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Sentiment Analysis of Customer Reviews for Airline Services Using Different NLP and Machine Learning Techniques

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Abstract— When it comes to researching a service provider's services, facilities, and market standing, sentiment analysis is a great resource due to the abundance of customer evaluations, opinions, and feelings that are accessible online. When it comes to connecting passengers with airlines, social media channels are crucial. As a means of measuring service quality and operational efficacy, evaluations and feedback from customers are becoming more important to airlines. NLP and other machine learning technologies have come a long way in the last several years, greatly easing the burden of huge data analysis. This research delves into the sentiment analysis of airline customer evaluations utilizing a range of ML models and NLP approaches, such as NB, LSTM, RF, and CNN. The dataset, sourced from Kaggle, comprises predominantly negative reviews, with neutral and other sentiments. Data preprocessing steps such as normalization, stop words removal, lemmatization, and stemming were employed to enhance model performance. The analysis revealed that the CNN model outperformed other models with a 97%accuracy, 97%precision, 96%recall, and a 96%F1-score, demonstrating its superior capability in comparison of the RF, LSTM, and NB models. This research highlights the effectiveness of CNNs in sentiment analysis of airline reviews and provides valuable insights for improving customer service based on automated sentiment detection.

Keywords— Sentimental analysis, Customer Reviews, Airline Services, natural language processing (NLP), machine learning, Deep learning, CNN.

I. INTRODUCTION

In today's digital Era, Internet has become rich source of information. The world has changed due to the fast spread of social media; we are no longer limited to the information of our close friends and family. Customers are naturally wary of trying out new service providers, and the intangible nature of travel services makes word-of-mouth advertising all the more crucial[1]. Internet evaluations are a fantastic resource for data that can be mined regarding customer experiences. Social media sites are essential channels of communication for travellers and airlines. Customer ratings and comments are becoming more and more important inputs for airlines to evaluate operational performance and service quality[2].

Because it is a fiercely competitive sector where customer satisfaction is essential to an organization's strengths and shortcomings, the aviation industry is an excellent case study for examining customer feedback. Through the examination of online customer evaluations, scholars may determine the elements influencing the perceived value, performance, and quality of various airlines. Customer thoughts, expectations, and feelings from people who have used the service directly are reflected in online evaluations, which are a significant source of data. Airline companies may find ways to improve by asking for customer input via surveys and other methods. Through the use of sentiment analysis, airlines may get a deeper understanding of consumer priorities by examining comments. The Internet has also made pricing more transparent, which has cut into airlines' profit margins and elevated the importance of the customer experience[3][4].

Airline service providers are required to analyse customer feedback since they deal with a large volume of it. A growing number of airlines are turning to sentiment analysis as a tool for better understanding consumer opinion and gauging service quality[5][6]. The quality of airline services is a significant aspect in an intensively competitive industry since it strongly influences the degree of consumer happiness and loyalty. Consequently, it is crucial for airlines to understand consumer sentiment and determine what elements influence it. This may be accomplished via the use of sentiment analysis, a method that analyses textual data like customer evaluations and can provide priceless information into the positive, negative, or neutral polarity of sentiment[7][8][9].

Sentiment analysis is now the front-runner in ML. Companies in the airline industry value customer feedback highly since it helps them improve their services and facilities. The airline industry does sentiment analysis using traditional consumer satisfaction surveys and forms[10][11]. Big data analysis has been greatly aided by the recent lightning-fast progress in ML, especially in the field of NLP [12]. The fields of NLP and emotion analysis work hand in hand to help people communicate with computers. Data extraction and analysis from text-based sources, such as online product evaluations and comments, is facilitated by text SA[13]. The proliferation of social networks, together with SA's commercial and scholarly uses, has elevated it to the status of a critical topic in natural language processing. Deep learning is acquiring knowledge by constructing higher-level information from lower-level data (such as images, sounds, etc.) using several layers of representation and abstraction. A subset of ML techniques, deep learning[14][3]. To enhance consumer evaluations of airline service, this research introduces a ML technique to analyse sentiment analysis.

