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A Comparative Analysis of Support Vector Machines and Logistic Regression for Analyzing User Sentiment Regarding App UI/UX

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Abstract
Advances in digital technology have driven an increase in the use of mobile and web applications, making the quality of the User Interface (UI) and User Experience (UX) crucial factors for user satisfaction. User comments on app stores can be leveraged to assess UI/UX quality through sentiment analysis. This study aims to evaluate the comparative performance of the Support Vector Machine (SVM) and Logistic Regression algorithms in classifying user sentiment regarding app UI/UX. Research data was obtained from the Sentiment Analysis Dataset—App Reviews available on Kaggle. The research process included data cleaning, feature extraction using the Term Frequency–Inverse Document Frequency (TF-IDF) method, model training, and model testing with an 80:20 training-to-test data split. Performance was measured using accuracy, precision, recall, and F1-score metrics. The findings show that SVM yields higher results compared to Logistic Regression, with an accuracy of 88.26%, precision of 91.13%, recall of 86.93%, and an F1-score of 88.98%. Meanwhile, Logistic Regression achieved an accuracy of 86.75% and an F1-score of 87.54%. These findings indicate that SVM is more effective for classifying user sentiment regarding the UI/UX of text-based applications.

1. Introduction

The user interface (UI) and user experience (UX) are two crucial factors that determine the success of an application, as they directly influence user comfort, ease of use, and satisfaction when interacting with the system [1]. UI focuses on the visual aspects and user interface interactions experienced by users when using an application, while UX encompasses the user's overall experience while interacting with the system [2]. Excellent UI/UX design can strengthen user loyalty and help ensure sustained app usage over the long term. As digital transformation continues to evolve, the quality of an app's user interface has become one of the key factors influencing how users evaluate digital services [3].

Advances in digital technology have contributed to an increase in the number of mobile and web app users, which in turn has led to a rise in the volume of user reviews on app distribution platforms such as the Google Play Store and the App Store. These reviews contain valuable information about the user experience, strengths, weaknesses, and quality of the apps in question. However, the sheer volume of review data makes manual analysis inefficient, time-consuming, and prone to subjectivity. Therefore, an automated approach is needed to process review data quickly, accurately, and objectively to support app evaluation and development.

One method commonly used to analyze user opinions is sentiment analysis. Sentiment analysis is a technique for identifying and categorizing users' views on a particular product or service by utilizing text data [4]. In digital applications, sentiment analysis can help identify users' views on UI/UX quality, enabling developers to better understand their needs [5]. In addition to classifying opinions as positive, negative, or neutral, sentiment analysis also helps developers identify the issues most frequently complained about by users [6]. Therefore, sentiment analysis is an efficient solution for assessing app quality by leveraging user review data.

In practice, sentiment analysis often employs machine learning techniques, such as Support Vector Machines (SVMs) and logistic regression. SVMs are classification algorithms that work by finding the optimal hyperplane to separate data across classes, giving them an advantage in handling high-dimensional text [7]. In addition, SVMs are known for producing consistent classification results on text with many features. On the other hand, logistic regression is a classification technique that predicts the probability of a class by taking into account the relationships between variables [8]. Logistic regression performs relatively simple yet effective computations for binary data classification. Both methods are frequently used in sentiment analysis studies because they achieve adequate accuracy and are efficient at classifying text.

Previous studies have indicated that the application of Support Vector Machine (SVM) and Logistic Regression algorithms to analyze sentiment in app reviews can yield competitive classification results. A study conducted by [9] shows that both techniques are capable of effectively classifying sentiment, but SVM demonstrates superior performance compared to Logistic Regression. This finding is consistent with the research by [10] which states that SVM has a higher classification stability rate on text data compared to a number of other classification algorithms. Furthermore, research by [11] It also confirms that SVMs can handle high-dimensional text data effectively, thereby improving accuracy in sentiment classification.

