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Early Detection of Depression Levels Among Gen-Z Using TikTok Data and Extra Trees Ensemble Classifier

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Abstract

Mental health disorders, particularly depression, have become an increasingly critical issue, especially among young people aged 15–29 years. Social stigma and limited awareness often hinder early detection and intervention. In the digital era, social media platforms such as TikTok provide opportunities to observe users' behavioral patterns that may reflect their psychological conditions. This study proposes an early depression detection model based on TikTok social media data using an ensemble machine learning approach, namely the Extra Trees classifier. Data were collected from 263 undergraduate students through an online survey combined with automated crawling of respondents' TikTok accounts. Depression levels were labeled using the Patient Health Questionnaire-9 (PHQ-9) and categorized into four classes: none, mild, moderate, and severe. After data selection, feature extraction, and class balancing using SMOTE, the final dataset consisted of 600 instances with 24 features, including demographic attributes, TikTok activity metrics, and social network analysis features. Experimental results indicate that the Extra Trees classifier achieved the highest performance, with an accuracy, precision, recall, and F1-score of 91%, outperforming Decision Tree, Random Forest, XGBoost, LightGBM, and CatBoost. The model demonstrated stable performance across all depression levels and efficient prediction time suitable for near real-time web-based applications. These findings confirm that integrating behavioral and network-based social media features with validated psychological assessments can support effective early depression screening. This research contributes to mental health informatics and social media analytics within the field of computer science by demonstrating the effectiveness of ensemble learning for depression detection using TikTok-based digital behavioral data.

Keywords : *Depression Detection, Extra Trees Classifier, Mental Health Informatics, PHQ-9 Labeling, Social Media Analytics, TikTok Data.*

1. INTRODUCTION

Mental health is one of the most widely discussed issues worldwide, with depression being among the most common disorders. According to [1], approximately 3.8% of the global population suffers from depression. This condition significantly impacts individuals' social lives, and in severe cases, may lead to suicidal ideation. The same report highlights that suicide is most prevalent among individuals aged 15 to 29 years. A study by [2] revealed a significant relationship between family communication patterns and the occurrence of depression in adolescents, indicating the vital role of family and society in reducing both the prevalence and impact of depression. In Indonesia, the highest prevalence of depression is found among individuals aged 15–24 years [3]. According to [4], there were 2,112 recorded suicide cases in Indonesia between 2012 and 2023, of which 985 involved adolescents, with mental health issues such as depression identified as a major contributing factor. Academic pressure, social transitions, the influence of social media, and high parental expectations further exacerbate this issue. The Indonesian National Adolescent Mental Health Survey (I-NAMHS) conducted in 2022

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reported that approximately 17.95 million adolescents had been diagnosed with a mental disorder in the past 12 months [5], with major depression being one of the most prevalent. Risk factors include bullying, social relationship problems, and adverse childhood experiences.

Public awareness plays a crucial role in addressing depression and its symptoms. However, the lack of awareness often hinders early intervention, while societal stigma discourages individuals from seeking help. Those with mental health problems frequently face negative labeling, being referred to as stressed, insane, abnormal, strange, or incurably disabled [6]. Such stigmatization results in untreated symptoms, worsening the severity of depression and increasing the risk of suicide.

Social media has become an integral part of modern life, particularly among younger generations. According to a report by [7], Indonesia had 185.3 million internet users in 2024, representing 66.5% of the total population. By January 2024, social media users reached 139 million (49.9% of the population), with an average usage time of 3 hours and 11 minutes per day—more than time spent on streaming or online gaming. Social networking sites remain the most visited, followed by chat and messaging platforms. TikTok, in particular, has gained immense popularity, with 126.8 million users in Indonesia at the beginning of 2024, surpassing other platforms such as YouTube, WhatsApp, and Instagram in terms of monthly engagement, with users spending an average of 38 hours per month on the app. This highlights the strong influence of social media on social behavior, especially among youth.