With the proliferation of online reviews, manually analyzing sentiments becomes impractical, necessitating automated methods. The study aims to develop and evaluate various machine learning models—CNN, Random Forest, LSTM, and Naive Bayes—along with NLP techniques to accurately classify customer sentiments. This research not only seeks to enhance the accuracy, precision, recall, and F1-score of sentiment classification but also aims to provide actionable insights for airlines to improve their services, ultimately leading to increased customer satisfaction and loyalty. By comparing these models, the study identifies the most effective techniques for sentiment analysis, thereby contributing to the advancement of customer review analytics in the airline industry. Here provide the key research contributions of this work:

- Comprehensive Evaluation of Models: This study provides a thorough comparison of various ML models (CNN, Random Forest, LSTM, and NB) according to their F1-score, recall, accuracy, and precision for sentiment analysis of airline customer reviews.
- Advanced Preprocessing Techniques: The research introduces effective data preprocessing steps, including normalization, stop words removal, lemmatization, and stemming, which significantly enhance the performance of sentiment classification models by reducing feature complexity and improving data quality.
- Feature Extraction and Representation: It showcases the implementation of n-gram representation for transforming raw text data into numerical formats suitable for analysis, demonstrating the importance of feature selection in sentiment analysis.
- Dataset Utilization: The study leverages a well-structured dataset from Kaggle, providing a balanced analysis of positive, negative, and neutral sentiments, which serves as a valuable resource for future research in sentiment analysis.
- Model Performance Insights: By visualizing and analyzing confusion matrices and performance metrics, the research offers detailed insights into the strengths and weaknesses of each model, guiding practitioners in selecting the most appropriate model for sentiment analysis tasks in the airline industry.

1.1 Structure of paper

The following is the outline for the remainder of the paper. A literature review is included in Section 2. The procedures used to compile this data are detailed in Section 3. Contains the suggested approach and resources as well. In Section 4, we provide the findings and discuss them. Section 5 concludes with our findings and a synopsis of our future endeavours.

II. LITERATURE REVIEW

This section summarises the prior research of a number of scholars who have studied the subject of sentiment analysis of consumer reviews using various machine learning methods.

In (Arpita et al., 2023), There has been tremendous growth in the competitive airline business within the last 20 years. The review of airline programs effectiveness heavily relies on feedback from consumers. An extensively gathered dataset of 67,993 reviews from the Google Play Store and the App Store based on the ten most well-known airlines. To enhance the precision of sentiment analysis, a word embedding method was used with

DL models including CNN, LSTM, and BiLSTM. Both LSTM and BiLSTM models achieved remarkable accuracy rates at 90% and 91% respectively, which is intriguing. However, BiLSTM was found to outperform other DL models regarding precision at 92%, recall at 91%, and F1-score at 91% among other outcomes[15].

In (Lakshmanarao, Gupta and Kiran, 2022)Airline tweets from the Kaggle dataset were used for sentiment analysis. El 11,540 evaluations are included in the dataset. For sentiment analysis, we suggested a CNN-LSTM ensemble design. In order to evaluate the proposed approach, LSTM was also tested independently on a comparable dataset. The suggested ensemble structure combining LSTM and CNN achieved an accuracy of 93%, whereas LSTM alone achieved 91%. When compared to more traditional methods, the results demonstrated that the suggested model produced more accurate results[16],.

In (Dahlan, Gunawan and Wibowo, 2022), Customer service is one area where digital information technology has made inroads. Traveloka is one app that has been in development since 2012. This research evaluates this Twitter application review using sentiment analysis. SVMs are the tools of choice for this sentiment analysis. This study's overarching goal is to deduce, from an examination of this application, the model's confusion matrix. Applications for desktop usage are subsequently built using these findings. The model's assessment results show an F1-Score of 0.8, an accuracy of 0.75, a precision of 0.67, and a recall of 1[17].

In (Manibalan and Jothi, 2024),focuses on analyzing airline customer reviews and predicting booking trends, specifically for British Airways. Methodologically, the study utilizes the Extra Trees Classifier for feature selection, focusing on 8 primary features, and employs the SMOTE technique for dealing with an unbalanced dataset. The predictive models experimented comprise of RF, LR, NB, and KNN. The models achieved an accuracy rate of 96%, 94%, 92%, and 94% respectively for booking prediction. The outcomes demonstrate an effectiveness of combining ML and text analytics in the airline industry[18].

In (Monika, Deivalakshmi and Janet, 2019),utilised to categorise six US airlines' tweets according to the polarity of their mood about flight services, identifying positive, negative, and neutral implications. Investigated the use of DL word embedding models (Word2Vec, Glove) to identify the polarity of sentiment in tweets. In this study, we looked at sentiment analysis utilising RNN and LSTM models, which can handle long-term relationships by including memory into a network model for visualisation and prediction. T The findings demonstrated a considerable improvement in the classification accuracy, indicating the reliability of our models for future prediction. In order to enhance this performance, further research utilises the Bi-LSTM[19].

