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Sentiment Analysis of Digital Korlantas Polri Apps Service Based on LSTM and SVM Methods

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Abstract

Advancements in digital technology have encouraged numerous innovations in public services, one of which is the Digital Korlantas Polri app. This application makes it easier for the public to access traffic services such as driver's license issuance and renewal, vehicle data checking, and accident reporting. However, despite the convenience it offers, there are still various user reviews that point to technical issues and dissatisfaction with the quality of service. This study applies sentiment analysis to understand public perception of the Digital Korlantas app, providing a basis for improving its quality. The collection of the dataset was achieved by web scraping 2,000 user reviews from the Google Play Store spanning the period from December 2023 to March 2025. The phases of the research encompass gathering data, pre-processing text, assigning sentiment labels based on lexicons, applying TF-IDF for word weighting, and performing classification using the Long Short-Term Memory (LSTM) and Support Vector Machine (SVM) algorithms. The performance of the model was assessed through a confusion matrix, utilizing accuracy, precision, recall, and F1-score as evaluation metrics. The findings indicated that, out of 2,000 reviews, 1,402 were identified as positive, 538 were categorized as negative, and 60 were considered neutral. The SVM model demonstrated the highest performance, obtaining an accuracy of 96.8%, a precision of 65.6%, a recall of 50.0%, and an F1-score of 55.0%. At the same time, the LSTM model attained an accuracy of 94.5%, with a precision of 31.5%, a recall of 33.3%, and an F1-score of 32.4%. These results show that SVM is superior at handling high-dimensional data, while LSTM remains effective at capturing long-term context patterns in review texts.

Keywords: *Sentiment Analysis; Korlantas Polri Digital App; Public Service Innovation; LSTM; SVM.*

I. INTRODUCTION

The rapid development of technology in today's digital age has become an important part of various public service sectors[1], including police services. The Indonesian National Police (Polri), via the Traffic Corps (Korlantas), is working to enhance public services by introducing a digital application designed to simplify access to traffic-related information and services. The Digital Korlantas Polri Apps provides various services, such as online processing of driver's licenses (SIMs), vehicle data verification, traffic monitoring, and quick, accurate accident reporting [2].

The problem with this study is that the Digital Korlantas Polri application continues to receive various feedback and criticism from users regarding service quality improvements to meet public expectations. Some users have experienced errors and bugs when using the application, including failed email and ID card verification, invalid payment transactions, and more. This issue shows that several aspects need improvement to meet user expectations for the application service [3]. Consequently, a system is required that can automatically categorize user comments according to sentiment, including positive, negative, or neutral. The existence of this system will help management understand public perceptions of the application more quickly and efficiently. To achieve this objective, the study assesses the performance of the Long Short-Term Memory (LSTM) model in comparison with the Support Vector Machine (SVM) method for sentiment classification, using review data collected from the Google Play Store.

Previous studies on sentiment analysis of the Digital Korlantas Polri app have used various methods to classify user reviews. The study [4] used the DistilBERT model and achieved 88% accuracy in sentiment analysis of Google Play Store reviews. Researchers [5] compared five machine learning algorithms and found that SVM produced the highest accuracy of 91.14%. In the meantime, researchers [6] employed the Naïve Bayes method and attained 88% accuracy, 88% precision, a recall of 91%, and an F1-score of 90%. The results of Research [7] used the SVM method. They obtained an accuracy of 82% using a 90:10 training-to-testing data split. Although SVM has proven effective, no research has compared LSTM and SVM for extracting important features from these application reviews, where SVM is used to classify sentiment. At the same time, LSTM captures long-term patterns and dependencies in the text, producing a more contextual representation before classification.

This study aims to examine user sentiment regarding the Digital Korlantas Polri app and to discern user reviews as positive, negative, or neutral. LSTM and SVM techniques are applied to evaluate user review information, where LSTM excels in handling lengthy text and preserving the context of words. SVM are effective for high-dimensional data classification. The Lexicon-Based method conducts sentiment labeling by automatically categorizing data as positive, negative, or neutral, thereby enabling the analysis of large datasets. The dataset was gathered from user reviews on the Google Play Store. After data collection, pre-processing was conducted, followed by sentiment labeling using a Lexicon-Based approach. Subsequently, the data is processed using the LSTM and SVM methods to perform sentiment classification. The model's performance was assessed through a confusion matrix, allowing for the computation of accuracy, precision, recall, and F1-score. This research seeks to give a more profound insight into how users view the quality of services offered by the Digital Korlantas Polri Apps. Previous findings indicate that user reviews play an important role in improving service quality. This study highlights the necessity for a more thorough sentiment analysis method to support developers in enhancing the quality and user satisfaction of the Korlantas Polri Digital application.

