JURTEKSI (Jurnal Teknologi dan Sistem Informasi) ISSN 2407-1811 (Print)
Vol. XII No 2, Maret 2026, hlm. 255 – 262 ISSN 2550-0201 (Online)
DOI: http://dx.doi.org/ 10.33330/jurteksi.v12i2.4199
Available online at http://jurnal.stmikroyal.ac.id/index.php/jurteksi

COMPARISON OF BILSTM, SVM FOR PBB-P2 TAX POLICY SENTIMENT ANALYSIS

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Abstract: The policy to increase the Rural and Urban Land and Building Tax (PBB-P2) in Indonesia often elicits mixed reactions from the public. Some support it because they believe it can strengthen regional fiscal capacity, while others reject it because they are concerned that it will increase the economic burden on the community. Understanding public sentiment towards this policy is important for evaluating the effectiveness of the policy and formulating appropriate communication strategies. This study aims to analyze public sentiment towards the PBB-P2 increase policy using data uploaded on Platform X (Twitter). The data were collected through crawling with the keyword "building tax," then processed through several preprocessing stages before classifying tweets into positive and negative sentiments. Two models were used: Support Vector Machine (SVM) and Bidirectional Long Short-Term Memory (BiLSTM). Results show that SVM outperformed BiLSTM, achieving training accuracy of 99.4% and testing accuracy of 85.9%, with accuracy 0.8595, precision 0.8536, recall 0.8595, and F1-score 0.8449. Meanwhile, BiLSTM achieved training accuracy of 86.9% and testing accuracy of 82.9%, with accuracy 0.8294, precision 0.8150, recall 0.8294, and F1-score 0.8080. These findings suggest SVM is more effective in classifying public sentiment and can support better evaluation of regional tax policies.

Keywords: sentiment analysis; PBB-P2; BiLSTM; SVM; X platform

Abstrak: Kebijakan kenaikan tarif Pajak Bumi dan Bangunan Perdesaan dan Perkotaan (PBB-P2) di In-donesia sering memunculkan beragam reaksi dari masyarakat. Sebagian mendukung karena dianggap dapat memperkuat kapasitas fiskal daerah, sementara lainnya menolak karena kha-watir menambah beban ekonomi masyarakat. Pemahaman terhadap sentimen publik atas ke-bijakan tersebut penting untuk mengevaluasi efektivitas kebijakan dan merumuskan strategi komunikasi yang tepat. Penelitian ini bertujuan menganalisis sentimen masyarakat terhadap kebijakan kenaikan PBB-P2 menggunakan data unggahan di Platform X (Twitter). Data dikumpulkan melalui proses crawling dengan kata kunci "pajak bangunan" kemudian diproses melalui beberapa tahap preprocessing sebelum diklasifikasikan menjadi sentimen positif dan negatif. Dua model digunakan dalam penelitian ini, yaitu Support Vector Machine (SVM) dan Bidirectional Long Short-Term Memory (BiLSTM). Hasil penelitian menunjukkan bahwa SVM memiliki kinerja lebih baik dibandingkan BiLSTM, dengan akurasi pelatihan 99,4% dan akurasi pengujian 85,9%. Nilai akurasi 0,8595, precision 0,8536, recall 0,8595, dan F1-score 0,8449. Sementara itu, BiLSTM memperoleh akurasi pelatihan 86,9% dan akurasi pengujian 82,9%, dengan akurasi 0,8294, precision 0,8150; recall 0,8294; dan F1-score 0,8080. Temuan ini menunjukkan bahwa SVM lebih efektif dalam mengklasifikasikan sentimen publik serta dapat mendukung evaluasi kebijakan pajak daerah dengan lebih baik.

Kata kunci: analisis sentimen; PBB-P2; BiLSTM; SVM; platform X

INTRODUCTION

Taxes serve as the main source of state revenue used to finance development and support equitable distribution of welfare among the people [1]. At the regional level, Rural and Urban Land and Building Tax (PBB-P2) is one of the main contributors to Regional Original Revenue (PAD) [2]. However, the policy of increasing PBB-P2 rates in several regions has sparked pros and cons. Some support it because it is considered to strengthen regional fiscal capacity, while others reject it because it is considered to increase the economic burden on the community [3].

