

AN ANALYSIS OF FEAR OF MISSING OUT (FOMO) AS A DRIVER OF HOAX DISSEMINATION IN THE PRABOWO ERA USING MLP

Irfan Saputra^{*1}, Agustina Heryati², Hendra Di Kesuma³

^{1,2,3}Sistem Informasi, Fakultas Ilmu Komputer dan Sains, Universitas Indo Global Mandiri, Palembang, Indonesia

Email: 1202210011@students.uigm.ac.id, 2agustina.heryati@uigm.ac.id, 3hendra.dikesuma@uigm.ac.id

(Received: April 18, 2026; Revised: April 24, 2026; Published: May 2, 2026)

Abstract

The rapid expansion of social media platforms has significantly increased the circulation of information, including misleading content such as hoaxes that may influence public perception and political stability. One psychological factor associated with this phenomenon is Fear of Missing Out (FOMO), which reflects an individual's concern about being left behind in accessing important information. This research aims to examine how FOMO contributes to the spread of political hoaxes related to the Prabowo era on social media. The dataset used in this study consists of 5,385 comments collected from TikTok and Facebook through web scraping techniques. The data were processed using text preprocessing methods and transformed into numerical features using TF-IDF. Classification was conducted using the Multi-Layer Perceptron (MLP) algorithm. The experimental findings indicate that the model achieved an accuracy of 0.82 for FOMO classification, 0.89 for hoax detection, and 0.84 for sentiment analysis. These results suggest that users exhibiting FOMO tendencies are more likely to interact with trending information without verification, thereby increasing the likelihood of hoax dissemination. This study emphasizes the importance of combining psychological perspectives with machine learning techniques to better understand misinformation behavior in digital environments.

Keywords: fear of missing out; hoax; social media; prabowo; multi-layer perceptron.

1. INTRODUCTION

The development of social media has significantly transformed the way information is produced and disseminated. Platforms such as TikTok and Facebook enable rapid information exchange, but also increase the risk of spreading misinformation and hoaxes [1]. Emotional and sensational content tends to spread faster, making users more vulnerable to unverified information [2].

Fear of Missing Out (FOMO) refers to a psychological condition in which individuals experience anxiety when they feel they might miss important information or events[3]. Previous studies indicate that individuals with high FOMO tend to engage more actively on social media and are more likely to share information without proper verification[4]. This behavior increases their vulnerability to misinformation, especially in fast-moving digital environments[5].

In the context of hoax detection, machine learning methods such as Multi-Layer Perceptron (MLP) have been widely used due to their ability to classify textual data effectively [6]-[7]. However, most previous studies focus only on textual features and ignore behavioral or psychological aspects such as FOMO [8]. This creates a research gap in understanding how psychological behavior influences the spread of misinformation [9].

Several studies have shown that individuals experiencing Fear of Missing Out (FOMO) tend to engage more actively in social media interactions and are more likely to share information without proper verification. This behavior significantly contributes to the rapid spread of fake news, especially in emotionally charged contexts such as political discussions [10]-[11]. In the case of government-related issues, hoax information is often designed to trigger urgency and anxiety, which aligns with FOMO characteristics [12].

Furthermore, in Indonesia, political hoaxes related to government figures and policies have become increasingly prevalent, particularly in the era of the Prabowo administration [13]. Despite this, studies that integrate psychological factors and machine learning approaches in analyzing political hoaxes remain limited [14].

Therefore, this study aims to analyze the role of FOMO as a behavioral factor in the spread of political hoaxes related to the Prabowo administration on social media [15]. This research proposes a novel approach by integrating psychological indicators of FOMO with a machine learning classification model using Multi-Layer Perceptron (MLP) [16]. The contribution of this study lies in combining behavioral analysis and computational methods to improve the understanding and detection of misinformation patterns in social media environments [17].

2. RESEARCH METHODS

2.1. Research Design

This study adopts a mixed-method approach that combines qualitative and quantitative analysis. The qualitative approach aims to understand the behavioral phenomenon of Fear of Missing Out (FOMO) in social media interactions, while the quantitative approach applies machine learning techniques to classify data and evaluate model performance.

