – All the missing values in the dataset were replaced with relevant substitutes such as mean value for numerical columns and mode value for categorical column.
- Encoding – Targeted encoding was executed on the dataset to train them for ML algorithms.

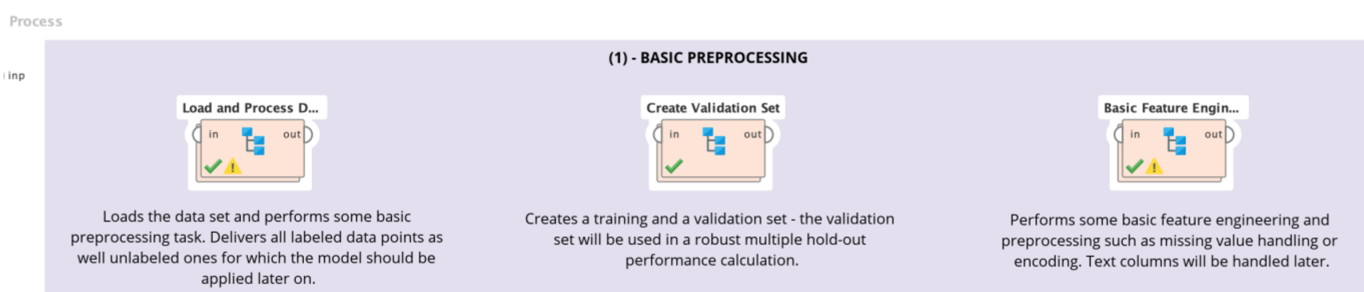


Figure 4 – Basic Preprocessing Steps.

2. Feature Engineering and Modelling:

i- Handle Text Columns:

- Text-processing-techniques were used to assess texts which includes standardization of texts through tokenization, lemmatization and removal of stop words as text data is transformed into numerical data to maximize the accuracy of ML models.

ii- Automatic Feature Engineering:

- Automatic feature engineering tools through RapidMiner were selected to identify the most relevant features of the dataset and enhance the performance of model by reducing dimensionality and biases.

3. Model Training:

- There are two ML models used in this research paper to enhance the performance of airlines industry.
- Random Forest – RF is an ensembled ML technique which combines multiple decision trees to derive results. As sentiment analysis is a classification problem, RF was trained with hyperparameters based on different variables in the dataset to optimize model's performance.
- Naïve Bayes is the other ML technique used in this research paper as it's a generative learning algorithm which allows the model to address classification problems. NB is used as a baseline method to compare the 2 models used in this research.
- Hyperparameter Tuning – This would allow us to run grid search method and optimize model's structure as it's very crucial for model's success. Hyperparameter tuning would allow RF and NB to provide optimal results. Grid Search divides the hyperparameters into different discrete grids, making it easier for the model to provide accurate results after thorough analysis.

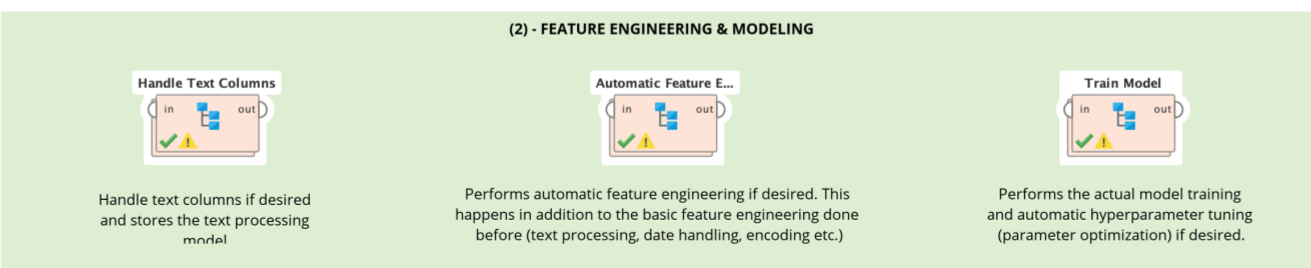


Figure 5: Feature Engineering & Modelling Steps.