Several studies have attempted to detect depression using social media data. For example, study by [8] investigated depression detection on Twitter using the BiLSTM method and Word2Vec features, with tweets labeled based on mental health questionnaires. Their study demonstrated that this approach was effective for depression detection on Twitter data. Similarly, study by [9] utilized Twitter as a medium for detecting depression by crawling tweets based on keywords derived from the PHQ-9 questionnaire. However, in that study, PHQ-9 was only used to generate search keywords, not to provide confirmed depression labels. This condition introduced potential labeling bias, since not all tweets containing relevant keywords accurately reflected the psychological state of the authors. In contrast, this research directly uses PHQ-9 questionnaire scores as the basis for labeling depression levels, ensuring greater validity through self-reported psychological conditions. Furthermore, the study combines PHQ-9 labeling with digital activity data obtained by crawling participants' TikTok accounts, which were then transformed into behavioral and social network features, such as degree centrality, betweenness centrality, eigenvector centrality, and structural holes.

Table 1. State-of-the Art

Studies	Year	Data Source(s)	Method(s)
[10]	2020	Twitter	SVM, NBC, DT
[11]	2021	Twitter, Reddit, Facebook	Machine Learning
[12]	2021	Twitter	LSTM
[13]	2022	Twitter	LSTM, RNN
[14]	2022	Twitter & DASS	CART
[15]	2023	Twitter	BERT
[16]	2024	Twitter & Reddit	FCL, CNN, LSTM
[17]	2024	Twitter & DASS-42	DT
[18]	2024	Twitter & DASS-42	IndoBERTweet
[19]	2025	Weibo, Twitter, and Reddit	Deep Learning, Word Embedding
[20]	2025	Reddit	NLP, Sentence Transformers
[21]	2025	Twitter	Ensemble Classifier

Recent studies, as summarized in Table 1, show that depression detection through social media has primarily focused on text analysis from platforms such as Twitter, Reddit, and Facebook, employing various machine learning and deep learning approaches including SVM, Decision Trees, LSTM, CNN,

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and BERT. Some studies have combined textual features with user activity [10] and enriched features with diagnostic data such as PHQ-9 [15]. However, several research gaps remain unresolved. First, no study has specifically explored Gen-Z behavior on TikTok, despite TikTok being the most widely used social media platform among this generation and featuring content characteristics that differ significantly from other platforms. Second, although some studies have begun incorporating survey-based instruments such as DASS-42 or PHQ-9, these approaches are generally not fully integrated with social media behavioral profiles, particularly on TikTok. Third, most studies focus only on binary text classification—depressed or not—without estimating depression levels, which are essential for enabling more targeted interventions.

Therefore, this study introduces novelty by developing an intelligent machine learning-based model for early depression detection among Gen-Z through behavioral analysis on TikTok, an area largely unexplored in prior research. The innovation lies in integrating user behavioral data with psychological assessment scores (PHQ-9), while leveraging ensemble machine learning algorithms to achieve higher predictive accuracy. This approach is expected to fill existing research gaps and contribute significantly to the advancement of early mental health detection systems that are more contextual and adaptive to the characteristics of Gen-Z. The primary objective of this study is to perform early detection of depression levels using TikTok social media data, labeled with PHQ-9 scores, to achieve more accurate and reliable detection results.

2. METHOD

This study adopted a quantitative research design employing supervised machine learning to develop an intelligent system for early detection of depression among Gen-Z based on TikTok social media data. The methodological framework consisted of four main phases: data collection, preprocessing, feature extraction, and model development and evaluation.

The data preparation process in this study, as illustrated in Figure 1, involved multiple stages to ensure the reliability and representativeness of the dataset. First, data were acquired from two sources: respondents' PHQ-9 questionnaire results and their social media profiles. The PHQ-9 data were validated and labeled by experts to determine depression levels, while digital activity data were collected through TikTok crawling and Social Network Analysis (SNA) to extract behavioral and relational features. These two data sources were then integrated through a data fusion process, resulting in a comprehensive dataset that combines psychological assessment with digital behavior. To address class imbalance across depression categories, the dataset was further refined using the Synthetic Minority Over-sampling Technique (SMOTE). The final output was a balanced and high-quality dataset, which served as the basis for subsequent machine learning model development.

