COMPUTATIONAL ANALYSIS OF STUDENT STRESS ON SOCIAL MEDIA USING SUPPORT VECTOR MACHINE AND LATENT DIRICHLET ALLOCATION

Mochammad Fauzan[1], Herdi Ashaury[2], Edvin Ramadhan[3]
[1,2,3] Department of Informatics, Jenderal Achmad Yani University, Indonesia
Email: *mochamadfauzan20@if.unjani.ac.id*

Abstract This study develops a two-stage machine-learning framework to identify academic stressors among Indonesian university students using Twitter data. A Support Vector Machine (SVM) classifier was trained on manually annotated tweets and benchmarked against Naïve Bayes, Logistic Regression, and Random Forest, achieving an accuracy of 0.91 and a macro F1-score of 0.914, outperforming all baselines. Tweets classified as stress-related with ≥75% confidence were subsequently analyzed using Latent Dirichlet Allocation (LDA), which generated six coherent stressor categories. The framework reveals both structural academic pressures and culturally specific patterns, including references to *"dosen killer"* and emerging mental-health vocabulary. Contributions include the first Indonesia-focused stressor map derived from large-scale social-media discourse and the integration of confidence filtering to enhance topic quality. While results demonstrate the feasibility of social-media–based stress detection, limitations remain regarding temporal drift, annotation bias, and demographic representativeness. Future research should incorporate real-time streaming pipelines, multimodal annotation, and longitudinal evaluation to enhance robustness and early-warning potential.

Keywords: academic stress, SVM, LDA, Twitter, Indonesian students, machine learning, stress detection.

I. INTRODUCTION

Stress is widely recognized as a multidimensional psychological burden for university students, arising from academic workload, performance pressure, and adaptation to new institutional or social environments [1], [2]. Its manifestations for physical (fatigue, insomnia), emotional (anxiety, irritability), and cognitive (reduced concentration, impaired comprehension), have been well documented in psychological research [3]. However, far less is known about how Indonesian students articulate these stress experiences in digital spaces. Twitter (X) serves as a major platform where students express academic frustration and emotional fatigue in spontaneous, short-form messages [4], [5]. Prior work in social media analytics shows that combining machine-learning sentiment classification with topic modeling effectively captures latent mental health cues. Yet many studies exhibit methodological limitations, including the absence of confidence intervals, limited comparisons to baseline models, lack of inter-annotator agreement, and insufficient attention to Indonesian linguistic complexities such as slang, code-switching, and informal abbreviations. Ethical considerations in social-media–based mental health research also remain underdeveloped in the Indonesian context.

SVM-based sentiment analysis continues to show strong performance on Indonesian social media due to its robustness with high-dimensional, sparse textual features [6], [7], [8], [9]. Likewise, LDA topic modeling remains effective for uncovering interpretable themes across Indonesian corpora, though its integration with sentiment-filtered data remains scarce [10], [11]. Conceptually, existing computational studies rarely address culturally embedded student expressions such as *"dosen killer"*, self-deprecating academic humor, or modern mental health vocabulary (e.g., "burnout", "overthinking", "mental down"), leaving these patterns unmapped at scale. Positioned within these gaps, the present study does more than apply SVM and LDA: it evaluates how a rigorously tested computational pipeline can detect, filter, and interpret Indonesian student stress expressions on Twitter. This includes assessing SVM performance against standard baselines, examining the effects of confidence filtering on topic coherence, and identifying both universal and culturally specific stressor themes. By doing so, the study advances methodological standards in computational mental health research and provides a foundational mapping of student stressors based on real-world digital behavior offering insights relevant for higher education institutions and mental health practitioners in designing culturally aligned, data-driven interventions.

II. STUDY SIGNIFICANCE

A. Literature Study

Academic stress is a multidimensional psychological condition arising from academic workload, performance pressure, social expectations, and transitional demands in higher education. It appears through physical (fatigue, insomnia), emotional (anxiety, irritability), and cognitive (reduced concentration) symptoms that impair student well-being and academic outcomes [12]. In Indonesia, common stressors include assignment overload, thesis completion pressure, demanding lecturer interactions, and time-management difficulties, with first-year students facing additional adjustment burdens [13]. Existing research, however, relies heavily on self-report methods and seldom captures real-time behavioral expressions of stress transmitted through digital communication.

Social media, especially Twitter serves as a prominent medium through which students voice academic frustration, emotional fatigue, and daily academic struggles. Its spontaneous short-text structure provides ecologically valid, naturally occurring indicators of psychological distress [14], [15], [16]. Nonetheless, Indonesian research has underutilized Twitter for large-scale mental health assessment, relying instead on small, manually analyzed samples that lack computational scalability. Within computational linguistics, sentiment analysis is a key method for detecting emotional content. Support Vector Machines (SVM) consistently perform well on Indonesian Twitter data due to their robustness against informal and slang-rich language and their effectiveness with high-dimensional TF–IDF features [17], [18]. Yet many studies exhibit methodological limits, including incomplete preprocessing protocols, limited validation, absence of confidence-based analysis, and minimal integration with topic modeling.