4. Model Evaluation:

Both models deployed for this research will be evaluated through different metrics. To get an in-depth analysis of sentiment analysis and how airline industries can improve their performance, metrics like accuracy, recall, precision, F1 score, AUC, sensitivity, and specificity are calculated by deploying these models on RapidMiner. For visualization of the performance of each model, confusion matrix along with ROC curve were generated. Confusion matrix helps in distinguishing the performance of both models by accurately predicting true positive, true negatives, false positives and false negatives. To ensure that models are robust, ROC curves were plotted for model which helped us in visualizing the performance of each model for the classification problem in this research paper. These metrics provided a comprehensive overview of both model's efficiency.

4.2 Algorithm Description and Architecture:

The system architecture in this research is based on several important steps, including data ingestion, preprocessing (basic and detailed both), feature engineering, training the model, model evaluation and visualization of each step and the results obtained from the deployment of RF and NB. The core purpose to use ML algorithms in this research is to assess customer sentiments in the airline industry and boost the performance by gathering actionable insights. Although no new models were developed, the implementation of existing models provided key factors that influence the customer satisfaction levels. Those valuable insights gathered from the deployment of these models would provide airline industries in assessing their strengths and weaknesses and can strategize in a way that can improve customer experience.

4. Implementation:

The implementation of research project was started from data collection, data preprocessing, feature engineering, model training and model evaluation and all these steps were conducted using RapidMiner. RapidMiner is an advanced data science platform that allows us to do data ingestion and create a robust ML model. It's user friendly and provides comprehensive set of features that allow data handling and efficient model development. Models were trained and deployed on RapidMiner based on prediction model. For training and development of these model, an Apple M1 2020 machine with 8 GB ram was used.

5.1 Output Produced:

1. Encoded and Cleaned Dataset:

Methods such as mean for numerical value and mode for categorical values were used in handling the missing values in the dataset. This step made sure that dataset was complete and ready for further analysis. Targeted encoding and one-hot coding were used through RapidMiner to convert the categorical data into numerical values. Standardization of numerical features helped in improving the model performance as all the values were on the same scale. Text processing of customer reviews through tokenization, stop word removal and lemmatization were used to transform text data into numerical features for further processing.

2. Feature Engineered Data:

Automatic feature engineering tools of RapidMiner were identified and used to create new features in the dataset. Relevant features of the existing dataset were selected and applied to understand the most important variables and discard the irrelevant ones to refine the dataset. New features helped in understanding the complex patterns of the dataset and enhanced the efficiency of model's predictive capabilities.

3. Models Developed:

i- Random Forest:

This model was built based on the ML capabilities of RapidMiner, and additionally, it fine-tuned the parameters with the help of Grid Search. Grid Search was used to find optimal number of trees, its depth and exploring other hyperparameters. The process of building RF included the training process as different parameters and processes of RF were configured and trained to enhance its efficiency. Model's efficiency was evaluated through cross-validation process which ensured that the built model is robust enough to be operated. The optimal evaluation metrics derived to assess the performance of RF were accuracy, recall, precision, F1 Score and AUC. RF was selected as a preferred model to do sentiment analysis on the airline company's dataset and identified the key factors that play a crucial role in deriving customer satisfaction.

ii- Naïve Bayes:

Naïve Bayes Model was developed through RapidMiner as it's a commonly used ML algorithm for classification problems. NB was developed as a baseline model to have a comparison of both ML models. This is a simple and efficient approach for classification tasks. Multiple parameters were configured to get the optimal results from NB. Similar metrics were used to evaluate the efficiency of NB.

4. Visualizations:

The primary reason of visualization is to visually showcase the results that are obtained from the deployment of ML models in this research. Results and key insights were visually portrayed through the following approaches.

1. Results for Both Models – Performance of both models are visualized through a table which highlights all the performance metrics that were explained above.

2. **Confusion Matrix for Both Models** – Purpose of confusion matrix in both models were to visualize the false positive and false negative rate and it helped in understanding model's performance for correctly predicting the instances, both positive and negative.