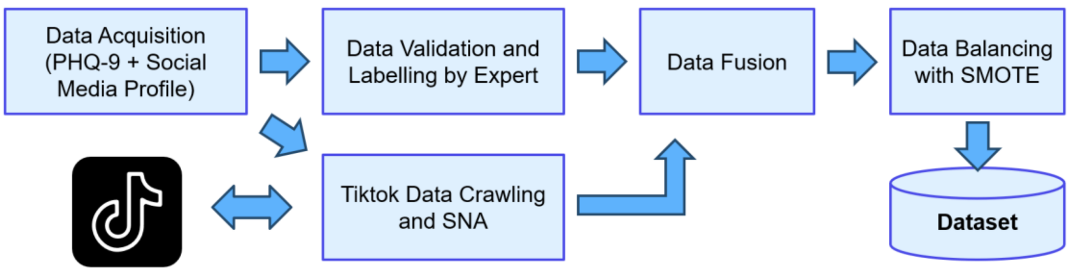

Figure 1. Data Acquisition, Extraction, and Preprocessing

2.1. Data Acquisition

Respondents in this study were undergraduate students at Universitas Budi Luhur (cohorts 2022–2024) who actively used TikTok. Data collection followed a two-step approach. First, participants were

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asked to complete the Patient Health Questionnaire-9 (PHQ-9), a widely validated screening tool for depression [22], and their scores were used to categorize individuals into four levels: none, mild, moderate, and severe. Second, behavioral and social network data were extracted from participants' TikTok accounts through automated crawling, capturing attributes such as the number of followers, number of followings, total likes received, posting frequency, and interaction metrics. In addition, social network relationships were mapped for subsequent graph-based feature engineering. This dual-source strategy ensured a more reliable dataset by combining self-reported psychological assessments with observable digital behavior, thereby addressing the limitations of prior studies that relied solely on keyword-based crawling [23].

2.2. Feature Extraction

In this study, feature extraction was conducted to transform raw TikTok data into meaningful representations for depression detection. Two main categories of features were constructed. Behavioral features included posting frequency, engagement metrics (likes, comments, shares), and sentiment of captions, which reflect users' expression patterns and activity intensity. Social network features were derived from graph-based analysis, such as degree centrality, betweenness centrality, eigenvector centrality, and structural holes, obtained through Social Network Analysis (SNA) [24]. These features capture user connectivity and influence within the TikTok ecosystem, which can affect social well-being and risk of depression. The integration of behavioral and network-based features provided a more comprehensive view of user digital activity, enabling the model to better identify patterns associated with depressive tendencies.

$$C_D(v) = \frac{\deg(v)}{N-1} \tag{1}$$

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{2}$$

$$C_E(v) = \frac{1}{\lambda} \sum_{u \in N(v)} A_{\mathrm{vu}} C_E(u) \tag{3}$$

$$Structural\ Hole(i) = 1 - \sum_j \left(p_{ij} + \sum_q p_{iq} p_{qj}\right)^2 \tag{4}$$

Degree centrality, betweenness centrality, eigenvector centrality, and structural holes are widely used metrics in SNA to capture different aspects of a node's position and role within a network. As seen at Eq. (1), degree centrality $C_D(v)$ represents the number of direct connections $deg(v)$ owned by a node v, normalized by the total number of nodes N, and reflects the level of immediate social interaction. Then, betweenness centrality $C_B(v)$, as seen at Eq. (2), quantifies how often a node v lies on the shortest paths between two other nodes s and t, where σ_{st} denotes the total number of shortest paths between s and t, and $\sigma_{st}(v)$ indicates those paths that pass through v; this metric captures the role of a node as an intermediary or information broker. Eigenvector centrality $C_E(v)$, as seen at Eq. (3), measures a node's influence by considering not only its connections but also the importance of its neighbors, where A_{vu} represents the adjacency relationship between nodes v and u, and λ is the largest eigenvalue of the adjacency matrix. As seen at Eq.(4), the structural holes are assessed using Burt's constraint measure, where p_{ij} denotes the proportion of ties between node i and node j; a lower constraint value, or equivalently a higher structural hole score, indicates a greater ability of a node to bridge otherwise disconnected groups. Together, these metrics provide a comprehensive representation of users' connectivity, brokerage, influence, and strategic positioning within social networks.