The overall research workflow consists of data collection, preprocessing, labeling, feature extraction, model development using Multi-Layer Perceptron (MLP), and evaluation using performance metrics.

2.2. Data Collection and Description

The dataset used in this study was obtained from TikTok and Facebook through web crawling using the Apify platform. A total of 5,385 comments related to discussions about the Prabowo-era government were collected. The dataset reflects informal language commonly found in social media, including slang, abbreviations, and emotional expressions. Each record contains attributes such as comment text, number of likes, replies, timestamps, and user identifiers, although only textual data were used for analysis. The data distribution is imbalanced, where approximately 34% of the data belong to the FOMO category and 66% to Non-FOMO, while 23% are classified as Hoax and 77% as Non-Hoax. This imbalance may influence model performance, especially in identifying minority classes.

2.3. Data Labeling

The dataset is manually labeled into several categories based on predefined indicators:

- a. FOMO and Non-FOMO, based on psychological indicators such as information anxiety, urgency, and impulsive behavior.
- b. Hoax and Non-Hoax, based on information validity, including misleading content, exaggeration, and lack of credible sources.
- c. Sentiment classification (Positive, Neutral, Negative), based on linguistic tone and emotional expression.

This labeling process is essential to define classification targets and support supervised learning in the MLP model.

2.4. Data Splitting

The dataset is divided into training and testing sets using an 80:20 ratio. A total of 4,308 data are used for training, while 1,077 data are used for testing. This split allows the model to learn patterns from the training data and evaluate its performance on unseen data, ensuring generalization capability. The model is evaluated using standard performance metrics including accuracy, precision, recall, and F1-score. The evaluation is conducted on the testing dataset using an 80:20 split.

2.5. Feature Extraction (TF-IDF)

Text data are transformed into numerical representations using the Term Frequency–Inverse Document Frequency (TF-IDF) method[18]. This technique assigns weights to words based on their frequency within a document and their uniqueness across the dataset. TF-IDF helps highlight important terms while reducing the impact of common words, allowing the model to better capture relevant patterns in the data.

2.6. Model Development (MLP)

The classification model used in this study is the Multi-Layer Perceptron (MLP), a type of artificial neural network capable of modeling non-linear relationships in data[19]. The model is configured with two hidden layers (128 and 64 neurons), using the ReLU activation function and trained for a maximum of 300 iterations. The model is implemented using a fixed random state to ensure reproducibility[20]. MLP is chosen due to its ability to handle high-dimensional text data and capture complex patterns in user behavior. The model is implemented using Python with libraries such as Scikit-learn for TF-IDF and MLP classification.

3. RESULTS AND DISCUSSION

3.1. Dataset Description

This study utilizes a dataset consisting of 5,385 social media comments collected from TikTok and Facebook platforms using web crawling techniques; the data represent public opinions related to issues surrounding the Prabowo-era government. Each entry contains several attributes, including comment text, number of likes, number of replies, timestamp, user ID, and URL source. However, only the textual comment attribute is used as the main variable for analysis, as it contains linguistic information relevant to classification tasks.

The dataset is written in Indonesian and reflects informal language commonly used on social media, including slang, abbreviations, and emotional expressions. This characteristic introduces challenges in text processing and classification due to high variability and noise in the data.

The dataset was divided into training and testing sets with a ratio of 80:20, resulting in 4,308 training data and 1,077 testing data. This division ensures that the model can be trained effectively and evaluated on unseen data. The data processing flow begins with raw comment extraction, followed by preprocessing, feature transformation using TF-IDF, and classification using the MLP model. Each stage contributes to improving the quality and interpretability of the data.