Understanding public sentiment towards taxation policy is important for evaluating and improving public communication strategies [4]. entiment analysis is often conducted on social media, especially Platform X (Twitter), which serves as a space for the public to express their opinions on policies [5]. Based on APJII 2024 data, 221.5 million internet users in Indonesia use social media as a representative channel for expressing their aspirations [3]. Platform X was chosen because it presents public opinion directly and in real time, making it relevant for tax policy analysis.

This study uses binary classification (positive-negative) [6]. Model performance is then evaluated using a confusion matrix, which describes the number of predictions that match or do not match the actual conditions in the positive and negative classes [7].

Both deep learning and machine learning methods have shown strong results in sentiment analysis. Two methods commonly used for binary classification (positive and negative) are SVM and BiLSTM. SVM is effective at finding the optimal hyperplane [8], while BiLSTM captures bidirectional context for richer meaning comprehension [9]. [10] Research Proved the effectiveness of BiLSTM in capturing bidirectional context, while improved accuracy through hybrid models [11]. Meanwhile, SVM has demonstrated versatility across domains: from text classification [12], sentiment analysis regarding renewable energy [13], and political sentiment analysis on Twitter [14]. These studies highlight the relevance of BiLSTM and SVM for sentiment classification tasks. Both methods were chosen because SVM is effective for simple text classification and handling imbalanced data, while BiLSTM is used to leverage contextual understanding in more complex sentiment analysis.

Recent studies show [6] compared SVM and BiLSTM for animal conservation issues, with BiLSTM slightly superior (84% vs. 83%). [15] compared SVM and K-NN for IKN issues, with SVM performing better (76% vs. 65%). [16] used BiLSTM with Attention Mechanism to achieve an accuracy of 91.98%.

This study aims to analyze public sentiment toward the PBB-P2 tariff increase using Platform X data, comparing SVM and BiLSTM for binary classification to support the evaluation of local tax and governance policies.

METHOD

The methodological stages in this study are described through the research flow shown in the following figure:

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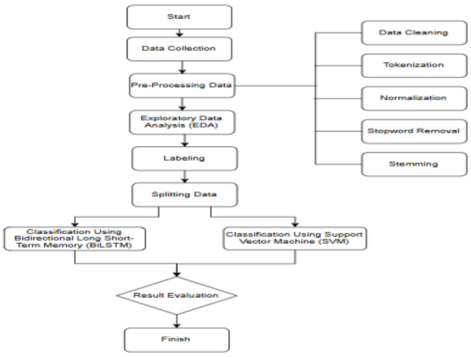

Figure 1. Research Stages of PBB-P2 Sentiment Analysis

The data in the sentiment analysis was collected from platform X (Twitter) on September 25, 2025, using web crawling techniques with the keyword "building tax," which generated 3,007 tweets with a limit of 3,000. After cleaning the data by removing empty values (NaN) and duplicates, the final dataset consisted of 2,990 rows and 15 columns, which were then used as the basis for sentiment analysis.

Pre-Processing Data

The preprocessing stage is crucial for cleaning and organizing raw data from Twitter, removing noise so that the model can process data more effectively and recognize patterns more accurately.

Data Cleaning

	full_text	text_clean
0	Pramono Teken Relaksasi Pajak Daerah Permudah ...	Pramono Teken Relaksasi Pajak Daerah Permudah ...
1	@himawawie Hai Kak. Rumah kos dalam PP 34 tahu...	Hai Kak Rumah kos dalam PP tahun termasuk dala...
2	Kejadian ini pernah saya alami Tiap tahun suda...	Kejadian ini pernah saya alami Tiap tahun suda...
3	kenapa kita harus bayar pajak bumi dan banguna...	kenapa kita harus bayar pajak bumi dan banguna...
4	Peraturan Pemerintah Nomor 16 Tahun 2000 Tenta...	Peraturan Pemerintah Nomor Tahun Tentang Pemba...

Figure 2. Data Cleaning on PBB-P2 Text

In Figure 2, the text data was cleaned by removing elements irrelevant to sentiment analysis, such as URLs, mentions (@username), hashtags (#), and other unnecessary components.

Tokenization

text_tokenizingText
[pramono, teken, relaksasi, pajak, daerah, per...
[hai, kak, rumah, kos, dalam, pp, tahun, terma...
[kejadian, ini, pernah, saya, alami, tiap, tah...
[kenapa, kita, harus, bayar, pajak, bumi, dan,...
[peraturan, pemerintah, nomor, tahun, tentang,...

