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Natural Language Processing and Random Forest for Mental Health Symptom Identification Using Social Media Data

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ABSTRACT

This study examines the use of Natural Language Processing (NLP) and the Random Forest algorithm to identify mental health symptoms from social media text data. The rapid growth of social media has produced large amounts of subjective and context-dependent text, making it challenging to detect expressions related to anxiety, depression, and stress. The objective of this research is to develop a text classification model that can recognize these mental health symptoms using machine learning techniques. The proposed approach applies a structured preprocessing pipeline, including case folding, text cleansing, language normalization, negation handling, stop word removal, and tokenization, followed by feature extraction using Term Frequency–Inverse Document Frequency (TF-IDF). The processed data are then classified using a Random Forest model. Experimental results show that the model achieves an overall accuracy of approximately 80%, indicating reliable performance in identifying mental health-related content, although prediction confidence remains moderate due to overlapping and ambiguous language patterns. This study contributes to the academic field by demonstrating the applicability of classical NLP-based machine learning methods for mental health text analysis and provides practical value as a foundation for automated early screening and monitoring systems using social media data.

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1. INTRODUCTION

Social media usage has become an inseparable part of daily life, with over 4.8 billion users as of 2023. Platforms like Facebook, Instagram, and Twitter influence many aspects of life, including users' mental health. Several studies show that interactions on social media can impact anxiety disorders, stress, and depression, especially among adolescents and young adults [1].

Previous research has employed systematic review methods and qualitative approaches. However, these studies have limitations in terms of result generalization, as they rely on subjective interpretation of data. In response to these challenges, the current research uses a quantitative approach by leveraging Machine Learning technology to identify mental health symptoms based on sentiments found in social media content [2].
Mental health, which forms the basis of this research, focuses on human information processing, including perception and pattern recognition in text. This research aims to identify mental health symptoms for social media users [3]. In this research, we implement Natural Language Processing (NLP) and Random Forest[4], two branches of Machine Learning. NLP identifies language patterns related to mental health, while the Random Forest model is used as a classification method to determine whether content shows symptoms of

anxiety, depression, or stress. The combination of NLP and Random Forest provides strength in processing text data and producing accurate classifications [5][6].

Natural Language Processing (NLP) is an artificial intelligence field focusing on the interaction between computers and humans using natural language[7]. NLP has experienced rapid development due to the availability of large amounts of text data and the need for more human-like communication between computers and humans [8][9]. Random Forest is an ensemble learning approach developed by Breiman to address classification and regression problems, using multiple models to improve accuracy in solving the same problem [10][11]. Despite the growing body of research on mental health analysis using social media data, significant gaps persist at the methodological and practical levels [12]. Existing studies largely rely on qualitative assessments or sentiment-based analyses, which are inherently subjective and difficult to generalize across large and diverse datasets. Conversely, recent approaches employing deep learning models often prioritize high predictive performance at the expense of computational efficiency, interpretability, and deployment feasibility, particularly in real-time or early screening contexts. Moreover, there is a lack of rigorous empirical studies that systematically evaluate classical machine learning models integrated with structured NLP preprocessing pipelines for multi-class mental health symptom identification[13]. This gap is especially evident in research that balances accuracy, model transparency, and computational cost while addressing overlapping linguistic patterns associated with anxiety, depression, and stress[14]. Therefore, a critical research gap exists in developing and validating an efficient, interpretable, and scalable machine learning framework that can reliably identify mental health symptoms from large-scale social media text data and support practical implementation in real-world mental health monitoring systems.

The main difference between this research and previous studies lies in the approach used. This research not only focuses on qualitative analysis but also applies quantitative methods through NLP and Random Forest to produce a faster, more accurate, and real-time detection system for monitoring mental health through social media.

2. METHOD

The methodology in this research is divided into several stages that follow the Agile approach, focusing on analysis, design, implementation, and testing. The data processing workflow includes data collection, preprocessing, feature extraction using TF-IDF, and classification using Random Forest.

