Classification of User Reviews on Online Travel Booking Applications in Bangladesh using Multinomial Naïve Bayes

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ABSTRACT
The exponential development of technology in Bangladesh has changed the face of the tourism sector, and even with the inclusion of application-based online travel ticket booking systems like Shohoz, GoZayaan and BDTickets. These apps are popular among Bangladeshi travelers. In this study, we examine an architecture where the Multinomial Naïve Bayes algorithm is used to classify user reviews of these travel apps into two categories, which are "Satisfied" and "Unhappy". The dataset is composed of 1339 reviews, which were gathered from the Google Play Store. The results were considered, considering the data was split into three scenarios (70:30, 80:20, 90:10 and validated using a confusion matrix and KFold Cross Validation. Among all models, 81.34% accuracy was obtained for the 9:1 split ratio with the model precision of 81.47%, recall of 81.43%, and F1-Score of 81.34%. A TF-IDF analysis showed that terms like "good," "nice," and "excellent" were the most prevalent in the "Satisfied" class, whereas terms such as "price," "can't," and "app" were more likely to be found in the "Unhappy" class. The results indicate that the Multinomial Naïve Bayes approach is efficient for the classification of user reviews of online travel booking applications in Bangladesh, and the performance increases as the data table size increases.

General Terms
Multinomial Naïve Bayes, Machine Learning, Natural Language Processing (NLP), Sentiment Analysis

Keywords
Classification, User Reviews, Multinomial Naïve Bayes, Online Travel Booking, Bangladesh

1. INTRODUCTION
Bangladesh is initially developing from the point of view of telecommunication as well as technology; it is only a matter of a few days to be a digital Bangladesh; now the country is decades ahead of this digital era. With the growing technology and digital connection in Bangladesh, tourism has also changed sharply. The online travel ticket booking apps have just made booking is super easy for Bangladeshi travelers, such as Shohoz and GoZayaan and BDTickets, for Bangladeshi users, transferring the maximum amount of travel information - destinations, flights, promotions, discounts, departure times, and facilities available - to smartphones.

Travel apps provide a convenient booking service, and that has created a really loyal user base. The ease of use, lower costs, and the ability to get real-time information about services provided by these applications are appealing to domestic as well as international travelers.

The latest growth in the country's tourism was the highest of the last five years, according to the Bangladesh Bureau of Statistics (BBS). The BBS data, released yesterday, also shows that domestic tourism in Bangladesh grew by 12.02 per cent month-on-month in November 2023 over the same month a year earlier. International tourist arrivals in the same period were up a stunning 110.86%. This rapid tourism growth shows the significance of appropriate travel booking apps in the Bangladesh travel industry.

In Bangladesh, online platforms such as Shohoz are becoming quite popular, mainly because of promotions and an easy-to-use interface for flight bookings, and other travel apps such as GoZayaan and BDTickets also operates in the market, with the primary focus being e-commerce and local services, not just listings for vacations or business trips.

Users often read reviews of an online travel application before deciding to make use of one on platforms like Google Play Store and the App Store. Reviews give users a sense of whether the app can be relied upon, but also whether the services are of good quality. Most reviews are either "satisfied" or "unhappy". When reviews are read, it becomes possible to decide which app meets specific requirements. Good reviews help users gain confidence in the app, while bad reviews generally act as an indicator for prospective users regarding the disadvantages of the app.

When people post reviews, it is impractical to classify them by hand or one by one. Hence, the development of an automated review the classification system to assist developers in understanding user sentiments more systematically is increasingly desirable. Through a set of computerized tools, developers will be able to identify the areas that need improvement from the feedback provided, prioritize issues, and improve the overall user experience in relation to travel applications.