II. RESEARCH METHOD

This study aims to improve the quality of the Digital Korlantas Polri application by examining user feedback. It employs LSTM and SVM techniques to achieve the highest level of accuracy. Figure 1 shows the stages of this study. The procedure starts with gathering data through web scraping, then moves on to pre-processing. This entails cleaning the data, converting text to lowercase, breaking it into tokens, removing stopwords, and stemming. Subsequently, the reviews were classified into three sentiment categories positive, negative, and neutral using a Lexicon-Based method. The upcoming task involves applying the TF-IDF technique to assign weights to words, followed by using the LSTM algorithm to identify patterns within the text. The last step involves assessing the model's effectiveness through a confusion matrix, which allows for the determination of accuracy, precision, and recall metrics.

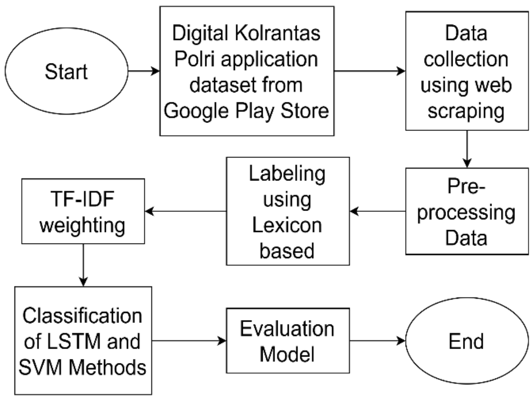

Figure 1. Research Flow

1) Data Collection: User feedback data for the Digital Korlantas Polri application was collected from the Google Play Store using web scraping techniques implemented in Python. This process utilizes available Application Programming Interfaces (APIs) and focuses on pertinent categories. The dataset obtained comprises raw, unprocessed data collected during the period from 2023 to 2025.

2) Pre-processing Data: Data pre-processing is the first phase of data handling where raw data is made ready for more straightforward analysis and processing [8]. This procedure involves steps such as removing interference or noise from data, reducing the dimensions of the data to discard unnecessary information, and structuring the data to enhance its organization [8]. Data pre-processing consists of several important steps aimed at preparing data for analysis. These stages encompass case folding, the removal of stop words, and stemming [8].

a. Cleaning involves the removal of unnecessary components from documents, which may include items like HTML tags, emoticons, hashtags, mentions, and URLs [9].
b. Case folding, also known as text normalization, involves changing all characters in a text to

lowercase in order to create a consistent data format [10].

c. Tokenizing is the process of separating a sentence into small units, each consisting of a single word, called tokens [10].
d. Stopword Removal is the process of removing terms considered irrelevant or that have little influence on sentiment analysis [10].
e. Stemming is a process that converts words with affixes to their base form, such as removing prefixes, suffixes, or infixes [10].

3) Labeling Data: The processed text will be labeled based on a set of words that have been predetermined in the lexicon. Each word in the text is compared with entries in the lexicon, after which the system assigns a sentiment label to the text. Sentiment can be positive (+1), negative (−1), neutral (0), or other labels predetermined for analysis [11]. The sentiment score for each matching word will be calculated, then added to obtain the text's total sentiment score. This is shown in Equation (1) [12].

$$Sentiment\_Score(S^i) = \sum_{i=1}^{n} S_i \quad (1)$$

Data labeling is an important step in data processing, in which labels such as positive, negative, or neutral are assigned to review texts [12]. This method offers context, allowing machine learning models to more effectively comprehend and learn the patterns within the data. Two people perform manual labeling, while rating-based labeling is determined by the following rules: ratings of 4–5 are labeled as positive, and ratings of 1–3 are labeled as negative. This study applied a lexicon-based approach for labeling, as mentioned in [13], which makes use of a dictionary (lexicon) to evaluate the sentiment value linked to each word. The words in the text are matched with a list of words that already have sentiment scores, such as +1 for positive, -1 for negative, and 0 for neutral [11].