Figure 3. Tokenization on PBB-P2 Text

In Figure 3, the text is broken down into smaller units called tokens. This tokenization stage plays a crucial role in allowing each word to be analyzed individually and integrated effectively into the analytical model.

Normalization

text_casefoldingText
pramono teken relaksasi pajak daerah permudah ...
hai kak rumah kos dalam pp tahun termasuk dala...
kejadian ini pernah saya alami tiap tahun suda...
kenapa kita harus bayar pajak bumi dan banguna...
peraturan pemerintah nomor tahun tentang pemba...

Figure 4. Normalization on PBB-P2 Text

In Figure 4, normalization is performed to standardize the spelling of words for consistency. All text is converted to lowercase (case folding), and non-standard words or social media abbreviations are converted to standard forms.

Stopword Removal

text_stopword
[pramono, teken, relaksasi, pajak, daerah, per...
[hai, kak, rumah, kos, pp, tahun, termasuk, ja...
[kejadian, pernah, alami, tiap, tahun, bayar, ...
[bayar, pajak, bumi, bangunan, yah, like, manf...
[peraturan, pemerintah, nomor, tahun, pembagia...

Figure 5. Stopword Removal on PBB-P2 Text

In Figure 5, stop-word removal is performed to remove common words that appear frequently but do not provide important information in sentiment analysis.

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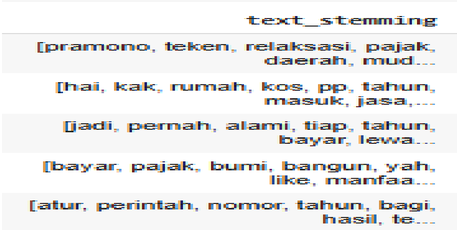
Examples of stopwords in Indonesian include "yang" (which), "dan" (and), 'di' (in), and "ke" (to). By removing stop-words, only words that truly convey sentiment are retained.

Stemming

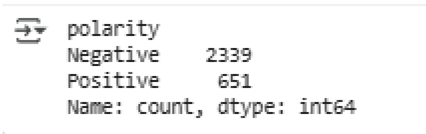


text_stemming
[pramono, teken, relaksasi, pajak, daerah, mud...
[hai, kak, rumah, kos, pp, tahun, masuk, jasa,...
[jadi, pernah, alami, tiap, tahun, bayar, lewa...
[bayar, pajak, bumi, bangun, yah, like, manfaa...
[atur, perintah, nomor, tahun, bagi, hasil, te...

Figure 6. Stemming on PBB-P2 Text

In Figure 6, stemming is performed to return each word to its base form. For example, the word "membayar" (to pay) will be returned as "bayar" (pay), or 'kenaikan' (increase) as "naik" (up).

Labelling



```
polarity
Negative    2339
Positive     651
Name: count, dtype: int64
```

Figure 7. Labelling PBB-P2

After preprocessing, labeling was performed as shown in Figure 7. Each tweet was labeled as positive or negative sentiment according to the context of the PBB-P2 issue. As a result, there were 2,339 negative tweets and 651 positive tweets, indicating a predominance of negative sentiment in the dataset.

Exploratory Data Analysis (EDA)

EDA is conducted to understand data characteristics prior to modeling, including sentiment distribution and dominant words that appear in relation to the research issue.

Sentiment Distribution

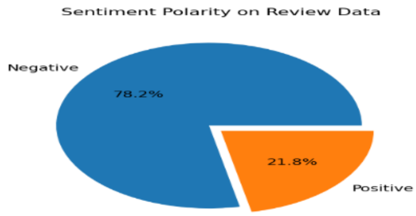


Figure 8. Pie chart PBB-P2

From the visualization in Figure 8, it can be seen that most tweets are classified as negative sentiments with a percentage of 78.2%, while positive sentiments only reach 21.8%. This shows that the majority of Twitter users responded negatively to the PBB-P2 increase policy.

Word Cloud

Figure 9. Word Cloud PBB-P2

Figure 9 is used to display the words that appear most frequently in tweet data related to the issue of Land and Building Tax (PBB). The overall visualization reveals that the terms "pajak," "bumi," and "bangunan" appear most prominently, emphasizing the central theme of public discussions surrounding PBB.