The above literature work summarizes in the table 1 below:

Table 1: Comparative Analysis of Sentiment Analysis of Customer Reviews

References	Methodology	Dataset	Performance	Limitations & Future Work
(Arpita et al., 2023)	Word embedding with CNN, LSTM, BiLSTM	67,993 reviews from Google Play Store and App Store	LSTM: 90% accuracy; BiLSTM: 91% accuracy; BiLSTM: 92% precision, 91% recall, 91% F1-score	Limitations: Focused only on top 10 airlines, potential bias in review collection. Future Work: Explore additional airlines, incorporate more diverse data sources, enhance model interpretability.
(Lakshmanarao, Gupta and Kiran, 2022)	Ensemble CNN, LSTM	Kaggle dataset of 11,540 airline tweets	LSTM: 91% accuracy; Ensemble CNN-LSTM: 93% accuracy	Limitations: Limited to Twitter data, potential overfitting due to small dataset size. Future Work: Expand dataset, test with other social media platforms, improve ensemble methods.
(Dahlan, Gunawan and Wibowo, 2022)	Support Vector Machine (SVM)	Reviews of Traveloka via Twitter	Accuracy: 0.75; Precision: 0.67; Recall: 1; F1-Score: 0.8	Limitations: Lower precision, small dataset. Future Work: Enhance model to improve precision, use larger and more diverse datasets, explore other ML models to improve accuracy.
(Manibalan and Jothi, 2024)	Extra Trees Classifier,	Customer reviews of	Random Forest: 96% accuracy; Logistic	Limitations: Focus on a single airline, potential class imbalance

	SMOTE, Random Forest, etc.	British Airways	Regression: 94% accuracy; Naive Bayes: 92% accuracy; KNN: 94% accuracy	issues. Future Work: Apply models to other airlines, incorporate additional features, explore real-time sentiment analysis.
(Monika, Deivalakshmi and Janet, 2019)	Word2Vec, Glove with RNN and LSTM	US airline tweets	RNN-LSTM: Reliable classification accuracy with 80% training, 20% testing split; Future Work: Further investigation with Bi-LSTM for better results	Limitations: Limited to six US airlines, potential overfitting due to specific dataset characteristics. Future Work: Broaden dataset to include international airlines, investigate hybrid models combining different techniques.

2.1 Research gaps

Even though different deep learning models and machine learning techniques have made big progress in airline sentiment analysis, there are still some study gaps. At the moment, most studies only look at a few airlines and depend on specific datasets like Twitter or app reviews, which can introduce bias and make the results less useful in real life. Models like LSTM, BiLSTM, and ensemble frameworks have shown high accuracy, precision, and recall. However, we need to look into more diverse and bigger datasets to make them more robust and useful. Real-time sentiment analysis, the ability to work with multiple languages, and the addition of more advanced NLP methods like transformer models are still not fully explored. Getting these gaps filled could give the airline business more complete and useful information that would help them improve service and make customers happier.

III. METHODOLOGY

The proposed methodology for sentiment analysis of customer reviews for airline services involves several key steps. First, the dataset of airline reviews is collected from Kaggle, including various details such as sentiment categories, airline names, passenger information, and comments. Data preprocessing is then performed to reduce feature complexity through normalization, stop words removal, lemmatization, and stemming. Feature selection follows, transforming the raw data into numerical representations suitable for analysis. The data is then partitioned into a training set and a testing set, with a ratio of 70:30. Various classification models, including CNN, RF, LSTM, and NB, are employed to analyze the reviews. Finally, model evaluation is conducted using metrics such as F1-score, recall, accuracy, and precision, calculated by a confusion matrix to determine an effectiveness of a classification models, shows in figure 1.