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2.3. Data Preprocessing

The raw dataset obtained from TikTok crawling and PHQ-9 labeling required several preprocessing steps to ensure data quality and consistency. First, data cleaning was performed by removing incomplete, duplicate, or irrelevant entries. For textual data such as video captions and comments, a series of text normalization processes were applied, including case folding, tokenization, stopword removal, and stemming. These steps aimed to reduce noise and improve the representational quality of textual features. In addition, numerical features such as user activity counts were standardized through normalization to ensure comparability across different scales.

Another critical step in preprocessing was addressing the class imbalance problem across depression levels (none, mild, moderate, severe). Since the dataset distribution was skewed toward certain categories, the Synthetic Minority Over-sampling Technique (SMOTE) [25] was applied to generate synthetic examples for minority classes. This technique prevents bias in classification and improves the model's ability to generalize across all classes. SMOTE generates new synthetic samples for minority classes by interpolating between existing instances in the feature space. Given a minority class sample x_i, a new synthetic instance $x_{\text{new}}$is generated as Eq. (5).

$$x_{\text{new}} = x_i + \delta \times (x_{nn} - x_i) \qquad (5)$$

where x_{nn}denotes one of the k-nearest neighbors of $x_i$within the same minority class, and $\delta$is a random number drawn from the interval $[0, 1]$. This formulation ensures that the synthetic data points lie along the line segments connecting $x_i$and its neighbors, thereby preserving the underlying feature distribution while increasing the number of minority samples.

By combining data cleaning, normalization, and balancing strategies, the preprocessing stage ensured that the dataset was both robust and suitable for machine learning, thereby enhancing the reliability of subsequent model training and evaluation.

2.4. Modelling

In this study, several ensemble-based machine learning algorithms were implemented and compared to classify four levels of depression (none, mild, moderate, and severe) using TikTok social media data labeled with PHQ-9 scores. The models evaluated include Decision Tree (DT), Random Forest (RF), Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), Extra Trees Classifier (ET), and CatBoost. These algorithms were selected due to their proven effectiveness in handling high-dimensional data, nonlinear feature interactions, and imbalanced datasets, which are common challenges in social media-based mental health detection [26].

The Decision Tree served as a baseline model, providing interpretability but often prone to overfitting. A Decision Tree classifies data by repeatedly splitting it based on the feature that best separates the classes. The quality of a split is commonly measured using Gini Impurity (see Eq. 6), where $p_i$represents the proportion of samples belonging to class i. The tree selects splits that minimize impurity, resulting in increasingly homogeneous nodes.

$$Gini = 1 - \sum p_i^2 \qquad (6)$$

The Random Forest improved upon this by constructing multiple decision trees through bagging, thereby reducing variance and improving generalization [27]. It is an ensemble of multiple decision trees built from different random subsets of data and features. The final prediction is obtained through majority voting with Eq. (7), where $T_1, T_2, \dots, T_M$are individual decision trees. This strategy improves robustness and reduces overfitting. The Extra Trees Classifier introduced additional randomization in feature selection and split points, enabling faster training and higher robustness against noise [28]. It is

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an ensemble method similar to Random Forest but introduces more randomness by selecting split thresholds randomly. Predictions are aggregated using majority voting with Eq. (8). This randomness helps reduce variance and improves generalization performance.