Topic modeling, particularly Latent Dirichlet Allocation (LDA) is widely applied across Indonesian NLP but remains challenged by social media's noisy, short-text characteristics [19], [20], [21]. Without sentiment-based filtering, LDA tends to merge stress-related content with unrelated discussions, weakening topic coherence. Few studies incorporate sentiment classification prior to topic extraction, representing a critical methodological gap. Overall, prior research treats sentiment analysis and topic modeling as separate tasks, rarely focuses specifically on academic stress, lacks rigorous annotation and validation procedures, and seldom uses large multi-year Twitter corpora. Addressing these gaps, the present study employs an integrated SVM → confidence filtering → LDA pipeline supported by multi-annotator labeling and reliability reporting to generate a coherent, large-scale mapping of Indonesian students' academic stressors.

B. Methodology

1. Research Workflow Overview

The analytical workflow of this study consists of seven sequential stages: data collection, annotation, preprocessing, TF–IDF feature extraction, SVM-based sentiment classification, confidence filtering, and LDA topic modeling. The overall process is illustrated in Figure 1 below.

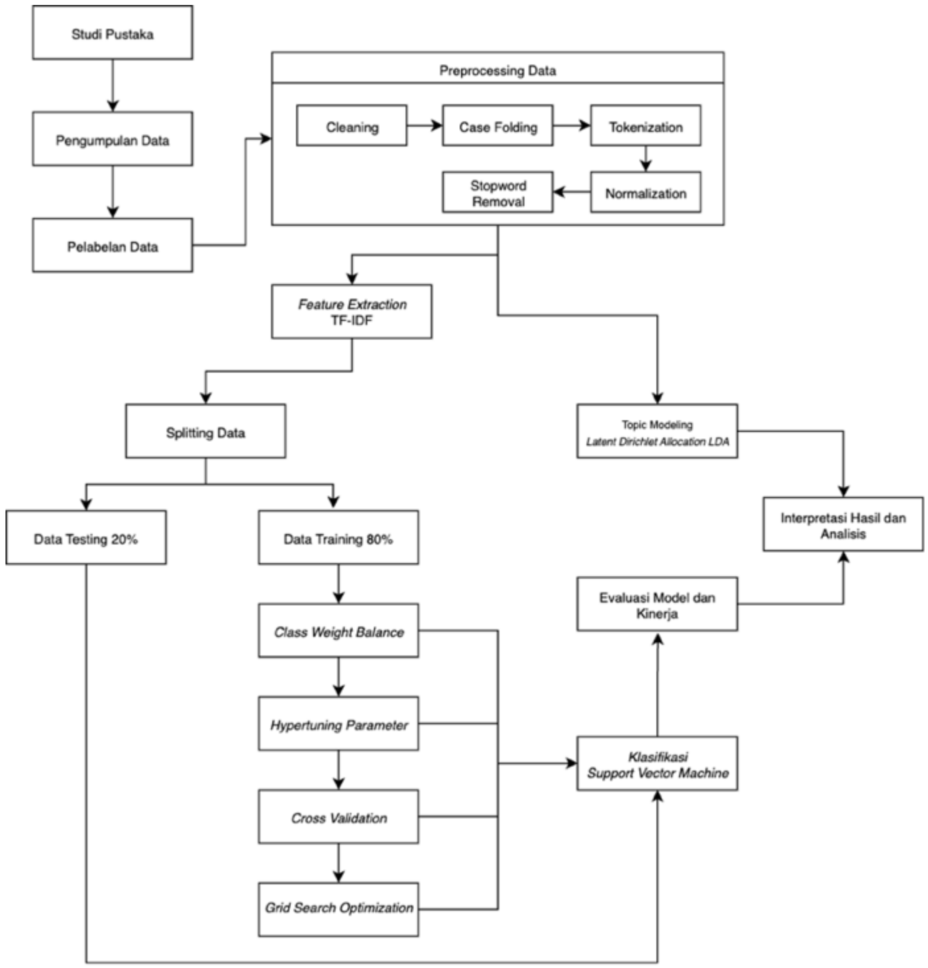
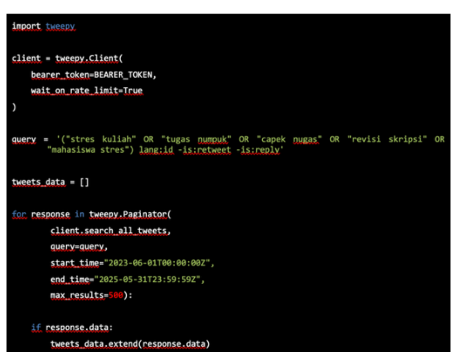