A study conducted by [12] indicates that the application of machine learning can produce effective sentiment analysis of digital app reviews. Furthermore, the work by [13] explains that the use of the Term Frequency–Inverse Document Frequency (TF-IDF) method improves the quality of text feature representation, which in turn enhances the performance of the classification model. The study by Kurniawan et al. [14] emphasizes that selecting the appropriate classification algorithm plays a crucial role in improving the accuracy of sentiment analysis. Furthermore, the findings of [15] shows that combining preprocessing techniques with machine learning algorithms can yield more accurate sentiment classification of user review data.

An international study confirms that the SVM algorithm remains one of the most effective approaches for sentiment analysis of text data. The study by [16] shows that SVM delivers more consistent performance than Logistic Regression in classifying the sentiment of app reviews using TF-IDF representation. Furthermore, the work by [17]. emphasizes that the quality of the preprocessing process and feature extraction techniques significantly influence the performance of machine learning-based sentiment classification models. Based on these findings, it can be concluded that the combination of data preprocessing, TF-IDF feature extraction, and the selection of an appropriate classification algorithm are crucial factors in improving the effectiveness of sentiment analysis in app user reviews.

The quality of sentiment analysis output is influenced by the data preprocessing and text feature extraction processes. Preprocessing is performed to clean the data of noise and improve the text structure prior to the classification stage. In this study, preprocessing includes case folding, tokenization, stopword removal, and text normalization to improve the quality of the text data. After the preprocessing stage, the text is converted into a numerical representation using the Term Frequency–Inverse Document Frequency (TF-IDF) technique. The TF-IDF technique calculates the weight of each word based on its frequency of occurrence within a document and across the entire dataset, thereby improving the quality of features for sentiment classification.

Although there have been numerous studies on sentiment analysis, the majority still focus on a specific algorithm or merely compare model performance without undergoing structured preprocessing steps. Furthermore, few studies specifically evaluate the performance comparison between SVM and Logistic Regression in analyzing user sentiment regarding an application's UI/UX using multi-metric evaluation. Some studies also rely solely on accuracy as an indicator of model performance, thus failing to provide a comprehensive picture of the model's classification capabilities.

Addressing gaps in previous research, this study introduces a novel contribution by comparing the performance of SVM and Logistic Regression in analyzing user application UI/UX sentiment, incorporating structured data preprocessing and a more comprehensive model evaluation. The evaluation does not rely solely on accuracy but also incorporates precision, recall, and F1-score to provide a more complete picture of model performance. Furthermore, this study utilizes the TF-IDF technique for feature extraction to improve the quality of text representation prior to the classification process.

Thus, this study aims to assess and compare the performance of the Support Vector Machine and Logistic Regression algorithms in classifying user sentiment regarding app UI/UX using preprocessing techniques and multi-metric evaluation. It is hoped that the findings of this study can serve as a reference in selecting a better sentiment classification method and assist in the development of machine learning-based UI/UX evaluation in a more efficient and accurate manner.

2. Research Methodology

This study employs a quantitative approach using machine learning-based classification techniques to assess users' UI/UX sentiment based on their reviews. The data used is sourced from the Sentiment Analysis Dataset App Reviews downloaded from Kaggle, which includes reviews labeled as positive or negative. The research process was conducted sequentially, encompassing data collection, preprocessing, feature extraction, model training, and evaluation of the classification model's performance. The research workflow is illustrated in Figure 1 below:

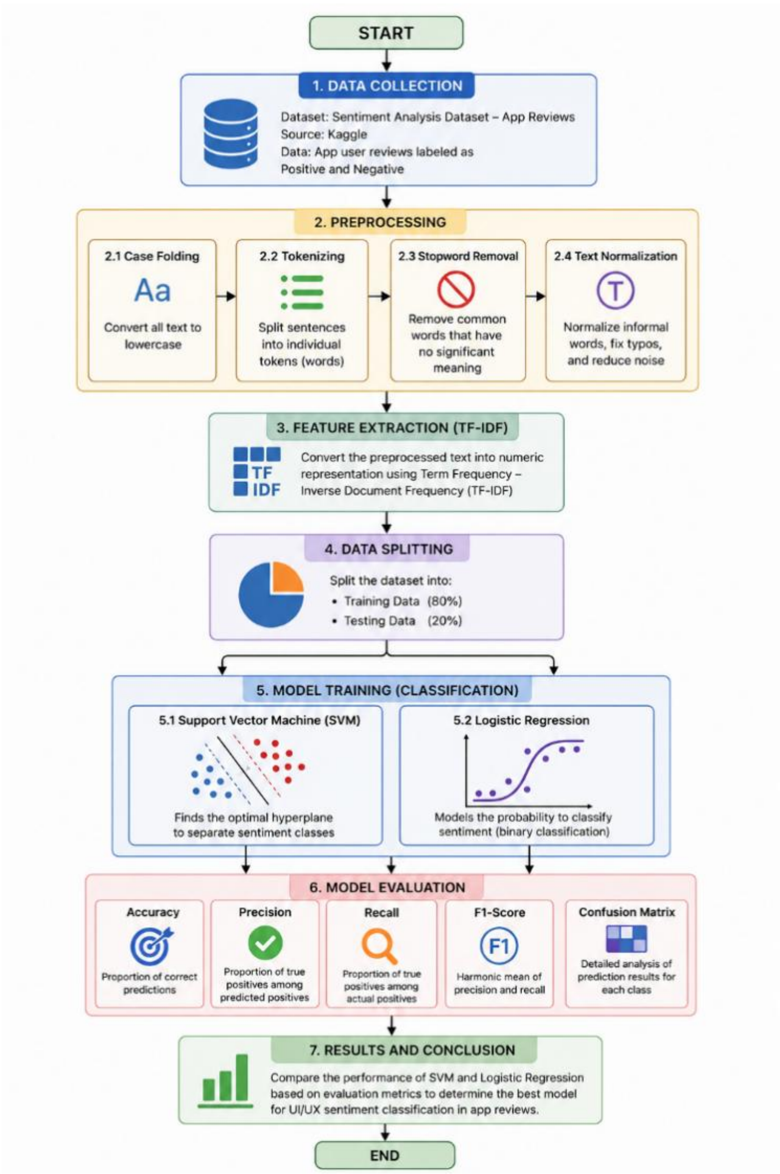

Figure 1. Reaserch Flowchat

The first step in the study involved collecting data from a collection of user reviews of the app. After the data was successfully collected, a preprocessing stage was conducted to clean the text so that it would be more structured and ready for use in the classification process. The preprocessing process includes case folding to convert all letters to lowercase, tokenization to split sentences into word tokens, stopword removal to eliminate words that do not provide significant meaning, and text normalization to correct non-standard terms and reduce noise in the text data. This stage aims to improve data quality and minimize errors in sentiment classification.

After the data undergoes preprocessing, it is converted into a numerical format using the Term Frequency–Inverse Document Frequency (TF-IDF) technique. The TF-IDF technique assigns weights to each word based on its frequency of occurrence within a document and across the entire dataset, thereby improving the representation of text features. The features extracted using TF-IDF are then used as input to train the classification model. In the classification stage, this study utilizes two machine learning methods: Support Vector Machine (SVM) and Logistic Regression. SVM was chosen because it can effectively handle high-dimensional text and generates an optimal hyperplane to separate sentiment classes. Meanwhile, Logistic Regression was used due to its simple computational process and effectiveness in classifying binary data. Next, the dataset is divided into a training set and a test set in an 80:20 ratio to train and test the model.

Model performance is evaluated using several evaluation metrics such as accuracy, precision, recall, and F1-score. Additionally, this study utilizes a confusion matrix to analyze classification results in greater detail for each sentiment class. This multi-metric evaluation approach aims to provide a more comprehensive analysis, thereby identifying the algorithm with the best performance in classifying user sentiment regarding the application's UI/UX.