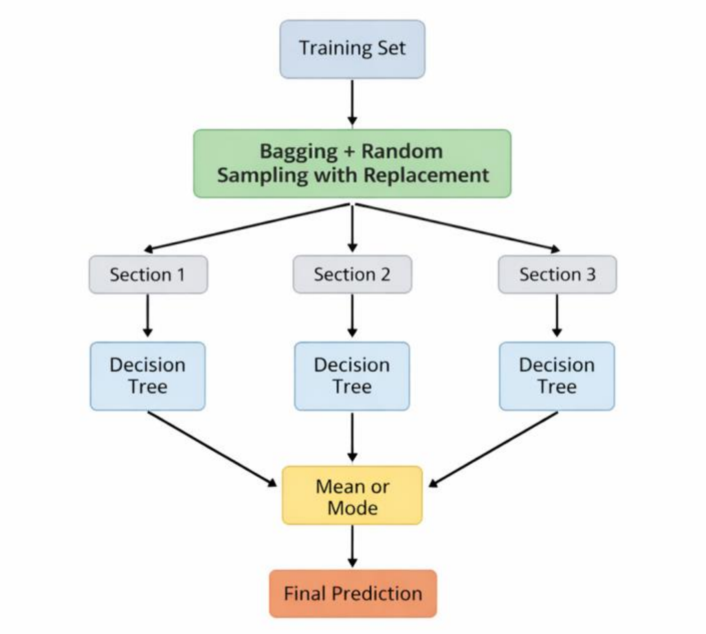

Figure 1. Flowchart Methodology

1.1 Data Collection

Data was collected through web scraping from Twitter using Python libraries Selenium and Beautiful Soup. Additionally, labeled datasets from Kaggle were used to train the model[15][16]. The total dataset included 93,720 entries, with 21,961 relevant labeled data points across three categories: anxiety, depression, and stress.

1.2 Text Preprocessing

Text preprocessing is a critical step in text classification. The following preprocessing steps were implemented:

a. Converting all text to lowercase to standardize the text format.
b. Removing non-alphabetic characters, symbols, and punctuation to reduce noise.
c. Standardizing text by converting slang or abbreviations to their standard forms.
d. Handling negation words by replacing them with standardized forms to maintain the semantic meaning.
e. Eliminating non-descriptive words such as articles and prepositions that don't contribute to the classification.
f. Breaking text into smaller units (tokens) for further processing.

Table 1. Case Folding

	Before		After
0	is upset that he can'tupdate his Facebook by ...	0	is upset that he can'tupdatehisfacebookby...
1	@Kenichan I dived manytimes for the ball. Man...	1	@kenichan i dived manytimesfortheball. man...
2	my whole body feelsitchy and like its on fire	2	my whole body feelsitchyandlikeitsonfire
3	@nationwideclass no,it's not behaving at all....	3	@nationwideclass no,it's not behaving at all....
4	@Kwesidei not the wholecrew	4	@kwesidei not the wholecrew

Table 2. Cleansing

	Before		After
0	is upset that he can'tupdate his facebook by ...	0	is upset that he can't update his facebook by ...
1	@kenichan i dived manytimes for the ball. man...	1	kenichan i dived many times for the ball man...
2	my whole body feelsitchy and like its on fire	2	my whole body feels itchy and like it's on fire
3	@nationwideclass no,it's not behaving at all....	3	nationwide class no it's not behaving at all....
4	@kwesidei not the wholecrew	4	Kwesi Dei not the whole crew

Table 3. Data Normalization

	Before	Non-standard word	After
0	is upset that he can't update hisFacebook by ...	Dived, man, feels, i t c h y , fire, it's, not Behaving, no, crew.	He is upset that he cannot update his Facebook...
1	kenichan i dived many times for the ball man...		Kenichan, I have dived many times for the ball, friend...
2	my whole body feels itchy and likeit's on fire		My whole body feels itchy and like it is burning.
3	nationwide class noit's not behaving at all....		Nationwideclass, no, it is not functioning at all...
			Kwesidei, not the whole team

Table 4. Convert Negation

	Before		After
0	is upset that he can'tupdate his Facebook by ...	0	is upset that he can'tupdate his Facebook by ...
1	kenichan i dived manytimesfortheballmanag...	1	kenichan i dived manytimesfortheballmanag...
2	my whole body feelsitchy and like its on fire	2	my whole body feelsitchy and like its on fire
3	nationwideclass no it snot behaving at all i ...	3	nationwideclass not itš not behaving at all i...
4	kwesideinotthewholecrew	4	kwesideinotthewholecrew

Table 5. Stopword Removal

	Before		After
0	is upset that he can t updatehis facebook by ...	0	upset update facebook textingmight cry result...
1	kenichan i dived many timesfor the ball manag...	1	kenichan dived many times ballmanaged save re...
2	my whole body feels itchyand like its on fire	2	whole body
3	nationwideclass not it s notbehaving at all i...	3	feels itchy like fire
4	kwesidei not the whole crew	4	nationwideclass behaving m mad see4 kwesidei whole crew

Table 6. Tokenizing

	Before		After
0	upset update facebooktexting might cryresult...	0	[upset, update,facebook, texting, might, cry,...
1	kenichan dived many times ball managed save re...	1	[kenichan, dived, many,times, ball, managed, ...
2	whole body feels itchy like fire	2	[whole, body,feels, itchy, like, fire]
3	nationwideclass behaving m mad see	3	[nationwideclass,behaving, m, mad, see]
4	kwesidei whole crew	4	[kwesidei, whole, crew]