Figure 10. Word Cloud Positif and Negative PBB-P2

Figure 10 shows a positive word cloud displays words such as "taxes,"

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"land," "buildings," "benefits," and "development," reflecting support for the UN's regional development efforts, while the negative word cloud is dominated by words such as "increase," "burden," and "land rights," indicating public opposition to tax increases.

Word Frequency Analysis

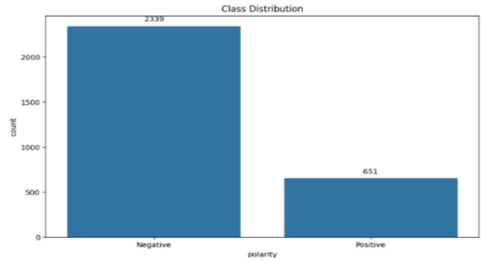

Figure 11. Word Frequency Analysis PBB-P2

Figure 11 shows the distribution of classes shows that negative tweets (2,339) are more dominant than positive ones (651), indicating that public response to the PBB-P2 tends to be negative in relation to tax increases and burdens.

Most Frequent Words (TF-IDF)

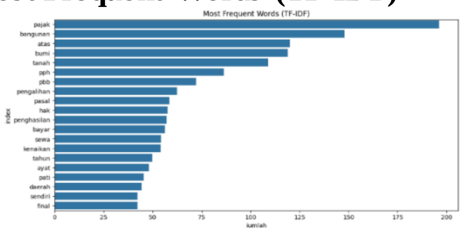

Figure 12. Most Frequent Words (TF-IDF) PBB-P2

Figure 12 shows a TF-IDF graph shows dominant words such as "tax," "building," "land," and "property," confirming that public conversation focused on the issue of Land and Building Tax (PBB) and related payment obligations.

Splitting Data

The dataset is split into two portions: 80% allocated for training and 20% for testing. The training data serves to build and optimize the model, whereas the testing data is utilized to assess how well the model performs on unseen data.

Classification

Bidirectional Long Short-Term Memory (BiLSTM)

The processed tweet data is then divided into training data and test data. Model evaluation is performed using a confusion matrix and classification report with accuracy, precision, recall, and F1-score metrics.

Support Vector Machine (SVM)

In this study, the SVM method uses TF-IDF to convert text into numerical features. Then, with stratification, the data is split into training and testing sets (80:20). A LinearSVC model is trained on training data and then evaluated on test data using metrics of accuracy, precision, recall, and F1-score.

Evaluation

The model evaluation process was carried out using a Confusion Matrix with accuracy, precision, recall, and F1-score metrics to assess the performance of PBB-P2 sentiment classification. Accuracy indicates the overall accuracy of the prediction, precision assesses the accuracy of positive class identification, recall measures the ability to recognize all actual positive data, while the F1-score balances precision and recall on unbalanced data.

RESULT AND DISCUSSION

BiLSTM Method

The confusion matrix results generated by the BiLSTM model are presented in the figure 13.

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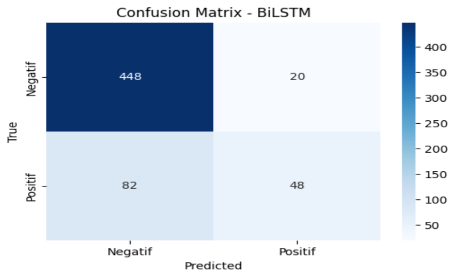

Figure 13. Confusion Matrix of the BiLSTM Method on PBB-P2

Based on Figure 13 regarding the confusion matrix, the BiLSTM model accurately identified the negative class 448 times and the positive class 48 times. However, it also produced 20 false positives, where negative samples were incorrectly classified as positive, and 82 false negatives, where positive samples were misclassified as negative. These findings suggest that the BiLSTM model demonstrates stronger performance in recognizing the negative class, as reflected by the significantly higher number of correct predictions compared to the positive class.

Table 1. BiLSTM Method Results

Class	BiLSTM Method Results			
	Precision	Recall	F1-Score	Akurasi
Negative	85%	96%	90%	83%
Positive	71%	37%	48%	

Table 1 shows that the accuracy value of the BiLSTM model is 83%. For the negative class, the precision, recall, and f1-score values are 85%, 96%, and 90%, respectively, while for the positive class, they are 71%, 37%, and 48%, respectively. These results indicate that BiLSTM performs significantly better in classifying the negative class than the positive class.

SVM Method

The following is the confusion matrix result from SVM, which can be seen in the figure 14.