In general, the research process includes data collection, preprocessing, feature extraction using TF-IDF, splitting the data into training and testing sets, classification using SVM and Logistic Regression algorithms, and model performance evaluation through various evaluation metrics. This methodological approach is systematically designed to yield efficient and accurate sentiment analysis that meets the criteria for publication in national journals.

3. Results and Discussion

This study compares the performance of the Support Vector Machine (SVM) algorithm with that of Logistic Regression in classifying user sentiment regarding the UI/UX of an application. The models were evaluated using various metrics, including accuracy, precision, recall, F1 score, and confusion matrix, to assess their ability to identify positive and negative sentiments in detail. This study compares the performance of the Support Vector Machine (SVM) algorithm with Logistic Regression in classifying user sentiment regarding app UI/UX. The models were evaluated using various metrics, including accuracy, precision, recall, F1 score, and confusion matrix, to assess their ability to identify positive and negative sentiments in detail.

Data Preprocessing Result

Preprocessing steps are performed to improve the quality of the text data before the classification process. These steps include case folding, tokenization, stop-word removal, and text normalization. After preprocessing, the text data becomes more structured and free of irrelevant words, thereby improving the quality of feature representations in sentiment classification.

Table 1. Example of Preprocessing Results

Original Text	Preprocessing Result
This app is very good and easy to use!!!	app good easy use
The interface is confusing and slow	interface confusing slow
Excellent UI and smooth experience	excellent ui smooth experience

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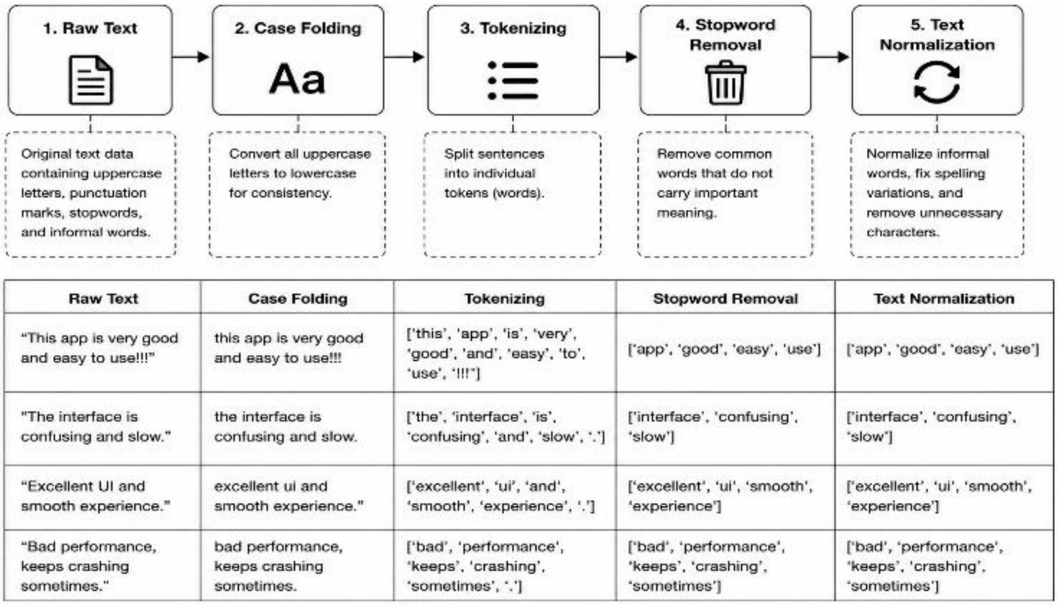

Figure 2. Preprocessing Proses

Feature Extraction Using TF-IDF

Once preprocessing is complete, the text is converted into a numerical format using the Term Frequency–Inverse Document Frequency (TF-IDF) technique. This technique assigns values to words based on their importance within the document and across the entire dataset. The resulting TF-IDF features are then used as input to train the classification model.