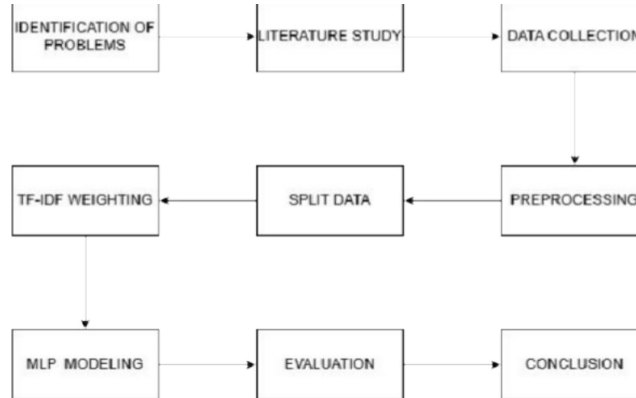


Figure 1. Research Procedure

3.2. Data Labeling Results

The labeling process was conducted to categorize each comment into several classes based on psychological and informational indicators. The dataset was classified into three main categories: FOMO and Non-FOMO, Hoax and Non-Hoax, and sentiment (Positive, Neutral, Negative). The results show that the dataset is dominated by Non-FOMO and Non-Hoax classes, as well as Neutral sentiment. Specifically, the number of FOMO comments is significantly lower compared to Non-FOMO, indicating an imbalance in the dataset. This imbalance affects model performance, as machine learning algorithms tend to perform better on majority classes. The dominance of Neutral sentiment also reflects that most users express opinions in a relatively moderate manner rather than extreme positive or negative reactions. The labeling process plays a crucial role in defining the classification boundaries and directly impacts the performance of the model.

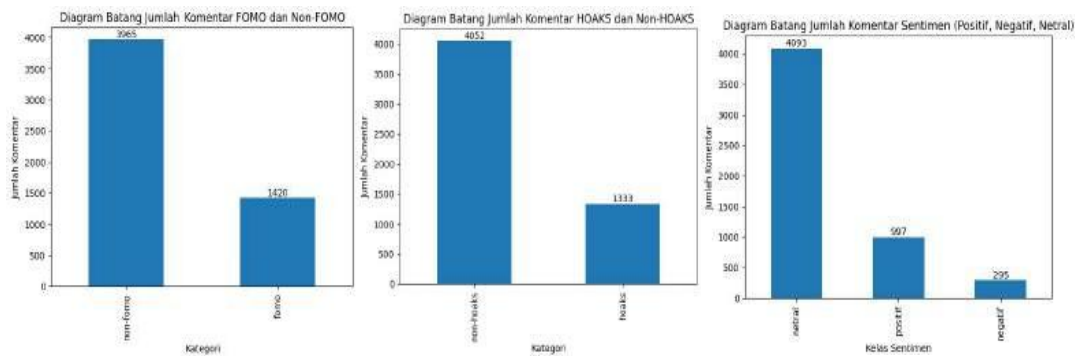


Figure 2. Labeling Results

3.3. Feature Extraction using TF-IDF

Feature extraction was performed using the Term Frequency-Inverse Document Frequency (TF-IDF) method. This method converts textual data into numerical vectors by assigning weights to each word based on its importance in a document relative to the entire dataset. TF-IDF successfully highlights significant terms that are relevant to the topic of discussion, while reducing the influence of common words that appear frequently across documents.

The resulting feature vectors serve as input for the classification model. This transformation allows the Multi-Layer Perceptron (MLP) model to process textual data effectively and identify patterns associated with FOMO behavior and hoax dissemination.

3.4. Model Performance Evaluation

a. FOMO and Non-FOMO Classification

The model achieved an accuracy of 0.82, indicating that it can generalize well in identifying dominant behavioral patterns. However, the relatively lower recall in the FOMO class suggests that the model struggles to detect implicit

psychological signals. An interesting finding in this study is that hoax content tends to mimic neutral or factual language, making it harder to detect than explicitly emotional content.

Additionally, FOMO-driven users are more likely to engage with trending topics rather than verifying information sources. One limitation of this study is the reliance on textual features without incorporating contextual or network-based information, which may further improve classification performance.