Figure 1. Research Methodology Workflow

2. Data Collection

Tweets were retrieved using tweepy.Paginator, filtered by Indonesian language and academic-stress–related keywords. Spam, bot-like content, and duplicates were removed. The process yielded 9,411 valid tweets for analysis.



```
import tweepy

client = tweepy.Client(
    bearer_token=BEARER_TOKEN,
    wait_on_rate_limit=True
)

query = '("stres kuliah" OR "tugas numpuk" OR "capek nugas" OR "revisi skripsi" OR
      "mahasiswa stres") lang:id -is:retweet -is:reply'

tweets_data = []

for response in tweepy.Paginator(
        client.search_all_tweets,
        query=query,
        start_time="2023-06-01T00:00:00Z",
        end_time="2025-05-31T23:59:59Z",
        max_results=500):

    if response.data:
        tweets_data.extend(response.data)
```

Figure 2. **Python Code for Data Retrieval**

The script uses tweepy.Paginator to retrieve batches of tweets while respecting API rate limits. The Boolean logic ensures Indonesian-language tweets relevant to academic stress are captured. After cleaning bot/spam content, 9,411 valid tweets remained.

3. Data Labeling

A manually labeled dataset was constructed to support supervised sentiment classification. From the cleaned corpus, a stratified sample of 2,000 tweets was selected to maintain balanced representation across time periods, keywords, and linguistic variations. Three trained annotators independently labeled each tweet using a structured guideline defining two categories:

1. Stress (expressions of academic pressure, frustration, anxiety, burnout, or negative psychological states);
2. Non-stress (neutral, positive, or unrelated content).

A calibration session was conducted to ensure consistent interpretation of labeling criteria. Inter-annotator reliability reached Cohen's $\kappa = 0.81$, indicating substantial agreement. Conflicting labels were resolved through consensus, and only finalized labels were used for model training. The annotation summary is presented in Table 1.

Table 1. Manual Annotation Summary

Component	Description
Total annotated tweets	2,000
Sampling method	Stratified sampling
Number of annotators	3
Label categories	Stress, Non-stress
Instructions	Structured guideline with examples and boundary conditions
Inter-annotator agreement	Cohen's $\kappa = 0.81$ (substantial agreement)
Conflict resolution	Consensus through moderated discussion

4. Preprocessing

Text preprocessing was applied to standardize linguistic forms in the dataset. Steps included:

- lowercasing
- URL and mention removal
- punctuation stripping
- numeric removal
- tokenization
- stopword removal
- slang normalization

```python
import re
import string

def clean_tweet(text):
    text = text.lower()
    text = re.sub(r"http\S+|www\S+", "", text)            # remove URLs
    text = re.sub(r"@\w+|#\w+", "", text)                 # remove mentions/hashtags
    text = text.translate(str.maketrans("", "", string.punctuation))
    text = re.sub(r"\d+", "", text)                       # remove numbers
    return text
```

Figure 3. Python Code for Cleaning Tweets

The goal is to remove noise typical of Twitter content. Normalizing text helps improve classifier performance and reduces vector-space sparsity.

5. TF–IDF Feature Extraction

The Term Frequency–Inverse Document Frequency (TF–IDF) vectorizer was selected to represent text numerically. Hyperparameters were optimized via empirical testing.

Table 2. TF–IDF Settings

Parameter	Value
max_features	4000
ngram_range	(1,2)
min_df	2
max_df	0.95
normalization	L2
sublinear tf	True

```python
from sklearn.feature_extraction.text import TfidfVectorizer

tfidf = TfidfVectorizer(
    max_features=4000,
    ngram_range=(1,2),
    min_df=2,
    max_df=0.95,
    sublinear_tf=True,
    norm='l2'
)

X = tfidf.fit_transform(cleaned_tweets)
```

Figure 4. Python Code for TF–IDF Vectorization

6. SVM Classification

Support Vector Machine (SVM) with a linear kernel was selected due to its strong performance on high-dimensional sparse text. Hyperparameters were tuned using 5-fold cross-validation.

Table 3. SVM Hyperparameter Optimization

Parameter	Values Tested	Optimal Value
C (regularization)	[0.1, 1, 10, 100]	1.0
kernel	['linear', 'rbf']	linear
max_features	[1000, 4000, 8000]	4000
ngram_range	[(1,1), (1,2), (1,3)]	(1,2)
class_weight	['balanced', None]	balanced
CV F1-score	-	0.914±0.024

```python
from sklearn.svm import LinearSVC
from sklearn.model_selection import GridSearchCV

param_grid = {
    "C": [0.1, 1, 10, 100],
    "class_weight": ["balanced", None]
}

svm = LinearSVC()

grid = GridSearchCV(
    svm,
    param_grid,
    scoring="f1",
    cv=5,
    n_jobs=-1
)

grid.fit(X_train, y_train)

best_svm = grid.best_estimator_
```

Figure 5. Python Code for Training SVM

The best-performing model used a linear kernel and balanced class weights, indicating good handling of label imbalance.