1.3 Feature Extraction with TF-IDF

Term Frequency-Inverse Document Frequency (TF-IDF) weighting was applied to represent the importance of each word in the document collection. This technique helped identify the most relevant terms for each mental health category. The implementation resulted in 65,433 unique terms extracted from the processed text [17].

```
# Lakukan pembobotan TF-IDF

# Impor modul yang diperlukan
from sklearn.feature_extraction.text import TfidfVectorizer

# Inisialisasi TfidfVectorizer
tfidf_vectorizer = TfidfVectorizer()

# Lakukan pembobotan TF-IDF pada data pelatihan X_train_tfidf =
tfidf_vectorizer.fit_transform(X_train)

# Transformasi data pengujian menggunakan vectorizer yangsama
X_test_tfidf = tfidf_vectorizer.transform(X_test)

print("Pembobotan TF-IDF selesai dilakukan.") print(f"Jumlah fitur:
{X_train_tfidf.shape[1]}")

# Latih model menggunakan data yang telah dibobotkan
model.fit(X_train_tfidf, y_train)

# Evaluasi model menggunakan data pengujian yang telahdibobotkan
y_pred_tfidf = model.predict(X_test_tfidf) accuracy_tfidf =
accuracy_score(y_test, y_pred_tfidf)print(f"\nAkurasi model dengan
pembobotan TF-IDF:
{accuracy_tfidf:.2f}")
```

Figure 2. TF-IDF formula

1.4 Random Forest Classification

The Random Forest algorithm was employed for classification due to its ability to handle high-dimensional data and reduce overfitting through ensemble learning. The model was trained on the preprocessed and TF-IDF weighted data to classify text into three categories: anxiety, depression, and stress[18].

1.5 System Architecture

A web-based dashboard was developed using Flask and Dash to provide a user-friendly interface for real-time text analysis. The system allows users to input text and receive predictions about potential mental health symptoms, along with visualization of the prediction probabilities.

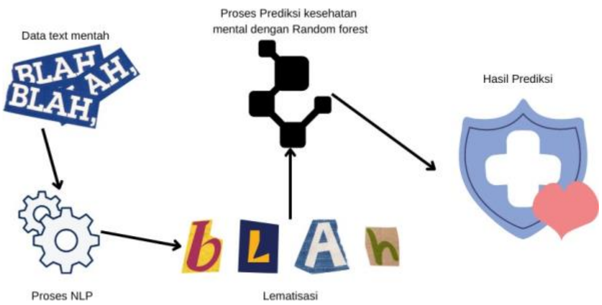

Figure 3 Workflow System

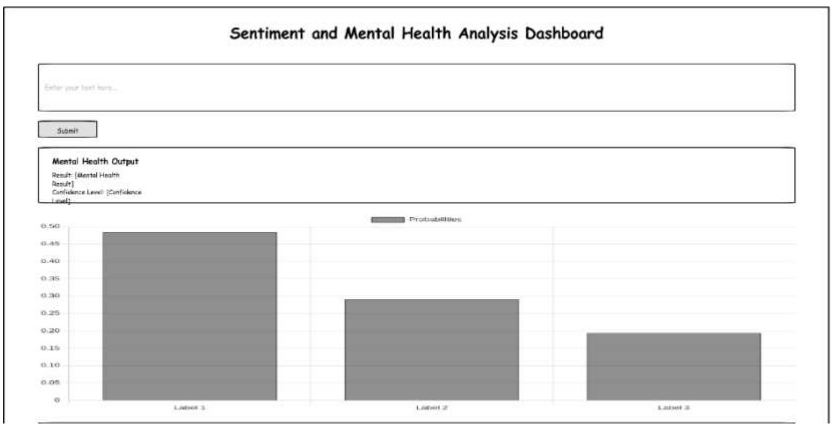

Figure 4 user interface design

3. RESULTS AND DISCUSSION

3.1 Model Performance

The Random Forest model achieved an overall accuracy of 80% in identifying mental health symptoms. The model performed particularly well in classifying depression, with a precision of 0.80 and recall of 0.94. For anxiety, the model achieved a precision of 0.85 and recall of 0.42, while for stress, it achieved a precision of 0.76 and recall of 0.68.

Laporan Klasifikasi:

	precision	recall	f1-score	support
Anxiety	0.85	0.42	0.57	1624
Depression	0.80	0.94	0.86	6269
Stress	0.76	0.68	0.72	2644
accuracy			0.80	10537
macro avg	0.81	0.68	0.72	10537
weighted avg	0.80	0.80	0.78	10537

The confusion matrix revealed that the model was most successful at identifying depression, followed by stress and anxiety. Some misclassifications occurred between anxiety and depression, which can be attributed to the overlap in symptoms and language patterns between these conditions.