4) Word Weighting: Assigns a value, or weight, to each word in a document, so that more relevant or important words can be identified and analyzed more effectively in a specific context. The stages of word weighting are as follows [14]: This can be seen in Equations (2) [14], (3) [14] and (4) [14].

erm Frequency (TF) refers to how often a particular word appears within a text. The rate at which particular words appear in the text might be employed as a component, based on Equation (2) [14].

$$TF(t,d) = \frac{f(t,d)}{N} \quad (2)$$

Document Frequency (DF): The Document Frequency measures how often a word appears across all documents. This document frequency value will later be used to calculate inverse document frequency [14].

$$DF(t) = |\{d \in D : t \in d\}| \quad (3)$$

Inverse Document Frequency (IDF) quantifies the significance of a term within a collection of documents. This method gives higher weight to less frequently occurring words, as they generally provide more information, as illustrated in Equation (4), where *N* denoting the total document count [14].

$$idf_t = log10\left(\frac{N}{df_{(t)}}\right) \quad (4)$$

5) LSTM Classification: Algorithms built on Deep Learning principles can achieve enhanced performance and operate with greater computational efficiency than traditional Machine Learning algorithms. A frequently employed Deep Learning algorithm in the process of word classification is the LSTM. LSTM is an enhancement of the RNN (Recurrent Neural Network) approach, incorporating a unique interaction mechanism within each component [15]. This algorithm uses memory cells with input, forget, and output gates to replace conventional RNN layers, thereby overcoming the vanishing gradient problem [16]. In addition, LSTM can store information for longer periods because it can learn long-term dependencies [15].

The initial gate in an LSTM is known as the forget gate, and it utilizes an equation to sift through information within the cell state (5). When the forget gate value is 0, the information is discarded from the cell state; conversely, a value of 1 ensures that the information is retained within the cell state.

$$ft = \sigma(Wf \times [xt + ht - 1] + bf) \quad (5)$$

The second gate is called the input gate, where information is processed through two layers, namely sigmoid calculated using Equation (6) and tanh calculated using Equation (7). The output values from both layers are then combined to form a new cell state.

$$it = \sigma(Wi \times [xt + ht - 1] + bi) \quad (6)$$

$$C\,t = \tanh(WC \times [xt + ht - 1] + bC) \quad (7)$$

Subsequently, the value of the cell state is updated using Equation (8). After the update, the process proceeds to the output gate, where the cell's state output is determined. At this stage, the sigmoid layer determines the relevant output based on the cell state using Equation (9), and the result is forwarded to the tanh layer, which is calculated using Equation (10).

$$Ct = ft . Ct - 1 + it . Ct \quad (8)$$

$$Ot = \sigma(Wo . [ht - 1, Xt] + bo \quad (9)$$

$$ht = Ot . tanh(Ct) \quad (10)$$

6) SVM Classification: SVM, used for classification and regression in supervised learning, constructs hyperplanes in spaces with high dimensions [17]. SVMs maximize the margin between classes, making them effective for separating nonlinear and complex data [18]. This method is widely applied in text classification, image object detection, and bioinformatics, and remains one of the most popular algorithms in machine learning [19]. The primary strength of SVM is its capability to prevent overfitting through the application of the maximum-margin principle [18]. Furthermore, SVM can be integrated with kernel functions to process data that are not linearly separable. With these characteristics, SVM is often chosen in research that requires high accuracy in large-dimensional data [19]. SVM is explained in Equation (11) [17].

$$K(x_i, x) = x_i\, x \quad (11)$$

The Polynomial Kernel is a type of kernel function used in algorithms such as SVM and other machine learning methods for tasks including classification and regression. The polynomial kernel formula is given in Equation (12) [20].

$$K(x_i, x) = (x_i\, x)d \quad (12)$$

The Gaussian Kernel, frequently referred to as the Radial Basis Function (RBF), is a widely used technique in the realm of machine learning, especially within SVM. The Gaussian Kernel Formula, or Radial Basis Function (RBF), is shown in Equation (13) [20].

$$K(x_i, x) = \exp\left(\frac{-\|x_i - \|2}{2\sigma^2}\right) \quad (13)$$

The Sigmoid kernel is one type of kernel used in SVM algorithms and other machine learning methods, as shown in Equation (14) [20].