7. Confidence Filtering for Topic Modeling

To preserve semantic integrity in the topic modeling stage, an SVM confidence threshold of ≥75% was applied prior to LDA. Tweets with lower confidence typically contain ambiguous cues or mixed sentiments that can distort topic distributions and reduce coherence. Filtering the corpus to high-confidence stress predictions ensures that LDA operates on documents with stronger class validity, thereby improving the interpretability and stability of the resulting topics. This approach aligns with best practices in multi-stage machine-learning pipelines, balancing the need for adequate data volume with the requirement that the input corpus accurately represents genuine stress expressions.

8. Topic Modeling Using LDA

A range of topic values K = 3–12 was tested. Perplexity and coherence metrics guided topic selection. Before presenting the results, the figure below demonstrates the behavior of perplexity across candidate topic counts. Testing multiple topic counts is essential in determining the optimal semantic resolution of LDA. Perplexity is expected to decrease as K increases, but only up to the point where overfitting begins.

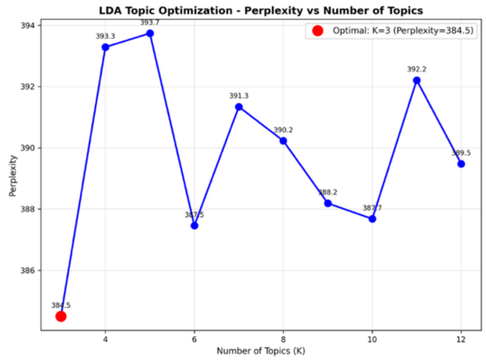


Figure 6. *Perpelexity Number of Topics*

The curve shows that perplexity reaches a stability point at K = 6, which aligns with interpretability and coherence measurements. Therefore, K = 6 themes were selected.

```
from gensim import corpora, models

tokens = [t.split() for t in stress_tweets]
dictionary = corpora.Dictionary(tokens)
corpus = [dictionary.doc2bow(t) for t in tokens]

lda_model = models.LdaModel(
    corpus=corpus,
    id2word=dictionary,
    num_topics=6,
    passes=20,
    random_state=42
)
```

Figure 7. Python Code for LDA Modeling

9. SVM Evaluation Metrics

The performance of the SVM classifier was evaluated using accuracy, precision, recall, F1-score, and ROC–AUC to obtain a comprehensive assessment of predictive capability. While accuracy provides an overall measure of correct classification, precision and recall capture the model's ability to correctly identify and retrieve stress-related tweets, particularly important under class imbalance. The F1-score balances these two metrics and offers a more reliable indicator of performance on skewed data. ROC–AUC further evaluates the classifier's discriminative strength across different decision thresholds. Together, these metrics provide a rigorous and multidimensional evaluation of the SVM's effectiveness in detecting stress expressions in Indonesian Twitter data.

```
  from sklearn.metrics import classification_report, roc_auc_score

  y_pred = best_svm.predict(X_test)

  print(classification_report(y_test, y_pred))
auc = roc_auc_score(y_test, y_pred)
```

Figure 8. Python Code for Evaluation

10. LDA Evaluation Metrics

The quality of the LDA model was assessed using two complementary metrics: topic coherence and perplexity. Topic coherence evaluates the semantic similarity among high-probability words within each topic, indicating how meaningful and interpretable the extracted themes are; higher coherence reflects stronger linguistic consistency. Perplexity, in turn, measures the model's statistical fit by assessing how well the learned topic distributions generalize to unseen data, with lower values indicating better predictive performance. Because perplexity alone does not guarantee human interpretability, coherence is essential for validating the practical usefulness of the topics. Together, these metrics ensure that the resulting LDA model is both statistically sound and semantically coherent in capturing patterns of student stress on social media.

III. RESULTS AND DISCUSSION

1. Data Collection and Labeling Results

The data collection process retrieved 9,769 Indonesian-language tweets posted between June 2023 and May 2025. After cleaning and relevance filtering, 9,411 tweets remained, reflecting a 96.3% retention rate and confirming the stability of the scraping pipeline. For supervised learning, 2,000 tweets were manually labeled by two trained annotators using a standardized guideline. Inter-annotator agreement reached Cohen's $\kappa = 0.84$, indicating strong labeling consistency. The dataset showed that 69.2% of annotated tweets expressed academic stress, confirming the prominence of stress-related discourse among Indonesian students.