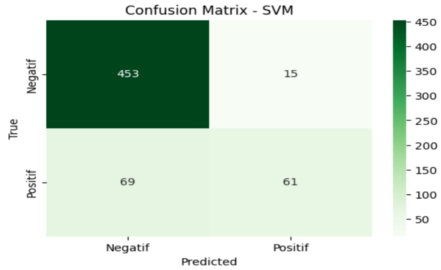

Figure 14. Confusion Matrix of the SVM Method on PBB-P2

Based on Figure 14 regarding the confusion matrix, it can be seen that the SVM model accurately classified the negative class 453 times and the positive class 61 times. Nevertheless, the model produced 15 false positives cases where negatives were predicted as positives and 69 false negatives cases where positives were predicted as negatives. These findings suggest that the SVM performs more effectively in recognizing negative instances than positive ones, as indicated by the significantly higher number of correct predictions in the negative class.

Table 2. SVM Method Results

Class	SVM Method Results			
	Precision	Recall	F1-Score	Akurasi
Negative	87%	97%	92%	86%
Positive	80%	47%	59%	

Table 3 shows that the accuracy value of the SVM model is 86%. Specifically, for the negative class, the precision, recall, and F1-score reached 87%, 97%, and 92%, respectively. In contrast, the positive class obtained lower scores of 80% for precision, 47% for recall, and 59% for F1-score. These results suggest that the SVM model performs more effectively in identifying negative instances, as reflected by the notably higher recall and F1-score in that class.

Comparison

The evaluation results show that the SVM method has superior performance compared to BiLSTM, with accuracies of 86% and 83%, respectively. In the negative class, SVM achieved a precision value of 87%, a recall of 97%, and an F1-score of 92%, while BiLSTM obtained 85%, 96%, and 90%. Meanwhile, in the positive class, SVM continued to show better performance with precision of 80%, recall of 47%, and F1-score of 59%, surpassing BiLSTM, which only achieved 71%, 37%, and 48%. Overall, SVM provided more consistent results in both classes, particularly in improving prediction capabilities in the positive class.

CONCLUSION

The results of this study indicate that both algorithms, BiLSTM and SVM, are capable of producing fairly good accuracy in classification, namely 83% for BiLSTM and 86% for SVM. Based on class-by-class evaluation, SVM excels in both negative and positive classes because it is able to optimize TF-IDF numerical features and is more resistant to overfitting. In the negative class, SVM achieved a precision of 87%, a recall of 97%, and an f1-score of 92%, while BiLSTM achieved a precision of 85%, a recall of 96%, and an f1-score of 90%. For the positive class, SVM also scored higher with a precision of 80%, recall of 47%, and f1-score of 59%, while BiLSTM only achieved a precision of 71%, recall of 37%, and f1-score of 48%. Thus, although BiLSTM is quite reliable in recognizing the negative class, overall SVM has more consistent and effective performance in predicting both classes, especially the positive class.

BIBLIOGRAPHY

[1] C. Kansil, “Peran Hukum Pajak dalam Mendorong Pembangunan Ekonomi Nasional untuk Mewujudkan Tujuan Negara,” *J. Multidisiplin Indones.*, vol. 3, no. 2, pp. 1655–1662, 2024.

[2] V. Salsabella, C. Belina, N. S. Budiarso, and A. Wangkar, “Analisis pelaksanaan pemungutan Pajak Bumi Dan Bangunan Perdesaan dan Perkotaan (PBB - P2) berdasarkan Peraturan Bupati No 18 Tahun 2014 di Kecamatan Pasan Kabupaten Minahasa Tenggara,” vol. 2, no. 2, pp. 126–136, 2024, doi: 10.58784/ramp.123.

[3] M. N. Huda and G. Wicaksono, “Analisis Efektivitas Dan Kontribusi Penerimaan Pajak Bumi Dan Bangunan Perdesaan Dan Perkotaan Terhadap Pendapatan Asli Daerah Kota Yogyakarta,” *Educoretax*, vol. 1, no. 4, pp. 284–290, 2021, doi: 10.54957/educoretax.v1i4.108.

[4] E. P. Adamansyah and A. Yudhistira, “Evaluasi Opini Publik di Media Sosial X terhadap Kebijakan Pajak Pertambahan Nilai 12% di Indonesia Menggunakan Naive Bayes dan Decision Tree,” *J. Pendidik. dan Teknol. Indones.*, vol. 5, no. 3, pp. 831–843, 2025, doi: 10.52436/1.jpti.710.