$$K(x_i, x) = tanh(\sigma(x_i\, x) + c) \quad (14)$$

The method of classifying data in SVM involves using Equation (10). In this context, x stands for the accessible dataset or training data, w represents the weight vector, and b denotes the scalar value, as demonstrated in the Equation (15) [20].

$$f(x) = w.x + b \quad (15)$$

The formula above describes the function f(x) used in the SVM classification process. This function accepts data to be classified, denoted by x, and returns the corresponding class label [19]. The variable xi, refers to the training data, while yi is the class label associated with that training data. The weight of each training data is represented by ai. Kernel function, denoted by $K(xi, x)$, is applied for each training data. Parameter b is the bias used in the classification process. Using this function, SVM can predict the appropriate class label for the data to be classified based on information obtained from the training data and calculated weights [20].

7) Evaluation Model: Evaluation metrics that are frequently utilized to measure the performance of classification models. This approach entails a number of assessments, including accuracy, precision, and recall. To determine the values for accuracy, precision, and recall, the following components are essential [21]. Providing an overview of how the Confusion Matrix predicts actual data, there are four parts to the class mapping process. True Positive (TP) denotes the number of instances where the actual class is accurately predicted as positive. True Negative (TN) denotes the number of instances where the actual class is correctly predicted as negative. The true value is actually negative. A False Positive (FP) occurs when an instance is incorrectly classified as positive, despite being negative in reality. False Negative (FN) denotes instances where the model predicts a negative class despite the actual class being positive. A confusion matrix is employed to assess the performance of a classification model, using metrics such as accuracy, precision, sensitivity, and F1-score.

a. Accuracy indicates the degree to which the model's predicted values correspond to the actual values. The model results are better if they achieve accuracy values close to 100%. The accuracy formula is written in Equation (16) [22].

$$Accuracy\ \frac{(TP + TN)}{(TP + TN + FP + FN)}\ x\ 100\% \quad (16)$$

b. Recall, also known as sensitivity, is a metric used to measure a model's ability to correctly identify data that belong to the positive class. The formula for calculating recall is expressed in an Equation (17) [22].

$$Recall\ \frac{TP}{(TP+FN)}\ x\ 100\% \qquad (17)$$

c. Precision is a metric used to evaluate the accuracy of a model in predicting instances that belong to the positive class. The formula is written in Equation (18) [22].

$$Precision\ \frac{TP}{(TP+FP)}\ x\ 100\% \qquad (18)$$

d. The F1-score denotes the harmonic mean of precision and recall, as specified by the formula in Equation (19) [22].

$$F1\ score = 2x\frac{RecallxPrecesion}{RecallxPrecesion}\ x100\% \qquad (19)$$

III. Result And Discussion

This study gathered data by extracting user reviews of the Digital Korlantas Polri application from the Google Play Store. The dataset consists of user reviews collected between December 2023 and March 2025, totaling 2,000 reviews. The data obtained through scraping is saved in a CSV file and presented in Table 1.

Table 1. Scraping Data CSV

Score	Date	Content
5	15/10/2025	*Ternyata bikin sim online bisa juga yah, enak nggak perlu ke Polres cukup di rumah saja lagipula harganya sesuai, terima kasih.*
4	14/10/2025	*aplikasi digital ada kendala pada pengiriman kode va bank tidak masuk ke email jadi tidak bisa bayar perpanjangan SIM, sudah bisa dan SIM sudah diterima.*
3	05/10/2025	*permohonan yang ditolak, uang yang sudah dibayar tidak dikembalikan, harusnya kalau ditolak, biaya dikembalikan, gimana tanggungjawabnya*
2	22/08/2025	*Mau login aja susahnya minta ampun 🙄kode otp ga dikirim-kirim 🙄 🙄*
1	08/08/2023	*Update aplikasi malah log out akun nya, mana log ini pakai pulsa lagi. Aneh bener ini aplikasi, bank juga gak gitu gitu amat*

Following data collection, the dataset cannot be analyzed immediately due to the presence of substantial noise. Therefore, the data pre-processing stage is a very important part of data mining. This step focuses on transforming raw data into a more organized format suitable for analysis, while also removing any unnecessary components for the upcoming process. This procedure involves cleaning the data, case folding, breaking the text into tokens, removing stopwords, and applying stemming.