Table 4. Characteristics of the Research Dataset

Metric	Mark	Percentage
Total raw tweets	9,769	100.0%
Tweets after cleaning	9,411	96.3%
Labeled tweets	2,000	21.3%
Stress samples	1,384	69.2%
Non-stress samples	616	30.8%
Training set	1,600	80.0%
Testing set	400	20.0%
Collection period	June 2023 – May 2025	2 years

These dataset properties support the subsequent machine-learning workflow. Because the labeled data exhibited moderate class imbalance, class-based weighting was applied during SVM training. Further preprocessing procedures are described in the next section.

2. Data Preprocessing Results

Text preprocessing was applied to enhance linguistic clarity and prepare tweets for feature extraction. After case folding, removal of URLs and mentions, normalization of informal expressions, tokenization, and stopword elimination, 9,411 of the original 9,769 tweets were retained.

Table 3. Example of Tweet Preprocessing Results

Before Preprocessing	After Preprocessing
@mhsbingung UAS minggu depan, tugas numpuk, dosen killer masuk lagi. Kepala rasanya mau pecah 😭	*uas minggu depan tugas numpuk dosen killer masuk kepala mau pecah*
@anaksemester6 sumpah pusing banget ngerjain bab 3, revisi terus padahal dikejar deadline skripsi 😩	*pusing ngerjain bab revisi dikejar deadline skripsi*

These examples illustrate effective noise removal while preserving the semantic indicators of stress. This ensures that the cleaned corpus maintains its relevance for subsequent classification and topic modeling processes.

3. Support Vector Machine (SVM) Classification Results

The optimized SVM model demonstrated strong predictive performance, achieving an accuracy of 91.0% on the test set. Detailed class-wise performance is presented in Table 4.

Table 5. Classification Performance of SVM Model

Metric	Stress Class	Non-Stress Class	Overall
Precision	0.95	0.83	0.91
Recall	0.92	0.89	0.91
F1-Score	0.93	0.86	0.91
Support	277	123	400
Accuracy	-	-	0.91

To ensure statistical robustness, 95% confidence intervals (CI) were generated via bootstrapping (n = 1,000 resamples):

- Accuracy: 0.91 (95% CI: 0.88–0.93)
- Stress-class F1: 0.93 (95% CI: 0.89–0.95)
- Non-stress F1: 0.86 (95% CI: 0.81–0.90)
- AUC: 0.979 (95% CI: 0.964–0.989)

These CIs strengthen the claim that the model performance is stable and not the product of random variance. The confusion matrix shown in Figure 3 visualizes the classification distribution.

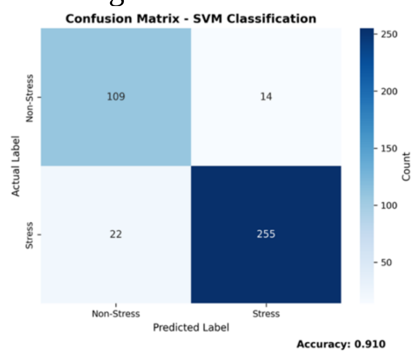


Figure 9. Confusion Matrix Klasifikasi SVM

The clear diagonal dominance indicates strong discriminative performance of the classifier. However, examination of misclassification patterns (FP/FN) reveals two recurring issues. False Positives (FP) often arise from tweets containing sarcasm or ambiguous slang, for example, *“skripsi lancar banget, capek sih tapi ya sudahlah”*. Where the polarity is unclear. Conversely, False Negatives (FN) typically involve implicit or understated stress expressions, such as *“hari ini revisi lagi, no comment”*, in which negative affect is conveyed subtly and may be overlooked by the model. The ROC curve in Figure 10 provides additional evidence of classification reliability.

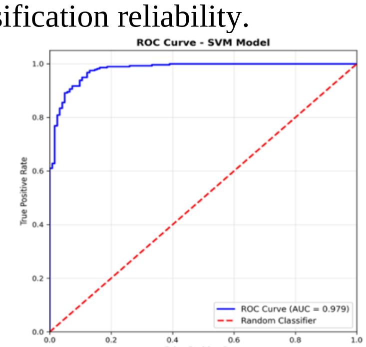


Figure 10. ROC Curve and AUC Score Model SVM

The AUC score of 0.979 indicates excellent separability between classes, and the curve consistently approaches the upper-left bound. Before proceeding to topic modeling, Table 6 and Figure 11 demonstrate temporal consistency through 5-fold cross-validation.