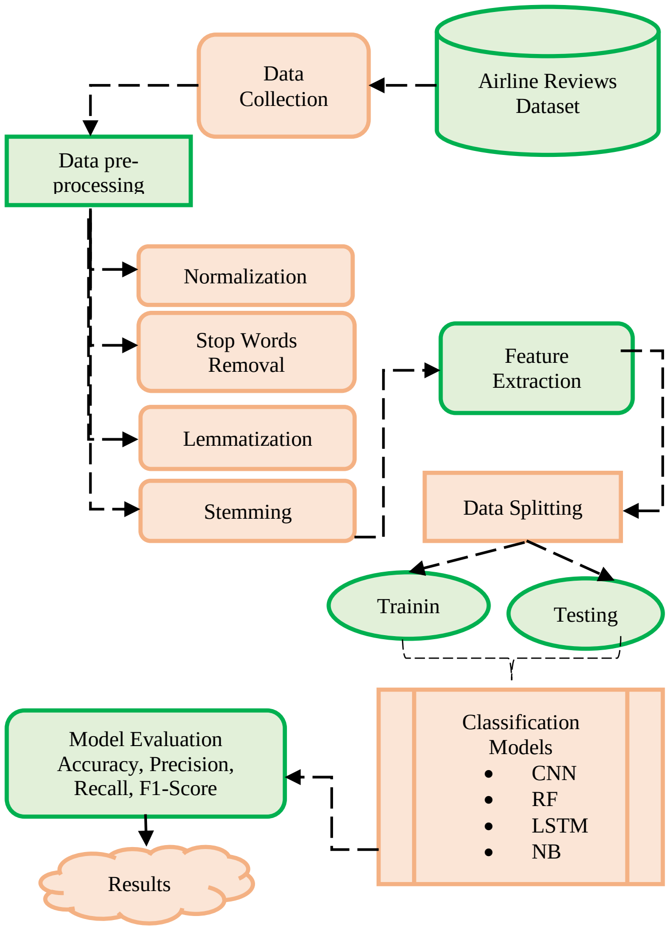

Figure 1: Proposed flowchart of SA of customer reviews for airline services

The following steps of the above flowchart diagram of methodology for sentiment analysis of customer reviews for airline services is explained below:

3.1.1 Data Collection

This study made use of an airline reviews dataset obtained from Kaggle. It shows data collected from people who have travelled with various airlines and shared their thoughts and views about those experiences. Among the data points included are the following: the passenger's sentiment towards the airline (positive, negative, or neutral), the passenger's location, the time and date of the comment's creation, the time zone in which the comment was made, and the passenger's actual comment or text. The dataset consists of 63% data that will be evaluated negatively, 21% data that will be evaluated neutrally, and 16% data that will be classified as "others."

Figure 2: Word Cloud for Airline Reviews

Figure 2 illustrates the word cloud of the airline review dataset. The most common terms or subjects included are "flight," "seat," "service," "plane," "time," "airline," "food," "staff," "airport," and so on.

3.1.2 Data Preprocessing

The goal of pre-processing is to simplify emotional classification and decrease the amount of characteristics used for review classification. As a result, throughput will be enhanced.

- **Normalization:** The goal of normalization is to decrease the feature count needed for categorization. Word tokenization is applied to both the training and test datasets. "This airline is good" becomes "This ','airline ','is ','good '" when tokenized. To improve pre-processing, the words are tokenized.
- **Stop words Removal:** In sentiment analysis, shortening texts by stop word removal is crucial. Filtering words is the method that doesn't really aid with digesting the papers. All of the texts have a few common terms, such as articles, pronouns, etc. None of these terms can tell you how someone feels about a paper. Some examples of terms that may be deleted from sentiment analysis are "the," "a," "these," and similar expressions.
- **Lemmatization:** Lemmatization is the process of restoring words to their dictionary form by eliminating inflectional ends via the use of vocabulary and morphological analysis. Using the word's parts of speech, lemmatization may scan the whole page and determine the word's meaning.
- **Stemming:** The term "stemming" refers to the act of reducing words to their most basic form, which includes their grammatical, derivational, and inflectional forms. It takes a word and strips it of its suffix. For instance, the words "connect," "connective," and "connectivity" are all shortened to just one word.

3.1.3 Feature Selection

In sentiment analysis, feature extraction is a crucial step. Before analysis can be conducted on raw data, it must first be processed and converted to a numerical form. Take the following tweet as an example: "The flight was so pleasant except that food quality can be improved." "The flight was," "flight was so," "was so pleasant," "so pleasant except," "pleasant except that," "except that food," "that food quality," "food quality can," "quality can be," and "can be improved" are the n-grams or three-gram representations of the tweet above.

3.1.4 Data Splitting

In this, the dataset has been divided in two sets that is training and testing data. They divided in the ratio 70:30, i.e. training is in 80%, and testing is in 20%.