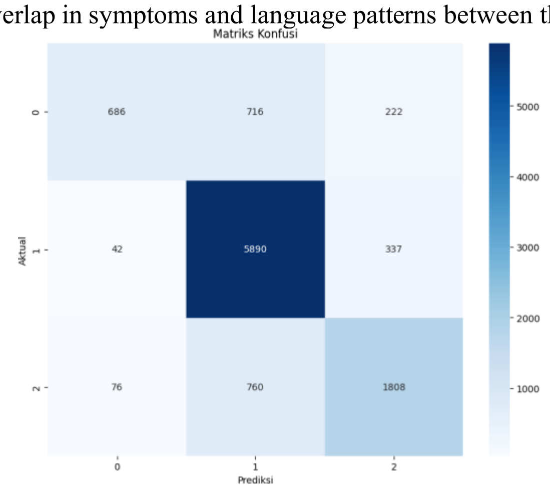

Figure 5. Confusion Matrix

3.2 Confidence Levels

While the model achieved high accuracy, the average confidence level was around 58%. This reflects the inherent challenges in working with subjective text data, where the same expressions might indicate different mental states depending on context. Despite this limitation, the model provides valuable insights for initial screening of mental health symptoms.

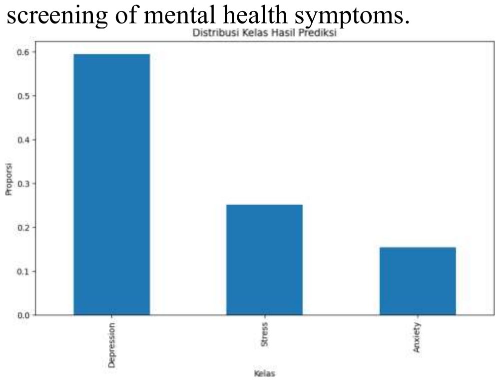

Figure 6. Class Distribution Chart

3.3 System Testing

The system was tested with random sentences containing keywords related to mental health symptoms. Results showed varying degrees of accuracy in correctly identifying conditions, with better performance on depression-related content compared to anxiety and stress. This aligns with the model's overall performance metrics, where depression had the highest precision and recall values.

Table 7 Anxiety Test

NO	Sentence	Confidance Score	Prediction Results	
			True	False
1	Anxiety is a mentalhealth conditioncharacterized bypersistent feelings of worry and fear, which can Interfere with daily life	56%	V	
2	People with Anxiety oftenexperience physical symptoms such asincreased heartrate, sweating, and trembling	63%	V	
3	I can't seem to stopthinking about allthe things that could go wrong.	49%	V	
4	My mind races constantly, and Ican't focus on anything.	55%	V	
5	I'm afraid of what might happen, andit keeps me up at night.	46%	V	

Table 8 Depression Test

NO	Sentence	Confidance Score	Prediction Results		
			True	False	
1	I feel like I'm trapped in a dark hole with no way out	48%	V		
2	Every day feels like a heavy burden, and I can'tfind the strength to carry on.			V	As Anxiety
3	I don't have theenergyor motivation to doanything, even the things I used to enjoy	38%	V		
4	It feels like aconstant cloud of sadness is hangingover me, and I can't escape it			V	Thot of as anxiety
5	I'm afraid of what might happen, andit keeps me up at night.	57%	V		

Table 9. Stress Test

NO	Sentence	Confidance Score	Prediction Results		
			True	False	
1	He's a complete mtherf**ker for abandoning his responsibilities.	57%	V		
2	I just want to scream at Everyone beingsuch a dck about everything			V	As Depression
3	’m at my breaking point, and I feel like I’m being treated like a psy for complaining			V	As Depression
4	This endless cycle is making me feel like a mtherf**ker who’s lost control.			V	Thot of as Depression
5	Everything feels like a ctstorm of problems, and I can't escape the stress	57%	V		

Figure 7. Implemented System

4. CONCLUSION

With an overall accuracy of over 80%, this study shows that combining Natural Language Processing with the Random Forest algorithm may successfully identify mental health symptoms from text data. These results show that, especially in large-scale, non-clinical environments like social media monitoring platforms, the suggested method has useful potential as an early screening tool to complement initial mental health assessment. By facilitating simple text analysis and result visualization, the web-based dashboard further improves usability and makes the system usable by both technical and non-technical users. However, this study has a number of drawbacks, such as a reliance on a single language and data source that may restrict generalizability and modest prediction confidence levels brought on by overlapping linguistic patterns among mental health problems. Furthermore, the model's capacity to extract more complex contextual and semantic information is constrained by the application of traditional machine learning approaches. In order to increase robustness and applicability across a variety of populations and real-world mental health screening scenarios, future research should concentrate on integrating contextual language representations, such as transformer-based models, performing comparative evaluations with cutting-edge deep learning approaches, and expanding multilingual support.

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