Table 2. Pre-processing Result

Raw Data	
Ternyata bikin sim online bisa juga yah, enak nggak perlu ke Polres cukup di rumah saja lagipula harganya sesuai, terima kasih.	
Text Pre-processing	
Cleaning	*Membuat SIM online dapat dilakukan dari rumah tanpa perlu ke Polres. Biayanya sesuai, terima kasih.*
Case Folding	*membuat sim online dapat dilakukan dari rumah tanpa perlu ke polres. biayanya sesuai, terima kasih.*
Tokenizing	*'membuat', 'sim', 'online', 'dapat', 'dilakukan', 'dari', 'rumah', 'tanpa', 'perlu', 'ke', 'polres', 'biayanya', 'sesuai', 'terima', 'kasih'*
Stopword Removal	*'membuat', 'sim', 'online', 'dilakukan', 'rumah', 'polres', 'biayanya', 'sesuai', 'terima', 'kasih'*
Steamming	*'buat', 'sim', 'online', 'laku', 'rumah', 'polres', 'biaya', 'sesuai', 'terima', 'kasih'*

Table 3. Labeling Result

Text Clean	Score	Sentiment
puas sekali memudahkan yang tinggal di luar kota tinggal online dan kirim	5	Positive
perpanjang sim prosesnya mudah ga ribet, hanya saja waktu tunggu sampai dengan cetak sim kurang lebih 3 minggu	0	Netral
verifikasi wajah selalu tidak bisa membuat gagal terus menerus, padahal untuk email dan nomor HP bisa. klo ga bisa bisa2 kami kecewa dengan pelayanan di aplikasi ini	-2	Negatif

When the data labeling is finished, the information is sorted into categories to determine the frequency of the most commonly appearing words. The word frequencies are subsequently represented visually using a word cloud. Each review is associated with a specific set of words, which are categorized as positive, negative, or neutral. Words like “satisfied,” “once,” “makes it easier,” “stay online,” and “send” frequently appear in positive reviews, as illustrated in Figure 2.

Figure 2. Positive Word Cloud

Figure 3 depicts that expressions like “extend driver’s license,” “the process,” and “until the driver’s license is printed” are most frequently found in neutral reviews.

Figure 3. Neutral Word Cloud

Figure 4 shows that the words “always impossible,” “continuous failure,” “disappointed,” and “service in this application” are the words most frequently used to give negative reviews.

Figure 4. Negative Word Cloud

The feature extraction was performed using the TF-IDF method in Python, transforming user reviews into vector representations according to word weights. Subsequently, the dataset of 2,000 Google Play Store reviews for the Digital Korlantas Polri application was evaluated using two classification algorithms: LSTM and SVM. After the data is processed, a classification model is created to predict user sentiment. The classification outcomes are subsequently utilized to examine user perceptions of the application based on the collected reviews. Figure 5 displays the sentiment analysis of user reviews for the Digital Korlantas Polri application conducted using LSTM and SVM.

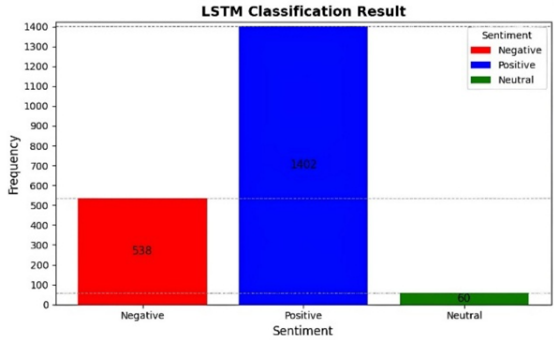

Figure 5. LSTM Classification

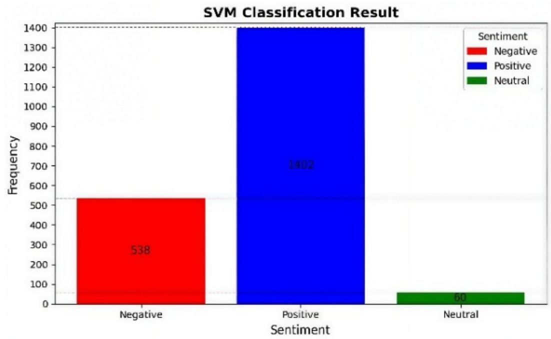

Figure 6. SVM Classification

The results of the SVM classification method are shown in Figure 6. The results show that 1.402 reviews were categorized as having positive sentiment. In comparison, 538 reviews were identified as negative, and 60 as neutral. Once thorough data testing has been finalized, the subsequent step involves assessing the performance of the model that has been implemented.