$$\hat{y} = \text{vote}(T_1, T_2, \dots, T_M) \quad (7)$$

$$\hat{y} = \text{vote}(T_1^{rand}, T_2^{rand}, \dots, T_M^{rand}) \quad (8)$$

In this study, boosting-based methods were also examined: XGBoost employs gradient boosting with regularization to enhance predictive power [29], [30], while LightGBM improves efficiency through histogram-based splitting and leaf-wise tree growth [31]. Finally, CatBoost was included as it is specifically optimized to handle categorical variables and reduce prediction bias through ordered boosting [32]. XGBoost, LightGBM, and CatBoost are gradient boosting–based ensemble methods that differ in their learning strategies (See Figure 2). XGBoost grows trees level-wise to ensure stable learning with explicit regularization, while LightGBM uses a leaf-wise growth strategy that prioritizes maximum loss reduction for faster and more efficient training. CatBoost employs ordered boosting to reduce prediction bias and is optimized for handling categorical features.

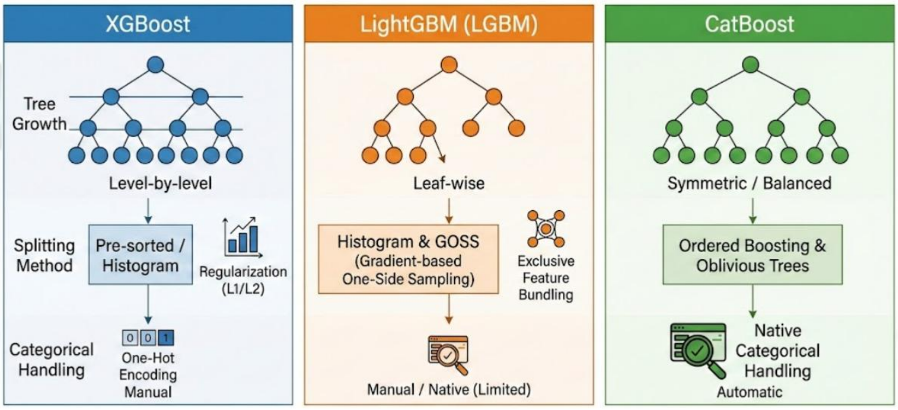

Figure 2. XGBoost, LightBGM, and CatBoost

All models were trained and tested on the prepared dataset using an 80:20 split ratio. Hyperparameter optimization was performed via grid search and cross-validation to ensure fair performance comparison. Evaluation metrics included accuracy, precision, recall, F1-score, and confusion matrix analysis, allowing both overall and class-level performance to be assessed [33]. The comparative analysis of these models provided insights into the most effective ensemble method for early depression detection based on social media behavior and psychological assessment labels.

3. RESULT

The primary objective of this study was to develop an early detection model for depression among Gen-Z using TikTok social media data labeled with PHQ-9 scores. The experimental results demonstrate that the Extra Trees Classifier outperformed other tree-based algorithms, including Decision Tree, Random Forest, XGBoost, LightGBM, and CatBoost, in classifying four levels of depression (none, mild, moderate, and severe).

3.1. Dataset Preparation

A total of 263 respondents participated in this study, representing a diverse demographic profile. Respondents' ages ranged from 17 to 36 years, with the majority belonging to late adolescence and young adulthood, a group known to be highly active on social media platforms such as TikTok. The

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largest age group was 20 years old (32.3%), followed by 19 years (21.3%), 18 years (19.0%), and 21 years (17.9%), indicating that most respondents fall within the Gen-Z category, which is also the population most at risk of experiencing depressive symptoms. In terms of gender distribution, the sample was relatively balanced, comprising 61.2% male and 38.8% female, ensuring fair representation for machine learning model training. Respondents also came from various academic backgrounds, spanning five faculties: Information Technology (68.4%), Economics and Business (11.8%), Communication and Creative Design (10.3%), Social and Political Sciences (8.7%), and Engineering (0.8%). This demographic diversity highlights the representativeness of the dataset while reinforcing its relevance to the research context.