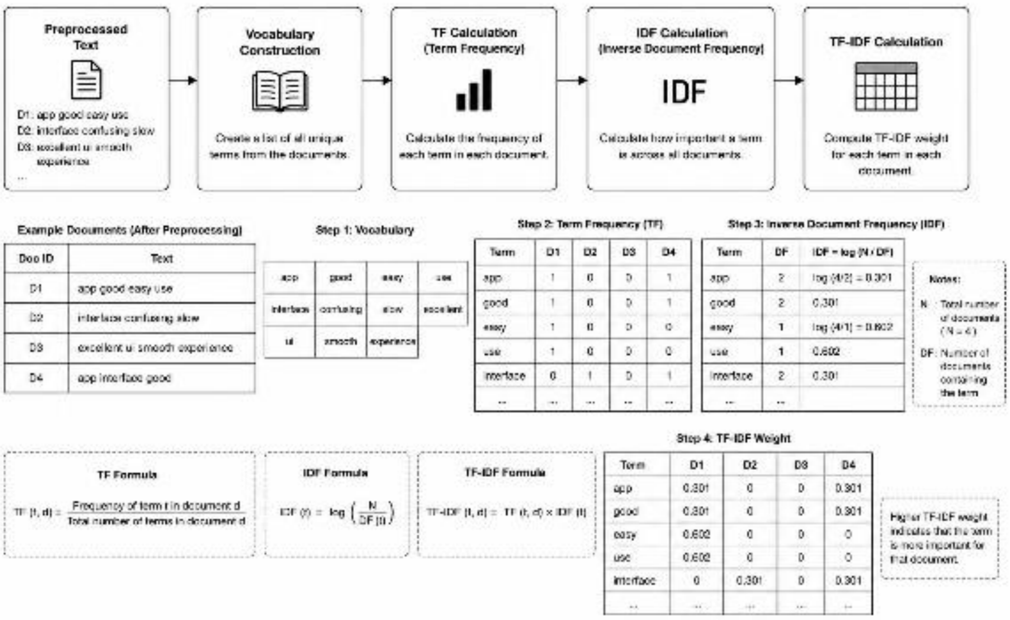

Figure 3. TF-IDF Feature Extraction Process

Classification Results of SVM and Logistic Regression

Classification was performed using the Support Vector Machine (SVM) algorithm and Logistic Regression, with a training-to-test data ratio of 80:20. Evaluation of the results showed that SVM outperformed Logistic Regression in classifying user sentiment regarding the app's UI/UX.

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Table 2. Comparison of Classification Performance

Model	Accuracy	Precision	Recall	F1-Score
Support Vector Machine (SVM)	88,26%	91,13%	86,93%	88,98%
Logistic Regression	88,75%	89,86%	85,34%	87,54%

Based on the data in Table 2, SVM achieved an accuracy of 88.26%, outperforming Logistic Regression, which achieved 86.75%. Additionally, the precision, recall, and F1-score metrics were also higher for SVM. These findings indicate that SVM is capable of performing more consistent classification on high-dimensional text compared to Logistic Regression. By finding the optimal hyperplane, SVM produces better sentiment class separation, thereby improving overall classification performance.