3.1.5 Classification Models

In this section provide machine learning for airline review analysis using different machine learning techniques which were discussed below:

1) Convolutional Neural Networks (CNN)

The CNN is a DL model that can automatically and adaptively learn spatial hierarchies of features, starting with low-level patterns and progressing to high-level ones. It is meant to handle input with a grid pattern, like photographs, and is inspired by the organisation of the animal visual cortex [20] [21]. Typically, convolutional, pooling, and fully connected layers make up a CNN, which is a mathematical construct. Convolution, a subset of linear operations, is one of several mathematical operations that make up a convolution layer, an essential component of CNNs.

2) Random Forest (RF)

A classifier that employs ensemble learning is known as a random forest classifier [22]. This method can sustain hundreds of source factors and large databases without eliminating any of them. Data point errors might be handled using such method. Random Forest may also be useful for sorting or regressing data. There are now many decision-making trees being installed. The biggest benefit of this approach is that you can use it for either classification or regression employing this Random Forest Technique. Choose the RF Algorithm if you want the most performance[23].

3) Long-Short-Term Memory (LSTM)

An additional popular RNN network type, LSTM was built to tackle the vanishing gradient issue [24] [25]. Analysis of patterns in time series data is where they really shine. The LSTM's capabilities are significantly improved due to the fact that the forget gate, input gate, and output gate are all nestled inside this block of memory. Both fresh and old data in the memory cell may be altered using 26 of these gate layouts. A cell's current state and its concealed state are sent to the cell next to it[26][27].

4) Naïve Bayes (NB)

The simplicity of the Naïve Bayes model, which gives equal weight to all qualities in making a final conclusion, makes it a popular choice for ML applications. The Naïve Bayes approach is appealing and applicable to many domains due to its computing efficiency and its simplicity [28][29]. NBC primarily focusses on three parts, namely, class conditional probability, prior, and posterior.

3.1.6 Model Evaluation

A crucial step in finding the top-performing model is deciding which assessment measures to use. The metrics that were utilised to assess our model are detailed in this section. Statistical figures such as these are the results of running the tested and optimised DL architectures on the testing set [30][31]: TN (True Negative), TP (True positive), FN (False Negative), and FP (False Positive). The F1-Score (F1), recall (REC), accuracy score (ACC), and precision score (PER) are all computed using these data. Metrics such as accuracy, precision, recall, specificity, and F1 score are used in a confusion matrix to evaluate the efficacy of the classification model. Those evaluation metrics are formulated as equation 1 to 4 follows:

The accuracy of the model's data classifications is evaluated in this study:

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \dots \dots (1)$$

The precision of a model's predictions is defined as the degree to which they match the specified data for true positive predictions.

$$Precision = \frac{TP}{TP + FP} \dots \dots (2)$$

The recall metric measures how well the model can retrieve data.

$$Recall = \frac{TP}{TP + FN} \dots \dots (3)$$

An F1 score is calculated by comparing the weighted average of recall and precision.

$$F1 - Score = \frac{2 * Precision * Recall}{(Precision + Recall)} \dots \dots (4)$$

The section below discusses the results of the experiment and analysis.

IV. RESULT ANALYSIS AND DISCUSSION

Experimental findings of ML models trained using NLP methods for sentiment analysis of airline service evaluations, measured by f1-score, recall, precision, and accuracy. Think about making a visualisation of the classifiers' confusion matrices for the bigger dataset. When we talk about the confusion matrix in terms of good, negative, and mixed reviews, we're referring to the columns where the sentiment is either positive, mixed, or negative. Try to compare the DL approach quickly while examining the confusion matrix using our way.

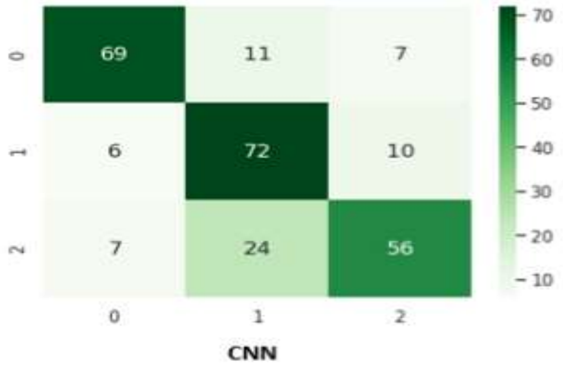

Figure 3: Confusion matrix of CNN model

The confusion matrix in Figure 3 shows the performance of a CNN model in classifying customer reviews of an airline into three categories. On the other hand, when it comes to negative sentiment (column 0) in the CNN classifier, 69 reviews are successfully categorized whereas 6 and 7 reviews are incorrectly classified. According to the positive sentiment metric (column 2), 56 reviews have been accurately identified, with 10 reviews showing misclassification and 7 reviews showing no misclassification. The first column shows the results for mixed sentiment reviews, which show that 72 reviews are correctly categorized and 11 and 24 reviews are misclassified.