Table 1. FOMO and Non-FOMO Evaluation Results

Category	Precision	Recall	F1-Score
FOMO	0,67	0,65	0,66
Non-FOMO	0,87	0,88	0,88
Accuracy	0,82		

b. Hoax and Non-Hoax Classification

The classification results for Hoax and Non-Hoax categories show strong performance, with an overall accuracy of 0.89. The model achieved a precision of 0.81 and recall of 0.74 for the Hoax class. The Non-Hoax class achieved higher performance, with precision and recall values exceeding 0.90. This indicates that the model is highly reliable in identifying valid information. However, some hoax data were misclassified due to similarities in linguistic patterns between factual and misleading information. This highlights the challenge of detecting hoaxes that are presented in a seemingly credible manner.

Table 2. Hoax and Non-Hoax Evaluation Results

Category	Precision	Recall	F1-Score
Hoaks	0,81	0,74	0,77
Non-Hoaks	0,92	0,94	0,93
Accuracy	0,89		

c. Sentiment Classification

The sentiment classification results show an overall accuracy of 0.84. The model performs best in the Neutral class, with precision and recall values above 0.88. In contrast, the Negative class shows the lowest performance, with precision and recall values around 0.58. The Positive class shows moderate performance. These results indicate that the model tends to be biased toward the Neutral class due to its dominance in the dataset. Additionally, the similarity in language patterns between Neutral and Negative comments makes classification more challenging.

Table 3 Positive, Negative and Neutral Evaluation Results

Category	Precision	Recall	F1-Score
Negatif	0,59	0,58	0,58
Netral	0,88	0,92	0,90
Positif	0,71	0,60	0,65
Accuracy	0,84		

3.5. Model Evaluation using Confusion Matrix

a. FOMO and Non-FOMO Classification

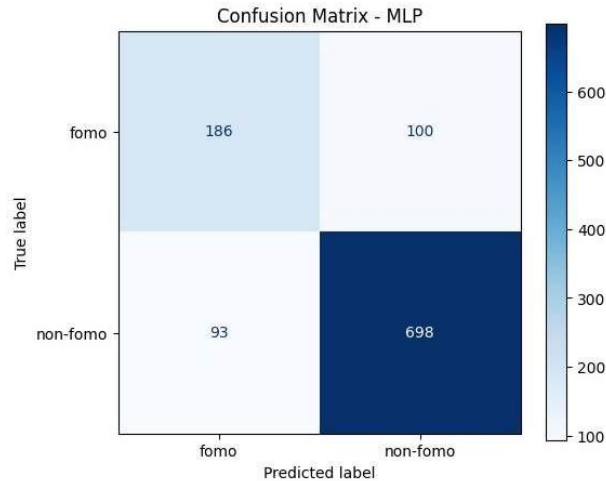


Figure 3. FOMO and Non-FOMO Classification

The confusion matrix results show that the Multi-Layer Perceptron (MLP) model achieved an overall accuracy of 0.82 in classifying FOMO and Non-FOMO data. For the FOMO class, 186 out of 286 data were correctly classified, while 100 data were misclassified as Non-FOMO. This indicates that the model still struggles to detect FOMO patterns, especially due to their implicit and context-dependent nature. The relatively high number of false negatives reflects the model’s limitation in identifying FOMO, which is consistent with the moderate recall value (0.65).

In contrast, the model performed significantly better in the Non-FOMO class, correctly classifying 698 out of 791 data. The small number of misclassifications indicates that Non-FOMO patterns are more explicit and easier to recognize by the model. Overall, the model shows a tendency to favor the majority class (Non-FOMO), indicating a potential data imbalance issue. As a result, although the model performs well in general, its ability to detect FOMO still needs improvement.