2. RELATED WORK
Sentiment analysis and classification of user reviews for online travel booking apps have been studied in the past using a range of Machine Learning techniques, such as the Naïve Bayes classifier and its improvement. One such project was conducted by Diekson et al. [4], which analyzed the sentiment of GoZayaan user reviews by a naïve Bayes algorithm and obtained an accuracy of 82.91%. This study proved that Naïve Bayes can be used to investigate user reviews, which are

expressed in natural language, and sentiment is the target of interest. Similarly, Yuyun et al. (2021) [5] have utilized Multinomial Naïve Bayes for sentiment classification of public opinion regarding COVID-19 management in Indonesia. This result achieved 74% accuracy, 74% precision, and 74% recall for the classification of public sentiment. By adopting a real-world event, the study demonstrated the adaptability of the Multinomial Naïve Bayes model in natural language processing textual data on social media platforms (e.g., Twitter) that resembles the unstructured data of user reviews. Another related work by Oktaviani et al. (2021) [6] also extracted sentiment from user reviews on GoZayaan and implemented a Naïve Bayes classifier to classify the reviews as positive and negative. The results have shown that Naïve Bayes obtained an accuracy of 91.20% which signifies its strong performance on travel application reviews. It can be concluded that the good performance in this study indicates the validity of Naïve Bayes for OTBS, and its use is appropriate for sentiment classification in this domain. A notable difference of this study is the application of a Multinomial Naïve Bayes classifier using TF-IDF-based feature selection for classifying user reviews of online travel booking apps of Bangladesh. With the addition of the TF-IDF mechanism, the traditional Naïve Bayes model is enhanced to maximize the importance of high-frequency words and perform more accurate analysis. The TF-IDF can be used to assign weights to words in each review, so that words which are likely to determine the polarity of the review (for instance: "customer service", "price", "booking ease", and "promotions") are given more weight in the sentiment classification. This approach has been widely used in other domains, such as e-commerce, product reviews, and social media analytics.
Moreover, other recent studies, including those of Ahmed et al. (2020) [7], investigated sentiment analysis of travel and tourism data related to Bangladesh, considering customer satisfaction and dissatisfaction in different platforms such as GoZayaan and BDTickets. Different machine learning techniques, such as Support Vector Machines (SVM) and Random Forests, were employed and compared with Naïve Bayes. The findings indicated that SVM performed slightly better, while Naïve Bayes remained the most suitable choice in terms of ease of implementation and performance for small datasets, making it more appropriate for the travel industry, including Bangladesh.

Furthermore, Hasan et al. (2021) [8] studied online reviews for local ticketing and travel agency Shohoz and BusBD using predictive models based on deep learning for accuracy improvement. The results indicated that LSTMs outperformed naïve Bayes-like methods on complicated reviews. However, the findings also demonstrated that for relatively straightforward datasets, such as word-wise classification of sentiment, traditional models like Naïve Bayes can still deliver effective results and are therefore considered practical for travel industry applications in Bangladesh, particularly for platforms with limited data.

Naïve Bayes for review analysis of Shohoz, GoZayaan and BDTickets. This approach provides opportunities for service upgrades, increased consumer satisfaction, and enhanced brand loyalty in the rapidly expanding travel market of Bangladesh. Positive sentiment reviews can be distinguished from negative ones to identify customer preferences and dislikes regarding various facilities, enabling better alignment of services with user requirements.

This study further leverages a larger, more diverse dataset covering multiple travel applications used in Bangladesh and, therefore, presents a more comprehensive study that should help the local travel industry in discovering customer demand and enhancing the quality of service. It also shows the potential of using simple machine learning algorithms like Naïve Bayes with TF-IDF feature extraction for filtered analysis of user reviews, which is especially useful for businesses willing to enhance customer satisfaction and engagement.

3. RESEARCH METHODOLOGY

3.1 Data Acquisition

The data used in the study were crawled from the Google Play Store. Data was scraped from the Play Store through the use of the Google Play Scraper library, which enables scraping of reviews from the Play Store. A total of 1339 reviews were collected from three major online travel Apps: Shohoz, GoZayaan, and BDTickets from April 18, 2017, through September 12, 2023.

Table 1. Data

No	Application	Size
1	Shohoz	499
2	GoZayaan	432
3	BDTickets	408
Total		**1339**

Table 1 represents the split of our dataset obtained in the research, namely the number of reviews we have collected from three popular online travel applications in Bangladesh: Shohoz, GoZayaan and BDTickets. We have a number of reviews collected from the Google Play Store in each application:

• **Shohoz:** We found 499 reviews.