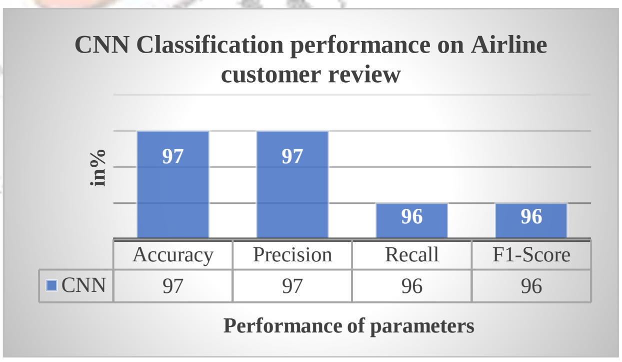

Figure 4: Bar graph of CNN model performance for Airline customer review

The bar graph in Figure 4 illustrates the performance of a CNN model in analyzing airline customer reviews, with each bar representing F1-score, recall, and precision for three classes of reviews. The CNN model get 97% accuracy, precision, and 96% recall and f1-score measure for analyzing airline customer reviews.

4.1 Comparison of ML models

The table 2 shows the comparison between different ML models for classification airline reviews of customer.

Table 2: Parameters comparison between different ML models for customer review analysis

Models	Accuracy	Precision	Recall	F1-Score
CNN	97	97	96	96
RF [32]	77	78	50	61
LSTM [33]	76	72	72	72
NB [34]	71	91	32	48

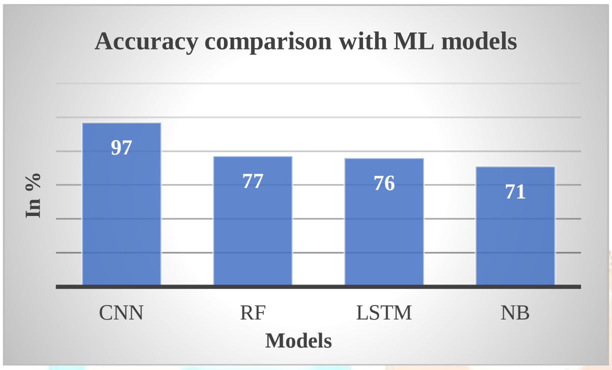

Figure 5: Bar graph of Accuracy comparison with ML models for customer review analysis

Figure 5 and table 2 shows the accuracy of various ML models utilized for customer review analysis. The Convolutional Neural Network (CNN) stands out with the highest accuracy of 97%, indicating its strong performance in correctly classifying reviews. This is significantly higher compared to the Random Forest (RF) model at 77%, the LSTM network at 76%, and the NB classifier at 71%. The CNN's high accuracy suggests it is particularly effective for this task, likely due to its ability to capture complex patterns in text data through its hierarchical feature extraction capabilities.

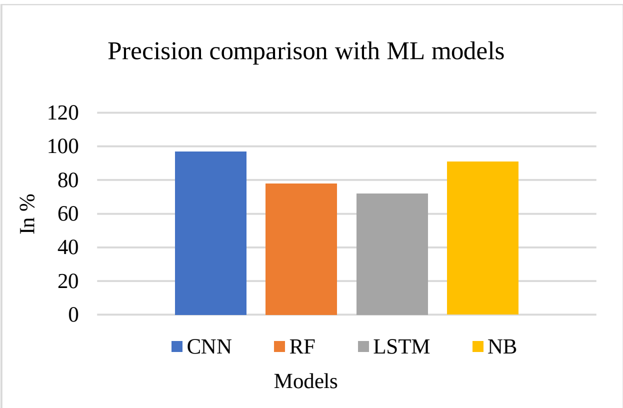

Figure 6: Bar graph of precision comparison with ML models for customer review analysis

In Figure 6, precision is compared across the models. The Naive Bayes model exhibits the highest precision at 91%, which indicates that when it predicts a positive sentiment, it is correct 91% of the time. This is followed by CNN with a precision of 97%, showing it also performs well in terms of precision. The Random Forest model has a precision of 78%, and LSTM has the lowest precision at 72%. The high precision of the Naive Bayes model suggests it is very effective at minimizing false positives in sentiment classification, though it is essential to balance this with other metrics such as recall.