b. Hoax and Non-Hoax Classification

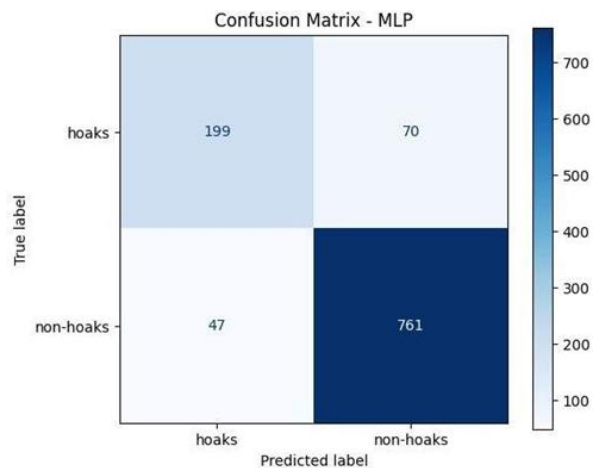


Figure 4. Hoax and Non-Hoax Classification

The confusion matrix evaluation for Hoax and Non-Hoax classification shows that the model achieved an accuracy of 0.89, indicating strong overall performance. For the Hoax class, 199 out of 269 data were correctly classified, while 70 data were misclassified as Non-Hoax. This suggests that the model still faces challenges in identifying certain hoax patterns, particularly those that resemble factual information. Meanwhile, the Non-Hoax class shows excellent performance, with 761 out of 808 data correctly classified.

The low number of false positives indicates that the model is highly reliable in recognizing valid information. Overall, the model demonstrates a bias toward the Non-Hoax class due to data imbalance. Although performance is high, improvements are needed to enhance the detection of hoax data, especially in reducing false negatives.

c. Sentiment Classification (Positive, Neutral, Negative)

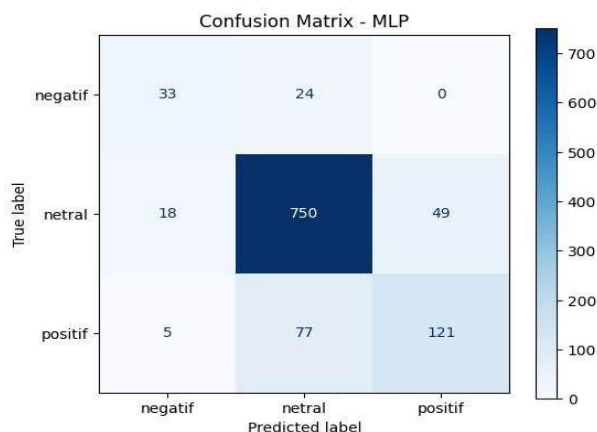


Figure 5. Sentiment Classification (Positive, Neutral, Negative)

The confusion matrix results for sentiment classification show that the model achieved an overall accuracy of 0.84, with varying performance across classes. The Neutral class demonstrates the highest performance, with 750 out of 817 data correctly classified. This indicates that neutral sentiment patterns are more consistent and easier for the model to learn. For the Positive class, 121 out of 203 data were correctly classified, while a significant portion was misclassified as Neutral. Similarly, in the Negative class, only 33 out of 57 data were correctly identified, with most errors also shifting toward the Neutral class. These results indicate that the model tends to be biased toward the Neutral class, likely due to its dominance in the dataset and overlapping linguistic characteristics between sentiment classes. Overall, although the model performs well, improvements such as data balancing and feature enhancement are necessary to improve classification performance for minority classes (Positive and Negative).

3.6. Discussion

The experimental results indicate that the MLP model performs well overall, particularly in detecting majority classes such as Non-FOMO and Non-Hoax, with accuracy values of 0.82 and 0.89 respectively. However, a deeper analysis reveals important insights regarding model limitations and behavioral patterns.

First, the relatively low recall value for the FOMO class (0.65) suggests that the model struggles to capture implicit psychological signals. This indicates that FOMO expressions are often subtle and context-dependent, making them harder to detect compared to explicit textual patterns.

Second, in the hoax classification task, although the model achieved high accuracy (0.89), the recall for the Hoax class (0.74) indicates that some hoax content is still misclassified as valid information. This occurs because many hoaxes mimic neutral or factual language, reducing the effectiveness of text-based classification.