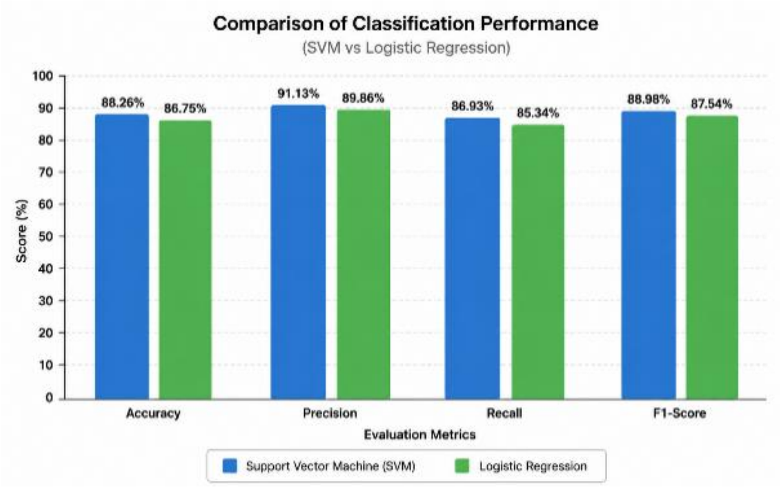

Figure 4. Comparison of Accuracy Between SVM and Logistic Regression

Confusion Matrix Analysis

A confusion matrix analysis was conducted to examine the details of the classification results for each sentiment class. Based on the experiments, the SVM model successfully classified the majority of positive and negative sentiment data with a lower error rate compared to Logistic Regression, indicating that SVM has better generalization capabilities in distinguishing the sentiment polarity of app users. On the other hand, Logistic Regression also demonstrated adequate performance, but still produced some misclassifications in sentiment data with complex text patterns. This difference in performance is influenced by the characteristics of the SVM algorithm, which is more optimal for handling high-dimensional text data.

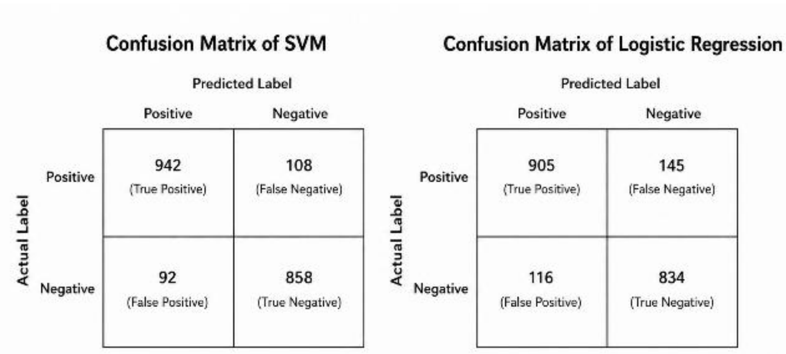

Figure 4. Confusion Matrix of SVM & Confusion Matrix of Regression

The results of this study indicate that the Support Vector Machine (SVM) algorithm yields superior results compared to Logistic Regression in classifying user sentiment regarding the UI/UX of an application. This superiority stems from SVM's ability to effectively separate data in high-dimensional spaces, making it better suited to handle text features extracted using TF-IDF. Furthermore, the implementation of preprocessing steps and TF-IDF feature extraction plays a role in improving data quality and the performance of the classification model. These results align with previous studies stating that SVM has higher classification stability compared to several other algorithms in text-based sentiment analysis [16][17].

The use of multi-metric evaluation in this study provides a more comprehensive picture of model performance, relying not solely on accuracy scores but also considering the balance of the model's ability to classify each sentiment class. Overall, this study demonstrates that the SVM algorithm is more suitable for analyzing user sentiment regarding an application's UI/UX compared to Logistic Regression. It is hoped that these findings can serve as a reference for the development of more efficient and accurate machine learning-based UI/UX evaluation systems.

4. Conclusion

Based on the results of this study, it can be concluded that the Support Vector Machine (SVM) and Logistic Regression algorithms can be used to classify user sentiment regarding the UI/UX of an application with satisfactory results. However, when evaluated using the metrics of accuracy, precision, recall, and F1-score, the SVM algorithm demonstrated superior performance compared to Logistic Regression in classifying user sentiment. The research also found that the pre-processing stage and feature extraction using the TF-IDF method play a crucial role in improving the quality of text data and the performance of the classification model. Furthermore, the application of multi-metric evaluation and the confusion matrix provides a more comprehensive analysis of model performance. Therefore, SVM can be considered a more effective method for machine learning-based UI/UX sentiment analysis. Future studies are expected to use larger datasets, expand the range of sentiment categories, and compare other algorithms such as Naïve Bayes, Random Forest, or deep learning approaches to optimally improve sentiment classification accuracy.

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