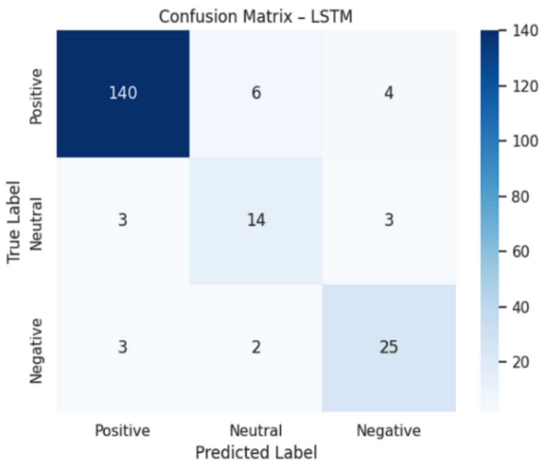

Figure 7. Confusion matrix LSTM

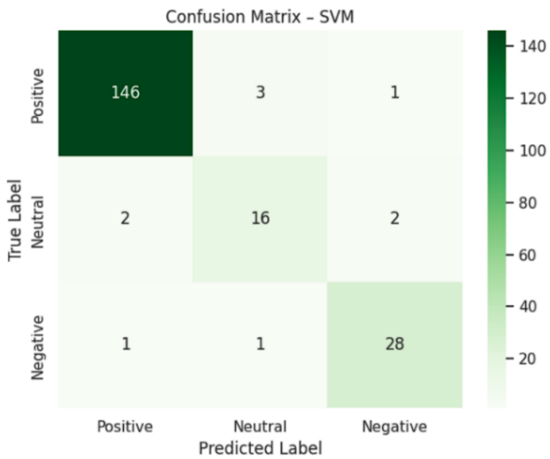

Figure 8. Confusion matrix SVM

Figures 7 and 8 present a comparison of evaluation metrics between the LSTM and SVM models. The SVM model consistently outperforms the LSTM model across all evaluation metrics, particularly in terms of F1-score, demonstrating a better balance between precision and recall. This result indicates that SVM is more effective for sentiment classification on high-dimensional text data with limited sequence length, as used in this studyIn this evaluation, a confusion matrix is employed to compute performance metrics, including accuracy, precision, recall, and F1-score, as shown in Table 4.

Table 4. Confusion matrix result

Models	Accuracy	Precision	Recall	F1-Score
LSTM	94.5%	31.5%	33.3%	32.4%
SVM	96.8%	65.6%	50.0%	55.0%

The results in Table 4 show that both the LSTM and SVM models can effectively classify sentiment. The SVM model achieved an accuracy of 96.8% and an F1-score of 55.0%, exceeding the performance of the LSTM model, which recorded 94.5% accuracy and a 32.4% F1-score. The LSTM model's relatively low F1-score is primarily affected by the nature of the dataset, which comprises short, unstructured user reviews and exhibits an imbalanced class distribution dominated by positive sentiments. These factors constrain the LSTM model's capacity to effectively learn contextual and sequential patterns, leading to a bias toward the majority class and consequently lower precision and recall. In contrast, SVM is more robust in handling sparse and high-dimensional TF-IDF features, allowing it to produce more balanced sentiment classification results. This shows that SVM is superior at handling complex class separation and produces more balanced predictions. At the same time, LSTM still performs well but tends to be less optimal at recognizing sentiment class variations.

IV. Conclusion

According to the research findings, 2,000 user reviews were collected from the Google Play Store to assess the sentiment of the Digital Korlantas Polri application. From the entire dataset, there were 1.402 positive reviews, 538 negative reviews, and 60 neutral reviews. This research utilizes LSTM and SVM classification techniques to detect and contrast sentiment within user reviews. The model evaluation shows that SVM demonstrates superior performance, achieving 96.8% accuracy, 65.6% precision, 50.0% recall, and an F1-score of 55.0%. In comparison, LSTM recorded 94.5% accuracy, 31.5% precision, 33.3% recall, and an F1-score of 32.4%. This distinction highlights that Support Vector Machines excel at managing high-dimensional datasets and intricate class separations. At the same time, LSTM still provides good results in recognizing long-term context patterns in user review texts.

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