3. **Feature Importance Analysis of Dataset** – The purpose of feature importance analysis was to identify and portray the importance of each feature that plays its part in deriving customer satisfaction. This further highlighted the top features that airline industry can focus on to transform its performance.

4. **ROC Comparison for Both Models**– ROC is crucial in comparing the two model's sensitivity rate as it's a trade-off between sensitivity and specificity. ROC comparison highlighted the robustness of ML models and validated the preferred machine learning approach for sentiment analysis in this research.

These visualizations provided a comprehensive overview of the model's performance as each approach in the visualizations offered a clear view of the performance for both models. The feature importance-analysis highlighted actionable insights based on the most important features that made customers happy.

6. Evaluation:

The given research was completed based on two ML methods which are primarily used for classification problems. As this research is based on classification issue, RF and NB were deployed to conduct sentiment analysis on airline company's dataset from Kaggle to understand the actionable insights that airlines can take and transform their services as per customer needs. Both these methods were executed on RapidMiner as it predicted the satisfaction level of customers based on their experiences they had with the airline. Through these tests, it helped in understanding the key factors that can enhance or worsen customer experiences, and all those insights are discussed in discussion heading. The metrics used in this research to compare both these models were accuracy, precision, recall, ROC curve, AUC score, confusion matrix and feature importance analysis.

6.1. Experiment 1 – Random Forest Performance Metrics:

The dataset was split into 80 to 20 ratio by RapidMiner for training and testing of the model. RF was deployed to predict whether customers were satisfied with airline's existing service as detailed information with different variables were mentioned in the dataset. The accuracy of using RF for sentiment analysis in this research was 0.891, precision was 0.896, recall was 0.907 and F1 score was 0.901. The classification error of RF was 0.109 and AUC score was 0.958 as mentioned in figure 6.

Criterion	Value
Accuracy	89.1%
Classification Error	10.9%
AUC	95.8%
Precision	89.5%
Recall	90.7%
F Measure	90.1%
Sensitivity	90.7%
Specificity	87.3%

Figure 6: Random Forest Performance.

Accuracy of 89.1% indicated that RF correctly classified majority of customer experiences as satisfied or dissatisfied. Similarly, precision rate explains that this model predicted customer satisfaction correctly by 89.6%. It's an excellent score as it indicates the model's efficiency. Recall of 90.7% means that the ML model accurately identified 90.7% of all satisfied customers. AUC of 95.8% reiterates on the excellent performance of model who's able to distinguish between satisfied and dissatisfied customers for the airline company from the given dataset. Confusion Matrix accurately assessing true positive rates reflects on the model's reliability and performs well in classifying the data between satisfied and dissatisfied customers.

	true dissatisfied	true satisfied	class precision
pred. dissatisfied	7048	913	88.53%
pred. satisfied	1028	8868	89.61%
class recall	87.27%	90.67%	

Figure 7: Confusion Matrix – Random Forest.

6.2 Experiment 2 – Naïve Bayes Performance Metrics:

The next model deployed in this research was Naïve Bayes to have a comprehensive overview of another ML model that fits the job for sentiment analysis. NB had a similar execution in RapidMiner on the same dataset to have a model for comparison. NB had accuracy of 0.793, precision of 0.91, recall of 0.691, F1 score of 0.785 and AUC of 0.893. Meanwhile the classification error for this approach was up to 0.207 as shown in the figure 8.

Criterion	Value
Accuracy	79.3%
Classification Error	20.7%
AUC	89.3%
Precision	91.0%
Recall	69.1%
F Measure	78.5%
Sensitivity	69.1%
Specificity	91.8%

Figure 8: Naïve Bayes Performance.