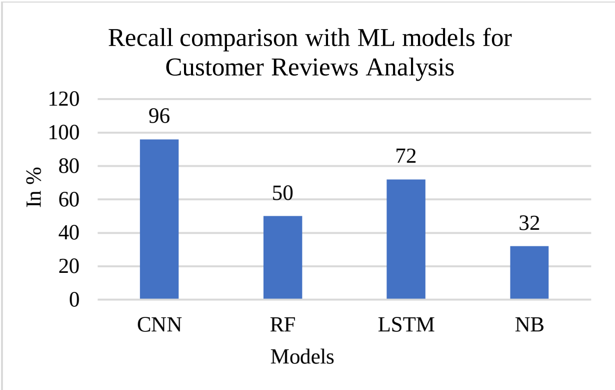

Figure 7: Bar graph of recall comparison with ML models for customer review analysis

Figure 7 illustrates the recall performance of the models. The LSTM network and Naive Bayes model both show a recall of 72% and 32%, respectively, highlighting their differing strengths. The CNN model achieves a recall of 96%, suggesting it is highly effective at identifying all relevant instances of positive sentiment in customer reviews. The Random Forest model has the lowest recall at 50%, indicating it misses a significant number of positive reviews. High recall in CNN signifies its robustness in detecting true positive sentiments, which is crucial for comprehensive sentiment analysis.

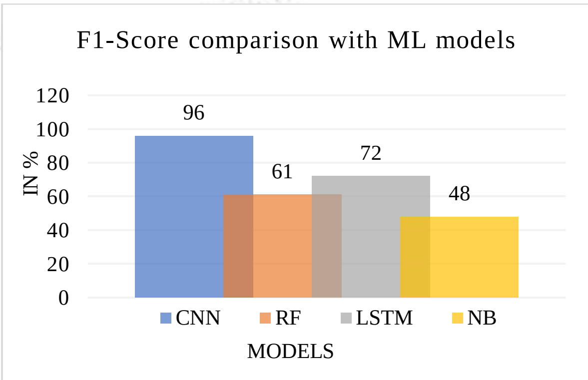

Figure 8: Bar graph of f1-score comparison with ML models for customer review analysis

The models' F1-score comparison is shown in Figure 8. The CNN model leads with an F1-score of 96%, reflecting a balanced performance between precision and recall. The RF model has an F1-score of 61%, while the LSTM network and Naive Bayes classifier show F1-scores of 72% and 48%, respectively. An important indicator that gives a more complete picture of the model's performance is the F1-score, which takes recall and precision and adds them together. The CNN's superior F1-score indicates its overall effectiveness in handling the sentiment analysis task, making it a well-rounded choice for this application.

V. CONCLUSION AND FUTURE SCOPE

An aim of this paper is to deduce the customers' assessment of their experience of Airline service using the customer reviews. This analysis can help the industry to provide better services and customer satisfaction. The need for thorough research into natural language processing approaches for data pretreatment has been highlighted by the many studies that have examined NLP algorithms for sentiment analysis using textual customer feedback. Using a dataset of airline reviews for sentiment analysis, we investigated the CNN model and its offspring in terms of machine learning. We fine-tuned the model even more by modifying its hyperparameters, which led to more reliable and accurate results. With accuracy, precision, recall, and f1-score sentiment classification jobs averaging 97% and 96%, respectively, CNN clearly emerged as the most effective and accurate model for analysing consumer sentiment in the airline business. The purpose of the study is to get a better understanding of consumer behaviour and their assessment of airline services. Future research might make better use of the limited quantity of internet reviews used to train the model, which is the primary shortcoming of this study. Increasing the amount of online evaluations allows us to build a more robust model and enhances the accuracy of classification. After we boost the quantity of online evaluations for the Bangladesh Airlines dataset, we will compare the results to those of other countries. The method described in this study may be used by Bangladeshi airlines to gauge customer satisfaction.

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