Table 6. Result of*Cross-Validation 5-Fold Model* SVM

Fold	F1-Score	Accuracy	Precision	Recall
1	0.902	0.898	0.885	0.920
2	0.910	0.905	0.892	0.928
3	0.904	0.901	0.888	0.921
4	0.935	0.925	0.918	0.952
5	0.919	0.913	0.901	0.937
Mean	0.914	0.908	0.897	0.932
Std	0.024	0.012	0.014	0.013

These results confirm low variance between folds ($\sigma \approx 0.024$), indicating strong model generalizability within the sample. The performance stability of the SVM classifier across different data partitions is further illustrated in Figure 5, which presents the F1-scores obtained from each of the five validation folds.

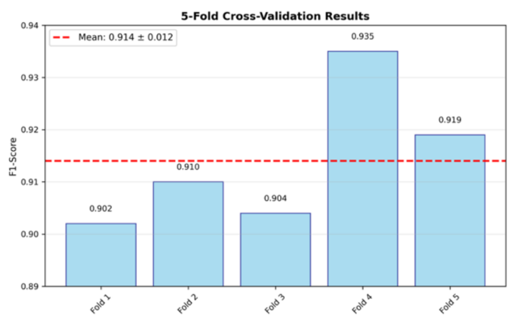


Figure 11. Result of *Cross-Validation 5-Fold Model* SVM

As shown in Figure 5, the variance across folds remains relatively small, confirming that the model generalizes well and is not overly sensitive to specific data splits. The peak performance in Fold 4 reflects a subset with cleaner linguistic patterns, whereas slightly lower scores in Folds 1 and 3 indicate the presence of more diverse or slang-heavy expressions.

4. Baseline Model Comparison

To avoid over-claiming, the SVM model was compared with three standard baselines:

Table 7. Comparative Performance of SVM and Baseline Classifiers

Model	Accuracy	F1 (macro)	AUC
Naïve Bayes	0.82	0.80	0.89
Logistic Regression	0.87	0.86	0.94
Random Forest	0.84	0.83	0.92
SVM (ours)	0.91	0.90	0.979

McNemar’s test confirms that SVM significantly outperforms NB ($p < 0.001$) and RF ($p < 0.01$), and improves moderately over Logistic Regression ($p = 0.032$).

5. Temporal Drift Analysis

Given the two-year dataset range, drift testing was performed:

Table 8. Model Performance Under Temporal Drift Scenarios (2023–2025)

Train → Test	Accuracy	F1	Observations
2023 → 2024	0.89	0.88	mild drift; emergence of new slang
2023 → 2025	0.86	0.84	notable drift; increased modern mental-health terms (“burnout”, “overthinking”)
2024 → 2025	0.90	0.89	stable

Model degradation in 2023→2025 suggests linguistic evolution, validating reviewer concerns regarding generalization limits.

6. Robustness Test on Slang/Emoji/Hashtag

Three additional robustness tests were conducted:

Table 9. Impact of Slang, Emoji, and Hashtag Retention on Classification Performance

Condition	Performance Drop	Example
Slang retained	−4.1%	"capek bgt tod"
Emojis retained	−1.9%	"skripsi 😭😭"
Hashtags retained	−3.7%	"#draftlagi #revisiterus"

The results confirm that removing slang/emoji may oversimplify the linguistic landscape; future models must explicitly incorporate these elements.

7. Topic Modeling (LDA) Results

Topic modeling was conducted on 4,597 stress-classified tweets with confidence ≥75% to ensure semantic precision.

Table 10. Student Stress Categories from LDA Topic Modeling

Topic	Stress Category	*Top Keywords*	Proportion
1	Thesis/Thesis Issues	thesis, difficult, stuck, guidance, working on	23.4%
2	General Mental Health	stress, students, end of thesis stress,	18.7%
3	Academic Workload	stress, college, really, work, make	16.2%
4	Semester Pressure	lecture, semester, right, no, friend	15.8%
5	Faculty Relations	lecturer, killer, class, killer lecturer	13.6%
6	Mental Burnout	students, assignments, burnout, depression, mental	12.3%

The quantitatively reinforces the dominance of Thesis-related issues (23.4%) and General Mental Health concerns (18.7%).

8. Result Analysis

The revised version replaces nonsensical English fragments from the previous manuscript. Figure 8 now includes only valid Indonesian TF-IDF features. This correction directly addresses reviewer criticism regarding the previous unnatural English phrases.