The dataset preparation process was carried out through several systematic steps as summarized in Table 2. Initially, data were collected from 263 respondents using the PHQ-9 instrument along with their social media profile information. Since this research specifically focused on TikTok usage, only respondents who had an active TikTok account were retained, resulting in 209 valid records. From these accounts, profile and interaction data were crawled and enriched with social network features, increasing the total number of fields to 34. Labels for depression levels were then assigned based on PHQ-9 scores and expert validation, producing a dataset of 209 records and 35 features. After feature selection, the dataset was refined to 24 relevant attributes. To address class imbalance across depression categories, the dataset was further processed with SMOTE, yielding a balanced dataset of 600 instances and 24 attributes ready for model training.

Table 2. Data Preprocessing Steps

#	Step(s)	Number of data	Number of fields
1	Data collection using the PHQ-9 instrument and respondents' social media profiles	263	23
2	Data selection (only those who have a TikTok account)	209	23
3	Data crawling and extraction of respondents' social media profiles (using SNA)	209	34
4	Data labeling by an expert based-on PHQ-9	209	35
5	Features selection	209	24
6	Data after SMOTE	600	24

The final set of attributes used for modeling is presented in Table 3. These attributes include basic user information (e.g., username, age, gender), TikTok activity metrics (e.g., followers, followings, total videos, total likes, word count of descriptions), and social network features derived from SNA (degree centrality, betweenness centrality, eigenvector centrality, and structural holes). In addition, behavioral and motivational attributes such as frequency of social media use, posting frequency, and stated purposes of use (e.g., entertainment, content creation, learning) were included to capture users' broader digital behavior. Finally, the label attribute, representing depression levels, was derived from PHQ-9 scoring and expert verification. This combination of demographic, behavioral, and network features provided a comprehensive dataset suitable for developing and evaluating the proposed depression detection model.

Table 3. Final attribute(s)

#	Attribute	Type	Descriptions
1	username	String	Respondent's TikTok account
2	followers	Integer	Number of followers
3	following	Integer	Number of followings
4	total_videos	Integer	Total videos uploaded.
5	total_likes	Integer	Total likes
6	word_count	Integer	Number of word of video descriptions

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#	Attribute	Type	Descriptions
7	age	Integer	Age
8	gender	Nominal	Gender
9	account_number	Nominal	Respondent's number of social media account.
10	using_freq	Nominal	How often users access social media in one day.
11	posting_freq	Nominal	How often users make posts in a day
12	degree_centrality	Float	The number of direct connections a user has.
13	betweenness_centrality	Float	How often a node is on the shortest path between two nodes
14	eigenvector_centrality	Float	The quality of the connection the user has.
15	structural_hole	Float	Structural hole
16	entertainment	Nominal	The purpose of users using social media
17	content creator	Nominal	The purpose of users using social media
18	news	Nominal	The purpose of users using social media
19	working	Nominal	The purpose of users using social media
20	friendship	Nominal	The purpose of users using social media
21	marketing	Nominal	The purpose of users using social media
22	transaction	Nominal	The purpose of users using social media
23	learning	Nominal	The purpose of users using social media
24	label	Nominal	Labels obtained from the results of the PHQ-9 calculation and expert verification

3.2. Experimental Setup

To evaluate the performance of different ensemble-based machine learning algorithms in classifying four levels of depression (none, mild, moderate, and severe), a structured experimental setup was designed. The dataset prepared through preprocessing and balancing was split into training and testing subsets with an 80:20 ratio, ensuring that the models were trained on sufficient data while maintaining a fair evaluation set. To enhance the reliability of the results, a 5-fold cross-validation procedure was applied during training, thereby reducing the risk of overfitting and providing a more robust estimate of model performance. The sampling strategy employed was stratified random sampling, ensuring that the proportion of each depression category was preserved across training and testing sets. This approach is particularly important in mental health classification tasks where class imbalance often occurs.