Third, the findings confirm that FOMO plays an indirect but significant role in hoax dissemination. Users with FOMO tendencies are more likely to engage with trending content without verification, which increases the probability of interacting with and spreading misleading information.

These results suggest that the relationship between FOMO and hoax spread is not purely linear but mediated by user engagement behavior. Therefore, incorporating contextual features, such as interaction patterns or network analysis, may improve model performance in future research.

4. CONCLUSION

This study demonstrates that the Fear of Missing Out (FOMO) phenomenon plays a significant role in influencing user behavior on social media, particularly in the context of hoax dissemination. Based on the experimental results, the MLP model achieved good performance, with an accuracy of 0.82 for FOMO classification and 0.89 for hoax detection. The results show that FOMO influences how users interact with information, where individuals with higher FOMO tendencies are more likely to engage with trending topics and share information without proper verification. This behavior creates conditions that facilitate the spread of hoaxes, especially when misleading information is presented in a neutral or seemingly factual manner.

However, the study also reveals limitations in detecting FOMO and hoax content, particularly due to the implicit nature of psychological expressions and dataset imbalance. The relatively lower recall values indicate that some FOMO and hoax instances are not fully captured by the model. For future improvement, several recommendations can be proposed. First, incorporating contextual features such as user interaction patterns and network analysis may enhance model performance. Second, applying data balancing techniques can improve the detection of minority classes. Third, the use of more advanced deep learning models, such as LSTM or transformer-based approaches, may provide better semantic understanding of textual data.

Overall, this study provides a more comprehensive understanding of how psychological factors and machine learning can be combined to analyze and mitigate the spread of misinformation on social media.