• **GoZayaan:** 432 reviews in total were gathered.

• **BDTickets:** A combined 408 reviews were obtained.

3.2 Preprocessing

• The goal of preprocessing is to clean the data so that the ML can effectively understand and process it. Preprocessing steps consist of cleaning, case folding, deleting stopwords, and lemmatization.

• First, the reviews are cleaned of the emoticons, punctuation, URLs, and extra white spaces.

• Then all text is converted to lowercase in the second step to normalize the data and reduce computation.

• Stopword elimination is performed, in which stopwords—words that do not add to the meaning of a sentence, e.g., a, the, in—are lemmatized.

• Words can also be normalized to the root forms based on the context to get more accurate results than using stemming.

3.3 TF-IDF (Term Frequency-Inverse Document Frequency)

Next, features are created by performing TF-IDF, which measures the importance of words in a review. The word frequency (TF) indicates how many times a word has appeared in a review, whereas inverse document frequency (IDF) indicates how rare the word is among the whole dataset. Words are considered significant if they are frequent in a given summary but rare in other summaries.

3.4 Multinomial Naïve Bayes

Multinomial Naïve Bayes is a robust Machine Learning

Algorithm based on probability, and it is very common in Natural Language Processing (NLP). It estimates the word that belongs to a document (class) using Bayes' Theorem. This technique is well-suited for the classification of textual data, hence suitable for this paper.

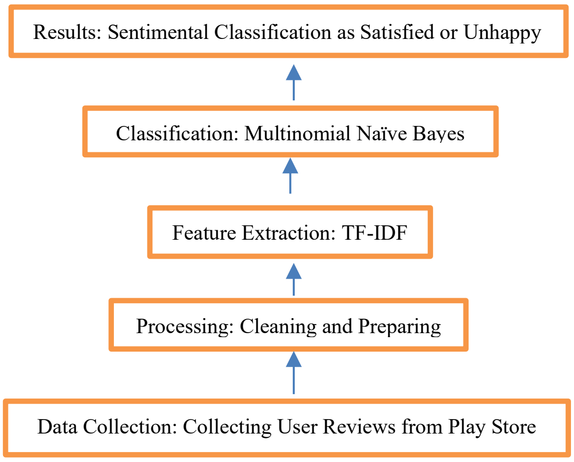


Fig 1: Flowchart for Travel App Sentiment Classification

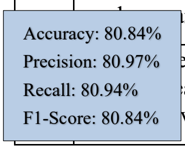
The flow chart (Figure 1) illustrates a method of classifying user reviews of travel applications as "Satisfied" or "Unhappy". It starts by scraping user reviews from platforms such as the Google Play Store. After that, the data is preprocessed, including cleaning the reviews by eliminating non-related content and normalizing the text. After preprocessing the reviews, features of the reviews are extracted with the TF-IDF method, which captures the importance of words. The reviews are then classified using the Multinomial Naïve Bayes model, which classifies the reviews based on the features extracted. Finally, we get the results, that is, every review labeled satisfied or unhappy, and these can be used to give us insight into user sentiment and can also be used to make the travel applications more brilliant.

4. RESULTS AND DISCUSSION

The crowdsourcing technique was used to label the user reviews' dataset of online travel applications in Bangladesh. Participants were instructed to categorize reviews as satisfied if the review was satisfied, or unhappy if the review was dissatisfied or contained complaints. This approach reduced subjectivity and maintained the accuracy of the annotation.

Table 2. Sample Dataset

No	Review	Sentiment
1	Good, fast response if any trouble, good solution	Satisfied
2	No verification code when purchasing with a credit card	Unhappy
3	Your website needs attention, as it gets stuck at the payment page	Unhappy
4	Daraz is very useful and user-friendly, [illegible]n get the best flight deals	Satisfied
[illegible]	[illegible]en using this for years, now [illegible]asier. Of course, there's room [illegible]vement	Satisfied



A sample of reviews 41 from online travel applications is shown in this table, having been manually categorized by sentiment. The dataset contains 5 example reviews with the sentiment labels. The sentiment labels are "Satisfied" or "Unhappy" according to the review content.