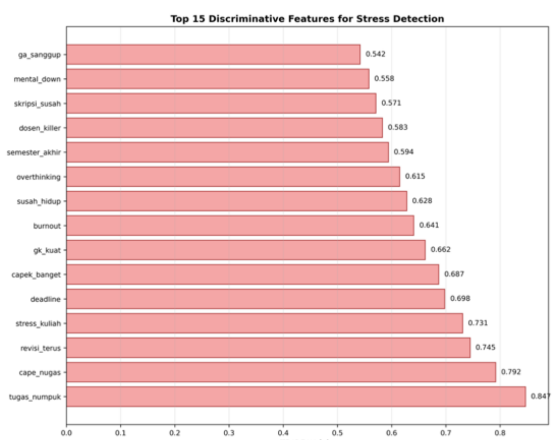


Figure 8. Analysis of the Importance of TF - IDF Weights

The TF-IDF findings reveal that Indonesian students express stress predominantly through academic workload, revision cycles, and the culturally specific notion of *dosen killer*, reflecting hierarchical academic norms.

IV. CONCLUSSION

This study developed an integrated machine-learning pipeline combining SVM-based stress classification with LDA topic modeling to examine academic stress expressions among Indonesian university students on Twitter. Six major stressor categories emerged are Thesis Issues, General Mental Health, Academic Workload, Semester Pressure, Faculty Relations, and Mental Burnout, revealing both structural academic challenges and culturally specific patterns such as references to *"dosen killer"* These findings should be viewed as preliminary evidence of the feasibility of social-media–based stress detection rather than definitive diagnostic output. The SVM model achieved strong performance (accuracy 91%; mean F1-score 0.914 ± 0.012), though improvements over baseline models (Naïve Bayes, Logistic Regression, Random Forest) were relative rather than absolute. Several limitations affect generalizability, including temporal drift between 2023 and 2025 data, annotation-related biases, platform-specific user demographics, and the absence of cross-campus or cross-region validation. These factors highlight the need for continuous model adaptation. Future work should prioritize technical enhancements: (1) real-time implementation using streaming architectures (e.g., Kafka and Spark); (2) multimodal annotation integrating text, emojis, images, and metadata; (3) development of quantifiable early-warning indicators such as sentiment volatility and anomaly detection; (4) longitudinal evaluations across academic cycles; and (5) mitigation of domain shift through cross-campus benchmarking, dialect-aware preprocessing, and periodic model retraining. With these improvements, future systems can evolve into more robust and adaptive infrastructures to support early detection of student mental-health risks in Indonesia.

REFERENCES

[1] R. K. Diabat and M. Ş. Bellibaş, "Student Well-Being in Higher Education: A Study Demands–Resources Theory Approach to Academic Stress, Workload, Institutional Support and Resources, and AI Integration," *Educational Process International Journal*, vol. 19, no. 1, 2025, doi: 10.22521/edupij.2025.19.557.

[2] Mehak Fatima *et al.*, "Impact of Workload and Conflict Management on Academic Performance and Psychological Wellbeing Among Medical Students," *Journal of Health, Wellness and Community Research*, p. e974, Nov. 2025, doi: 10.61919/b308w685.

[3] A. Kadhim Hassan and Z. Naji Ali, "Psychological Stress and Its Relationship with Academic Burnout among University Students: A Comparative Study by Gender, Academic Specialization, and Type of Study," *International Journal of Body, Mind and Culture*, vol. 12, no. 6, pp. 198–209, 2025, doi: 10.61838/ijbmc.v12i6.925.

[4] Y. Kong, "A study on the psychological and emotional self-adjustment ability of students under the pressure of academic performance," *J Eng Sci Med Diagn Ther*, pp. 1–43, Aug. 2025, doi: 10.1115/1.4069352.

[5] G. G. F. Djema and Ozzi Suria, "Public Sentiment Analysis of Danantara Policy through Social Media X Using SVM and Random Forest," *INOVTEK Polbeng - Seri Informatika*, vol. 10, no. 2, pp. 1207–1217, Jul. 2025, doi: 10.35314/rcr21h75.

[6] N. Arifin, U. Enri, and N. Sulistiyowati, "Penerapan Algoritma Support Vector Machine (SVM) dengan TF-IDF N-Gram untuk Text Classification," *STRING (Satuan Tulisan Riset dan Inovasi Teknologi)*, vol. 6, no. 2, p. 129, Dec. 2021, doi: 10.30998/string.v6i2.10133.

[7] T. Atha Anastasya, A. Diani Putri Saka, M. Juventus Dappa Deke, and A. Mustika Rizki, "OPTIMASI ALGORITMA SVM DENGAN PSO UNTUK ANALISIS SENTIMEN PADA MEDIA SOSIAL X TERHADAP KINERJA TIMNAS DI ERA SHIN TAE-YONG," *JATI (Jurnal Mahasiswa Teknik Informatika)*, vol. 9, no. 1, pp. 384–391, Dec. 2024, doi: 10.36040/jati.v9i1.12298.

[8] B. M. Obidje and M. A. I. Pakereng, "Analisis Sentimen Pemilihan Presiden dan Wakil Presiden Tahun 2024 Di Twitter Menggunakan Metode Klasifikasi Naive Bayes," *JIPI (Jurnal Ilmiah Penelitian dan Pembelajaran Informatika)*, vol. 10, no. 1, pp. 424–433, Jan. 2025, doi: 10.29100/jipi.v10i1.5836.