NB had an accuracy of 79.3% on the same dataset that we used in deploying RF. This indicates that NB is less efficient in classifying customer satisfaction compared to RF. It's precision rate of 91% explains that it's slightly more efficient in predicting satisfied customers however the recall rate of 69.1% highlights that it missed out on a huge proportion of customer who are satisfied. AUC is lesser than of RF which is 89.3% which explains that NB is less effective in differentiating between satisfied and dissatisfied customers of the airline. Confusion Matrix in NB also has a higher rate of false negatives compared to RF which highlights that it's not as reliable and less efficient compared to the other model.

	true dissatisfied	true satisfied	class precision
pred. dissatisfied	15414	6281	71.05%
pred. satisfied	1384	14030	91.02%
class recall	91.76%	69.08%	

Figure 9: Confusion Matrix – Naïve Bayes.

6.3 Experiment 3 – Feature Importance Analysis:

Along with the comparison of both models, weights-by-correlation highlighted the key variables that can play a vital role for airline industry to transform their business performance and improve profitability. Most important features that derived customer satisfaction based on the tests and dataset we had were:

- Inflight Entertainment (0.518) – Most impactful factor on customer satisfaction,
- Ease of Online Booking (0.424) – Second most impactful factor in making customers happy,

- Online Support (0.381) – It played a vital role in determining customer satisfaction.

These 3 variables were the most crucial along with other factors that are associated with in-flight services, pre, post arrival and departure services airlines provide. The key insights gathered from weights-by-correlation were that inflight entertainment should be top notch and airlines should focus on enhancing it further as it impacts the satisfaction of customers significantly. Similarly, airlines can improve the process of online booking and make it simple and seamless would help in transforming their business and making customers happy. Online support is very crucial for airline industry as customer often have different queries related to their flights or other factors. Airlines must focus on providing excellent customer services to retain customers and attract the new ones towards their business.

Weights by Correlation

Attribute	Weight
Inflight entertainment	0.518
Ease of Online booking	0.424
Online support	0.381
On-board service	0.347
Online boarding	0.329
Class	0.310
Leg room service	0.301
Customer Type	0.292
Checkin service	0.259
Cleanliness	0.255
Baggage handling	0.255
Seat comfort	0.240
Inflight wifi service	0.222
Gender	0.208
Food and drink	0.121
Age	0.114
Type of Travel	0.111
Arrival Delay in Minutes	0.076
Departure Delay in Minutes	0.071
Flight Distance	0.044
Departure/Arrival time convenient	0.016
Gate location	0.013

Figure 10: Feature Importance Analysis.

6.4 Experiment 4 – ROC Comparison:

ROC curve is graphical visualization of the of classifier's performance across all classification metrics. It is a trade-off between the true positive rate and false positive rate at each point of the curve.