Review 1 (Positive): "Satisfied". A quick response was provided and the problem was solved in the way desired.

Review 2: In Review 2, a problem with buying is mentioned; in particular, no verification code when using a credit card. This results in the sentiment being tagged as "Unhappy".

Review 3: Complains about a technical issue with the website: It would jam when an attempt was made to make a payment. Since this expresses an unpleasant feeling, its tone is marked as "Unhappy".
Review 4: Quick access to the best flights or the best deals leads to a "Satisfied" sentiment.

Review 4: Quick access to the best flights or the best deals leads to a "Satisfied" sentiment.

Review 5: Addresses, Long-term use and Usability, with a bit of comment adding to room for improvement, but still maintaining positive feedback, and is therefore classified as "Happy".

The dataset that has been collected and preprocessed will be divided into two parts: training data and test data. The ratio for splitting the training data and test data refers to previous research conducted by [11], where the dataset will be divided into three ratios: 7:3, 8:2, and 9:1.

Table 3. Dataset Splitting

Test	Split Ratio	Train Data	Test Data
1	7:3	937	402
2	8:2	1071	268
3	9:1	1205	134

Based on the experimental results with the three data splitting scenarios, the 9:1 data split scenario achieved the highest accuracy of 81.34%, indicating that the model was able to perform well in classification. The next best accuracy was achieved by the 7:3 scenario, with an accuracy of 80.84%, followed by the 8:2 scenario with an accuracy of 79.48%. This can be seen in the following:

Table 4. Test Results

Test	Data Split Ratio	Accuracy	Precision	Recall	F1-Score
1	7:3	80.84%	80.97%	80.94%	80.84%
2	8:2	79.48%	79.71%	79.60%	79.47%
3	9:1	81.34%	81.47%	81.43%	81.34%

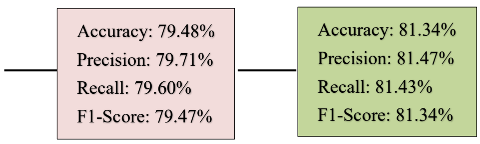


Fig 2: Test Result Flowchart

This flowchart (Figure 2) provides a visual of the flow of the

Test Results from the three data splitting ratios (7:3, 8:2, 9:1). It graphically displays the accuracy, precision, recall, and F1-Score measures of all the test cases for the identification of user reviews of online travel applications. The sequential boxes from Test 1 (7:3) to Test 2 (8:2) to Test 3 (9:1) lead a clear pathway, where the results under each scenario are described.

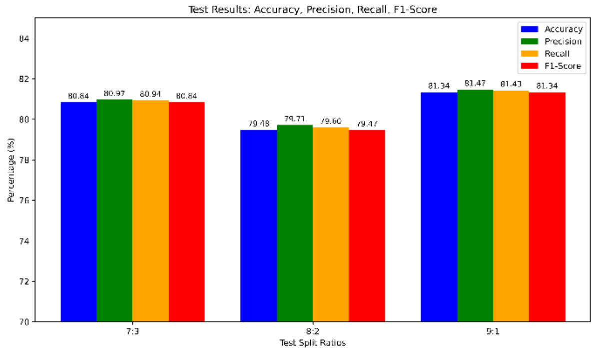


Fig 3: Test Results: Accuracy, Precision, Recall, F1-Score

Figure 3 is a test results bar chart of Accuracy, Precision, Recall, and F1-Score for 3 data significance cut ratios: 7:3, 8:2, 9:1.

• The blue bars reflect accuracy.

• Precision is shown in green.

• The orange bars show the recall.

• The red bars represent the F1-score.