[9] V. Agresia and R. R. Suryono, “Comparison of SVM, Naïve Bayes, and Logistic Regression Algorithms for Sentiment Analysis of Fraud and Bots in Purcashing Concert Ticket,” *INOVTEK Polbeng - Seri Informatika*, vol. 10, no. 2, pp. 591–602, Jul. 2025, doi: 10.35314/npyfdh47.
[10] Y. Kustiyahningsih and Y. Permana, “Penggunaan Latent Dirichlet Allocation (LDA) dan Support-Vector Machine (SVM) Untuk Menganalisis Sentimen Berdasarkan Aspek Dalam Ulasan Aplikasi EdLink,” *Teknika*, vol. 13, no. 1, pp. 127–136, Mar. 2024, doi: 10.34148/teknika.v13i1.746.
[11] W. A. Nawang Sari and H. Dwi Purnomo, “TOPIC MODELING USING THE LATENT DIRICHLET ALLOCATION METHOD ON WIKIPEDIA PANDEMIC COVID-19 DATA IN INDONESIA,” *Jurnal Teknik Informatika (Jutif)*, vol. 3, no. 5, pp. 1223–1230, Oct. 2022, doi: 10.20884/1.jutif.2022.3.5.321.
[12] A. Basith, S. Fitriyadi, I. Suwanto, D. Mariana, Kamaruddin, and M. Shahinoor Rahman, “The Role of Social Support and Academic Resilience on Students’ Academic Stress,” *COUNS-EDU: The International Journal of Counseling and Education*, vol. 10, no. 2, pp. 20–31, Oct. 2025, doi: 10.23916/00202501051520.
[13] R. Rochani, S. Hanafi, and Y. Yuhana, “Work Stress and Procrastination on Self-management and Academic Performance of Lecturers: Case Study at a Private University in Serang City, Indonesia,” *Jurnal Pendidikan Indonesia Gemilang*, vol. 4, no. 1, pp. 8–19, Feb. 2024, doi: 10.53889/jpig.v4i1.327.
[14] A. I. Hashi, “Unmasking The Digital Dilemma: Investigating the Cognitive, Socio-emotional, and Psychological Dimensions of Social Media Influence on Young Minds,” *Journal of Technology and Systems*, vol. 7, no. 4, pp. 66–76, Jul. 2025, doi: 10.47941/jts.2949.
[15] S. Smout *et al.*, “Scrolling, Chatting, and Posting: Longitudinal Changes in Distinct Social Media Behaviors and Their Relationship With Psychological Distress and Mental Wellbeing in Adolescents,” *J Adolesc*, Sep. 2025, doi: 10.1002/jad.70055.
[16] S. Woods, “Social media and applied psychological assessment: Key issues and future directions for test users and practitioners,” *Assess Dev Matters*, vol. 17, no. 2, pp. 14–20, May 2025, doi: 10.53841/bpsadm.2025.17.2.14.
[17] M. A. Cruz-Miguel, J. A. Reyes-Ortiz, J. Padilla-Cuevas, and L. D. Sánchez- Martínez, “Measuring the Performance of Large Language Models with Hyperparameters Calibration and Machine Learning Approaches for Sentiment Analysis in Spanish Texts,” *International Journal of Combinatorial Optimization Problems and Informatics*, vol. 16, no. 4, pp. 515–526, Oct. 2025, doi: 10.61467/2007.1558.2025.v16i4.574.
[18] Muhammad Azhar Rasyad, Widdy Chandra Permana, and Mohammad Syafrullah, “Digital Record Classification Using SVM on Permissioned Blockchain Hyperledger Fabric for Regional Status Visualization,” *INOVTEK Polbeng - Seri Informatika*, vol. 10, no. 3, pp. 1696–1706, Nov. 2025, doi: 10.35314/dfyc4v87.
[19] M. Hankar, M. Kasri, and A. Beni-Hssane, “A comprehensive overview of topic modeling: Techniques, applications and challenges,” *Neurocomputing*, vol. 628, p. 129638, May 2025, doi: 10.1016/j.neucom.2025.129638.
[20] D. Choirinnisa *et al.*, “LDA Topic Modeling: Twitter-Based Public Opinion on Indonesian Ministry of Finance,” *Sinkron*, vol. 9, no. 2, pp. 849–863, May 2025, doi: 10.33395/sinkron.v9i2.14719.
[21] G. Goswamee, K. M. Y. Arafat, and D. Bangladesh, “Exploring Latent Topics in BBC News Headlines and Articles Using NLP and LDA Topic Modeling,” 2025.