[5] S. Asmara and F. I. Butsi, “Twitter dan Public Sphere: Studi Fenomenologi Tentang Twitter Sebagai Media Alternatif Komunkasi Politik,” *J. Ilm. Ilmu Komun. Commun.*, vol. 2, no. 2, pp. 75–84, 2020, doi: 10.62144/jikq.v2i2.30.

[6] R. Nursyanti, N. Alamsyah, and T. M. Yusuf, “Aisyah Journal of Informatics and Electrical Engineering,” *Aisyah J.*

Informatics Electr. Eng., vol. 7, no. 1, pp. 137–145, 2025, [Online]. Available: http://jti.aisyahuniversity.ac.id/index.php/AJIEE

[7] M. F. Amin, "Confusion matrix in three-class classification problems: A step-by-step tutorial," *J. Eng. Res.*, vol. 6, no. 5, 2023, [Online]. Available: https://erjeng.journals.ekb.eg/article_296718_30a98aac15193d04dc73ba9bc00cf046.pdf

[8] A. Yudhistira, "Analisis Sentimen Petani Milenial Pada Media Sosial X Menggunakan Algortitma Support Vector Machine (SVM) Fakultas Teknik dan Ilmu Komputer , Universitas Teknokrat Indonesia , Indonesia Sentiment Analysis of Millennial Farmers on Social Media X Using th," vol. 5, no. 3, pp. 845–857, 2025, doi: https://doi.org/10.52436/1.jpti.717.

[9] P. Utami, M. R. Ningsih, D. Ananda, and A. Pertiwi, "Sentimen based-emotion classification using bidirectional long," pp. 281–289, 2024, doi: https://doi.org/10.52465/joscex.v5i3.461.

[10] P. Arsi, R. A. Firmanda, I. Prayoga, and P. Subarkah, "Opinion Mining on Spotify Music App Reviews Using Bidirectional LSTM and BERT," vol. 11, no. 2, pp. 68–74, 2025.

[11] P. Subarkah, H. A. A. Rozaq, P. Arsi, S. A. Sholikhatin, R. Riyanto, and H. Marcos, "Implementation of Text Mining to Detect Emotions of Fuel Price Increase using BERT-LSTM Methods," *Gazi Univ. J. Sci.*, vol. 37, no. 4, pp. 1707–1716, 2024, doi: 10.35378/gujs.1424742.

[12] A. A. Rashifa, H. Marcos, P. Subarkah, and S. A. Sholikhatin, "Comparison of Svm and Naïve Bayes Classifier Algorithms on Student Interest in Joining Msib," *JITK (Jurnal Ilmu Pengetah. dan Teknol. Komputer)*, vol. 10, no. 1, pp. 116–123, 2024, doi: 10.33480/jitk.v10i1.5270.

[13] P. Subarkah, B. A. Kusuma, and P. Arsi, "Sentiment Analysis on Renewable Energy Electric Using Support Vector Machine (Svm) Based Optimization," *JITK (Jurnal Ilmu Pengetah. dan Teknol. Komputer)*, vol. 10, no. 2, pp. 252–260, 2024, doi: 10.33480/jitk.v10i2.5575.

[14] A. J. N. Kisma, P. Arsi, and P. Subarkah, "Sentiment Analysis Regarding Candidate Presidential 2024 Using Support Vector Machine Backpropagation Based," *JTAM (Jurnal Teor. dan Apl. Mat.*, vol. 8, no. 1, p. 96, 2024, doi: 10.31764/jtam.v8i1.17294.

[15] D. Haliza and M. Ikhsan, "Sentiment Analysis on Public Perception of the Nusantara Capital on Social Media X Using Support Vector Machine (SVM) and K-Nearest Neighbor (K-NN) Methods," *J. Appl. Informatics Comput.*, vol. 9, no. 3, pp. 716–723, 2025, doi: 10.30871/jaic.v9i3.9318.

[16] B. Omarov and Z. Zhumanov, "Bidirectional Long-Short-Term Memory with Attention Mechanism for Emotion Analysis in Textual Content," *Int. J. Adv. Comput. Sci. Appl.*, vol. 14, no. 6, pp. 129–136, 2023, doi: 10.14569/IJACSA.2023.0140615.