Each group of colored bars represents a test, and the metric values of the test are reported to indicate the model performance in the three data split ratios:

7:3 (left side of the chart) are as follows:
Accuracy: 80.84%
Precision: 80.97%
Recall: 80.94%
F1-Score: 80.84%

8:2 (middle section) shows:
Accuracy: 79.48%
Precision: 79.71%
Recall: 79.60%
F1-Score: 79.47%

9:1 (right) reaches to the maximum values:

Accuracy: 81.34%

Precision: 81.47%

Recall: 81.43%

F1-Score: 81.34%

This is depicted in the chart (with error bars) where the overall evaluation of these two metrics is compared visually between various test scenario, while 9:1 data split ratio performed the best in term of all the metrics.

The findings extracted from the dataset of user reviews on online travel applications in Bangladesh via crowdsourcing in the existing labelling process will be summarized in the section that follows. A crowdsourcing task was used to achieve an objective and homogeneous labeling of the reviews, i.e., participants were asked to label the reviews as "Satisfied" or "Unhappy". By categorizing every review based on expressed sentiment, this approach minimized the subjectivity inherent in manual annotation. Therefore, the dataset remained valid, such that a model that could be trained on the data could be relied upon to generate valid classifications.

The Multinomial Naïve Bayes model trained on the labeled dataset performed well. Our model was tested with three different data split ratios: 7:3, 8:2, and 9:1. According to the results, the highest accuracy is obtained for the 9:1 data split ratio (81.34%). This implies that the good results of the model were due to more available data. This is consistent with the theory of machine learning, in which a larger training dataset is expected to let the model learn better and generalize well to new, unseen patients.

The data splitting with the ratio of 7:3 came next, and obtained an accuracy of 80.84%. Although it was not a 9:1 ratio, we still get good performance on the model, indicating that a relatively small size of training data is efficient to train a Multinomial Naïve Bayes model. The accuracy of the 8:2 ratio, 79.48% was the lowest; it is likely due to the smaller training set compared to 7:3 and 9:1. This finding further demonstrates the effect of the amount of available training data on model prediction.

The precision, recall, and F1-score metrics also offer interesting observations. The best precision, recall, and F1-score, 81.47%, 81.43% and 81.34%, respectively, were achieved with the 9:1 split, indicating that the model detected not only most of the "Satisfied" and the "Unhappy" reviews but also with a low abundance of false positives and false negatives. This shows the good generalization capacity of the Multinomial Naïve Bayes Model on the task of sentiment classification.

Both the 7:3 and 8:2 splits had slightly lower performance but still had reasonable precision and recall, with F1-scores of 80.84% and 79.47%, respectively. This indicates that the model could retain its reliable classification ability even after being trained with reduced data. Nonetheless, it is obvious that the larger the training set, the more the model becomes accurate, both in terms of generalizing and acting on a broad spectrum of input games.

The good performance of the Multinomial Naïve Bayes model could be justified by the model's simplicity and effectiveness for text classification. By making use of the word frequency approach, the probability that a review belongs to a sentiment class is computed; thus, it is a powerful model to process a large amount of text data efficiently. Furthermore, by using TF-IDF (Term Frequency-Inverse Document Frequency) weighting, we could emphasize more relevant words and improve discrimination between positive and negative reviews.

Furthermore, the model's accuracy and F1-scores prove that it can be used for sentiment analysis of online travel applications in Bangladesh. This also verifies that the model could be employed in practical applications in the tourism field, where customer comments are essential data used to make services better and improve user experience.

5. LIMITATIONS

Although the study yielded acceptable responses, there are limitations to be noted. One possible drawback is that we only use one Machine Learning Algorithm, which can be powerful but is not the best choice for all possible situations. While the Multinomial Naïve Bayes algorithm is effective in classifying text, there may be better classifiers, such as Support Vector Machines (SVM) or deep learning architectures like the LSTM, which can achieve higher accuracy, particularly on non-trivial datasets. Further research might be carried out by comparing different kinds of algorithms, such as to see if a combined approach would provide better performance.