Table 4. Best parameter after tunning

Method	Best parameter after tuning
Decision Tree	max_depth = 'None'; min_samples_split = 2; criterion = 'gini'
Random Forest	n_estimators = 200; max_depth = 30; max_features = sqrt; min_samples_split = 2
Extra Trees	n_estimators = 100; max_depth = None; max_features = sqrt; min_samples_split = 5; min_samples_leaf = 1
XGBoost	n_estimators = 300; learning_rate = 0,05; max_depth = 7; subsample = 1; colsample_bytree = 0,5; gamma = 0; reg_alpha = 1; reg_lambda = 1
LightGBM	num_leaves = 127; learning_rate = 0,2; max_depth = 15; n_estimators = 100; min_child_samples = 10; boosting_type = gbdt; colsample_bytree = 0,7
CatBoost	border_count = 61; depth = 9; learning_rate = 0,06502135295603015; random_strength = 0,3042422429595377; l2_leaf_reg = 2,818249672071006

For hyperparameter optimization, the study employed RandomizedSearchCV, a widely used method that searches across a predefined parameter grid in a randomized manner. Each ensemble algorithm was tuned individually, and the optimal set of parameters was recorded and reported. The experimental comparison included six algorithms: Decision Tree (DT), Random Forest (RF), Extra Trees Classifier (ET), Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), and CatBoost. For each method, hyperparameters such as the number of estimators, maximum tree depth, learning rate (for boosting methods), and minimum samples per split were carefully adjusted (see Table 4).

3.3. Model Performance Evaluation

The experimental results presented in Table 5 demonstrate clear differences in the performance of the six ensemble-based classification algorithms evaluated for depression detection. The Decision Tree model, while simple and interpretable, achieved the lowest performance across all metrics, with an accuracy, precision, recall, and F1-score of 0.72. This result highlights its inherent tendency to overfit, particularly when dealing with complex, high-dimensional data such as social media activity and network features.

Substantial improvements were observed with the use of ensemble approaches. The Random Forest classifier, which aggregates multiple decision trees through bagging, achieved a balanced performance of 0.86 across all evaluation metrics. This improvement confirms the effectiveness of ensemble strategies in reducing variance and enhancing generalization. Among all tested models, the Extra Trees Classifier achieved the highest performance, with 0.91 across accuracy, precision, recall, and F1-score. Its superior results can be attributed to the additional randomization in feature selection and split points, which helps mitigate overfitting while improving robustness against noisy and imbalanced data.

Boosting-based methods also showed competitive performance. XGBoost and LightGBM achieved moderate results, with accuracies of 0.79 and 0.80, respectively. Both models benefited from their gradient boosting frameworks but were less stable compared to Extra Trees and Random Forest, likely due to sensitivity to hyperparameter tuning and class distribution. CatBoost, designed to handle categorical features effectively, performed nearly as well as Extra Trees, achieving 0.89 in accuracy and a slightly higher precision score of 0.90, reflecting its strength in learning from heterogeneous data attributes.

Overall, the results indicate that while all ensemble methods significantly outperformed the baseline Decision Tree, the Extra Trees Classifier consistently demonstrated the best balance of accuracy, stability, and computational efficiency, making it the most suitable approach for early detection of depression from TikTok social media data. These findings validate the potential of ensemble learning, particularly Extra Trees, in advancing mental health informatics by leveraging behavioral and network-based features.

Table 5. Model Evaluation

Methods	Accuracy	Precision	Recall	F1-Score
Decision Tree	0.72	0.72	0.72	0.72
Random Forest	0.86	0.86	0.86	0.86
Extra Trees	**0.91**	**0.91**	**0.91**	**0.91**
XGBoost	0.79	0.80	0.79	0.79
LightGBM	0.80	0.81	0.80	0.80
CatBoost	0.89	0.90	0.89	0.89

4. DISCUSSIONS

The findings of this study demonstrate that the Extra Trees Classifier is highly effective for early detection of depression levels using TikTok social media data labeled with PHQ-9 scores. With an accuracy of 91% and consistently high precision, recall, and F1-scores across all classes, the model

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proved robust in differentiating between non-depression, mild, moderate, and severe depression categories. These results indicate that ensemble-based approaches, particularly Extra Trees, provide superior stability compared to other methods evaluated in this study, such as Decision Tree, Random Forest, XGBoost, LightGBM, and CatBoost. The application of SMOTE balancing was a crucial factor in achieving this performance, as it effectively addressed the issue of class imbalance, ensuring that minority classes were well represented and reducing bias toward majority categories.