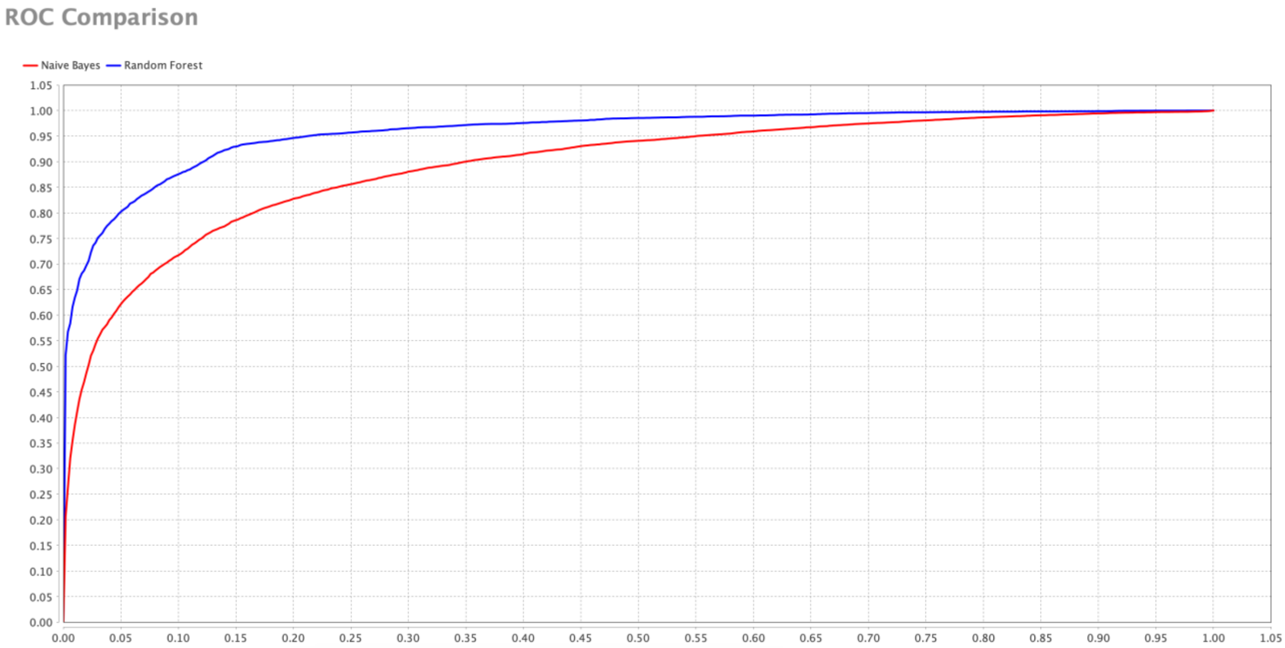


Figure 11: ROC Comparison.

As indicated in the figure above, blue line depicts RF while the red line depicts Naïve Bayes. The curve for RF is closer to the top left corner which explains its effective performance in this research while the NB line is away from the left side and highlights the less effective approach for sentiment analysis in this research. This graphical visualization indicates that RF is a better classifier for sentiment analysis and correctly distinguishes between positive and negative classes. Furthermore, it highlights the robustness of RF in effectively predicting satisfied and dissatisfied customers. RF ensembled nature avoids overfitting and provide better results based on the nature of the dataset in this research. This is a more effective choice sentiment analysis in this research with better accuracy, precision, recall rate.

6.5 Discussion:

The dataset was processed on RapidMiner and after comprehensive analysis through hyperparameters, the results for both ML models are presented in the table below:

Model	Accuracy
Random Forest	0.891
Naïve Bayes	0.793

As mentioned in the table above and in results section, RF outperforms NB in terms of accuracy, recall, and AUC which made it a superior choice for sentiment analysis in transforming the performance of Airline Industry. RF robustness to overfitting and its ability to tackle complex and diverse dataset resulted in a better performance of the model. The ensembled nature of RF allows variance to be tackled in a more effective way than NB.

7. Conclusion:

The extensive competition in Airline industries can be tackled by creating a competitive advantage over other airline companies. This research aimed at identifying the actionable insights by conducting sentiment analysis of airline companies so the industry can act upon the key findings and transform their performance. As a result of the deployment of ML models, this research highlights the key factors that are most important for customers and derive their satisfaction levels. Dataset was ingested in RapidMiner for preprocessing and RF and NB were deployed to assess sentiment analysis on the dataset. RF outperformed NB with higher accuracy rate along with better ROC, precision, recall and F1 score. This research highlighted the areas where airlines can improve and focus on the factors that determine the satisfaction of customers. It provides airline companies with targeted areas that can be worked upon and transform their performance. It is evident that RF is more suited in this research compared to NB to understand customer sentiments and act upon the actionable insights that we have gathered after conducting this research. Those insights would help airline industry in transforming its performance and enhancing customer experience for their airlines. The results align with existing research that demonstrate RF as an efficient tool for sentiment analysis.

8. Future Work:

For future work, we can incorporate social media feedback regarding the airline and customer interactions to gather more data about their customers. We can explore neural networks in sentiment analysis and assess how it pans out along with other classification techniques. Airlines can create a real-time customer feedback application that would allow them to instantly act on customer feedback and improve their flight experience. As the world gets digital, customer engagement remains the key for such competitive industry to progress hence the need for sentiment analysis and development of real-time feedback apps is necessary. Possible limitation of this research is that data set is not diverse enough and social media sentiments can be added to enhance the efficiency and improve model’s performance.

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