Another disadvantage of the proposed strategy is the relatively unbalanced dataset. At the same time, the dataset was collected from widely used travel applications such as Shohoz and GoZayaan and BDTickets may not represent the whole spectrum of the population of users from all regional areas in Bangladesh. The dataset may be biased towards reviews by urban-based users or those who have more access to technology. As such, future efforts can be directed to collect a more balanced dataset, which is more representative of various demographic groups that can include users from rural areas, which will inherently increase the model's robustness.

Also, the human-labelled reviews for categorizing into “Satisfied” and “Unhappy” classes are prone to subjective bias, as the sentiment expressed in a few reviews can be very subtle/muted. One way to alleviate the problem is to use a more advanced labeling process that may reduce the bias and provide more consistent labelings, for example, collect labels using crowdsourcing with more annotators in a future study.

6. FUTURE WORKS

Based on this study, there are some directions to follow as future work:

1. **Comparison to advanced models:** As discussed, other machine learning methods (like Random Forest, SVM, and deep learning models, especially RNNs or Transformer-based architectures that have obtained excellent results in natural language processing tasks) could be considered for testing in future research regarding their predictive power when applied to predict sentiment and subsidence combined. This would give a complete knowledge of which models are appropriate for classifying user reviews of online travel applications in Bangladesh.
2. **Multilingual Sentiment Analysis:** Since Bangladesh has a relatively unique linguistic context, with its primary language being Bengali and the frequent use of English on digital media, we can develop a multilingual sentiment analysis. This would make it possible to have classification across reviews from users in Bengali and English as well, extending the dataset and making the model more generalizable across different user demographics.
3. **Sentiment Aspect Mining:** Another potential future work direction is sentiment aspect analysis. This method entails finding dedicated components to be extracted from the application (eg, “price”, “customer support”, “user interface”, “booking process”) and splitting sentiment for each component. Developers can have better visibility on which part of the application needs improvement by concentrating on the particular feature that users refer to in reviews.
4. **Real-Time Analysis and Feedback:** One interesting application of sentiment classification can be real-time feedback to an application developer. In the future, integration of our proposed model with the real-time review monitoring system would allow the companies to be alerted instantly and accomplish the countermeasures, e.g., regarding user experiences or service quality. Such a system would enable developers to react quickly to user feedback and thus be motivated to increase user satisfaction and to improve the quality of the travel applications.
5. **Generalization of the dataset:** In the future, it would be good to have the dataset with multiple travel application users, not only from a single country, in order to get a better approach to small travel service providers in Bangladesh, rather than any popular one. This would be a more holistic view of the travel industry, and sentiments could be classified more effectively across the broader spectrum of travel apps used in the country.
6. **Utilizing External Data:** Another promising direction for future work is to combine external sources of data, such as social media (eg, Facebook, Twitter) and customer service interactions (eg, chatbots, emails). Examining more varied data sources may contribute to a fuller understanding of customer attitudes, thus achieving higher accuracy in user behavior prediction.

In summary, although the study accomplished the task of classifying user reviews of online travel applications in Bangladesh using the Multinomial Naïve Bayes approach, there is scope for enhancement and future work. Subsequent works should compare various algorithms, support multilingual and diverse data, and provide real-time sentiment analysis to enrich the users and to enhance the quality of the travel services in Bangladesh.

7. CONCLUSION

The empirical results show that the Multinomial Naïve Bayes approach achieved its goal by being applied to the classification of online travel applications' user reviews in Bangladesh. It is worthwhile noting that, among the multiple data split ratios experimented with, 9:1 presented the highest accuracy of 81.34%, which then indicated that the model could perform better with a larger training dataset. This is consistent with the well-known fact that Machine Learning Models only get better with more training data, as they can learn from a greater diversity of examples. Variation in the dataset also contributed to the sensitivity in the prediction. In this way, the spread of user experiences, given both positive and negative reviews, was given a full representation in the tables. Consequently, the model was better suited for generalisation and therefore able to perform well on new data, and predict correctly the sentiment for unseen reviews. It was observed that the introduction of TFIDF feature extraction improved the model's performance by enabling the Multinomial Naïve Bayes algorithm to concentrate on the most pertinent terms to increase the accuracy of the classification for both "Satisfied" and "Unhappy" classes.

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