REFERENCES

- [1] Aris Sarjito., “Hoaks, Disinformasi, dan Ketahanan Nasional: Ancaman Teknologi Informasi dalam Masyarakat Digital Indonesia,” 2024.
- [2] Arfan Maulana Hafizh, Fajar Hidayat, and Amril Suansyah, “Fomo Vs Jomo: Understanding The Psychology Behind Social Media Consumption Behavior And Its Impact On Mental Well-Being With A Communication Psychology Approach,” *World J. Islam. Learn. Teach.*, vol. 1, no. 2, pp. 10–18, 2024, doi: 10.61132/wjilt.v1i2.37.
- [3] C. Gong and Y. Ren., “PTSD, FOMO and fake news beliefs: a cross-sectional study of Wenchuan earthquake survivors,” *BMC Public Health*, vol. 23, no. 1, pp. 1–11, 2023, doi: 10.1186/s12889-023-17151-z.
- [4] H. Amanda, N. Faiza, and L. S. Harahap, “Implementasi Multilayer Perceptron untuk Klasifikasi Berita Hoax dalam Media Sosial,” vol. 2, no. 1, 2025.
- [5] A. G. Rinepta., “Kominfo DIY Pastikan Isu Prabowo Tebar Ancaman Jika Batal Jadi Presiden Hoax,” *detikJogja*. [Online]. Available: https://www.detik.com/jogja/berita/d-7064331/kominfo-diy-pastikan-isu-prabowo-tebar-ancaman-jika-batal-jadi-presiden-hoax?utm_source=chatgpt.com#google_vignette
- [6] K. Arunthavachelvan, S. Raza, and C. Ding, “A deep neural network approach for fake news detection using linguistic and psychological features,” *User Model. User-adapt. Interact.*, vol. 34, no. 4, pp. 1043–1070, 2024, doi: 10.1007/s11257-024-09413-1.
- [7] H. Hanifah, L. Salsabillah, A. T. Fitri, and R. M. Febriani, “Landasan Teori , Penelitian Relevan , Kerangka Berpikir Dan,” vol. 3, no. April, pp. 391–404, 2025.
- [8] Rahmawati, Marilang, and M. H. Nonci, “Konstruk Teori dan Paradigma Pengetahuan,” *Socius J. Penelit. Ilmu-Ilmu Sos.*, vol. 1, no. 6, pp. 173–179, 2024, [Online]. Available: <https://doi.org/10.5281/zenodo.10514453>
- [9] Y. A. D. & Y. Triwianti., “Jurnal Social Library,” *J. Soc. Libr.*, vol. 4, no. 2, pp. 324–331, 2024, [Online]. Available: <https://scholar.archive.org/work/26zcv7soi5dkbdnjf6arhi66rm/access/wayback/http://penelitimuda.com/index.php/SL/article/download/78/pdf>
- [10] S. Syaqla Ananthasya and D. Deni., “Fenomena Waduk Sebagai Ruang Destinasi Malam Hari Remaja Di Kota Lhokseumawe,” pp. 175–183, 2022.
- [11] C. Montag, M. Müller, H. M. Pontes, and J. D. Elhai, “On fear of missing out, social networks use disorder tendencies and meaning in life,” *BMC Psychol.*, vol. 11, no. 1, pp. 1–8, 2023, doi: 10.1186/s40359-023-01342-9.
- [12] I. Listiana, D. C. Anbiya, F. R. Abrar, E. Nurharyati, and A. Saefudin, “Dampak fenomena fear of missing out (FOMO) terhadap perilaku konsumtif mahasiswa UIN Syarif Hidayatullah Jakarta,” vol. 7, pp. 84–95, 2026, doi: 10.37373/bemas.v7i1.2000.
- [13] I. Artikel, “Meningkatkan Efektivitas Pemasaran Melalui Desain Banner UMKM Warkop Warung Ijo Di Kelurahan Sumber Rejo,” vol. 6, no. 1, pp. 1446–1450, 2025.
- [14] Q. Angraini, K. N. Situmeang, L. Hasna, D. Zakiyah, and U. Riau, “HOAKS DI INDONESIA : PENYEBARAN DAN KONSEKUENSI,” vol. 9, no. 11, pp. 123–127, 2025.
- [15] A. Ayu Armaya, A. Syafitri Yasmin, D. Agustina, and N. Nurbaiti, “Pemanfaatan Media Sosial Sebagai Sarana Pengembangan Komunitas Virtual,” *Madani J. Ilm. Multidisiplin*, vol. 1, no. 11, pp. 829–834, 2023, [Online]. Available: <https://doi.org/10.5281/zenodo.10393672>
- [16] D. Jupriono, A. Andayani, and B. Sigit Pramono, “Perubahan Sosial Akibat Media Sosial,” *RELASI J. Penelit. Komun. (e-ISSN 2807-6818)*, vol. 4, no. 01, pp. 18–25, 2024, doi: 10.69957/relasi.v4i01.1400.
- [17] D. F. Sjoraida, B. Wibawa, K. Guna, and A. R. Nugraha, “Public Opinion Formation in the Digital Age : A Review of Literature,” vol. 2, no. April, pp. 290–297, 2024.
- [18] K. Cindy Astuti, A. Firmansyah, and A. Riyadi, “Implementasi Text Mining Untuk Analisis Sentimen Masyarakat Terhadap Ulasan Aplikasi Digital Korlantas Polri pada Google Play Store,” *REMIK Ris. dan E-Jurnal Manaj. Inform. Komput.*, vol. 8, no. 1, pp. 383–394, 2024, [Online]. Available: <https://www.jurnal.polgan.ac.id/index.php/remik/article/view/13421>
- [19] I. Iskandar Abdurrahman Arasy., Surya agustian, Lestari handayani, “MALCOM: Indonesian Journal of Machine Learning and Computer Science Sentiment Classification Using Multilayer Perceptron Algorithm with TF-IDF Features Klasifikasi Sentimen Menggunakan Metode Multilayer Perceptron dengan Fitur TF-IDF,” vol. 5, no. July, pp. 908–919, 2025.
- [20] I. Daniel, A. F. Limas Ptr, and A. Ichsan, “Klasifikasi Risiko Penyakit Jantung Dengan Multilayer Perceptron,” *Data Sci. Indones.*, vol. 4, no. 1, pp. 78–82, 2024, doi: 10.47709/dsi.v4i1.4667.