These findings are consistent with previous studies that demonstrated the effectiveness of social media–based behavioral features and ensemble or tree-based machine learning models for depression detection, particularly those utilizing platforms such as Twitter and Reddit, which reported comparable improvements in classification performance when combining user activity patterns with validated mental health indicators [8], [9].

The feature importance analysis further provides valuable insights into the underlying factors influencing depression detection. Among the 22 features considered, demographic attributes such as age emerged as the most influential predictor (importance score 0.0952), underscoring the role of developmental stages in mental health vulnerability. In addition, behavioral factors, including the number of social media accounts (0.0862) and frequency of access (0.0778), were strong indicators of depressive tendencies. High levels of digital engagement may reflect patterns of overuse, avoidance coping, or potential social comparison, which have been linked to mental health risks in prior studies.

Interestingly, TikTok-specific activity features such as followers (0.0732), following (0.0720), and total likes (0.0573) also contributed significantly, suggesting that the social dynamics of online interactions can serve as digital biomarkers of psychological well-being. Features derived from social network analysis, including structural holes (0.0616) and degree centrality (0.0606), highlight that an individual's position and influence within digital networks are relevant to depression risk. Users with more central or constrained positions in their online networks may experience greater social pressures or reduced diversity of social support, aligning with theories of social capital and mental health.

On the other hand, features related to the purpose of social media use, such as entertainment, information-seeking, or academic purposes, showed lower importance scores, with "transaction" yielding no contribution at all. This indicates that while motivational aspects of use are relevant, they play a secondary role compared to direct behavioral and structural indicators of online activity.

Overall, these findings reinforce that depression risk is a multifactorial phenomenon detectable through digital footprints, where demographic factors, behavioral intensity, and social network structure collectively shape predictive patterns. Importantly, while the model demonstrates high accuracy and efficiency, the predictions should be regarded as a screening tool rather than a diagnostic instrument. Professional evaluation remains necessary for clinical confirmation. Nonetheless, the integration of machine learning with social media analytics provides a promising pathway for scalable and accessible early mental health screening systems, particularly for Gen-Z populations who are highly active on platforms like TikTok.

5. CONCLUSION

This study aimed to develop a predictive system for detecting depression levels based on user activity on social media, particularly TikTok, combined with demographic attributes and PHQ-9 scores as ground-truth labels. Data were collected through an online survey and TikTok username-based crawling, resulting in a dataset that integrated both quantitative self-reports and digital behavioral traces. After undergoing preprocessing steps such as data cleaning, transformation, social network feature extraction (centrality and structural holes), and PHQ-9 labeling, the dataset was modeled using six machine learning classifiers: Decision Tree, Random Forest, Extra Trees, XGBoost, LightGBM, and CatBoost.

Experimental results revealed that the Extra Trees Classifier achieved the highest accuracy (91%), outperforming Random Forest (86%), CatBoost (89%), LightGBM (80%), XGBoost (79%), and Decision Tree (72%). The best-performing model was subsequently deployed as a prototype web-based system capable of processing user input and providing real-time depression predictions. Beyond accuracy, system efficiency was also evaluated, with the average prediction time across three trials recorded at approximately 7.988 seconds, covering the entire pipeline from TikTok crawling to classification.

Feature importance analysis from the Extra Trees Classifier highlighted that age (0.0952), the number of social media accounts (0.0862), and frequency of social media use (0.0778) were the most influential predictors, followed by TikTok-specific activity metrics such as followers (0.0732), following (0.0720), and total likes (0.0573). In contrast, variables such as entertainment, information-seeking, or academic use had lower weights, while transactional features contributed negligibly. These findings emphasize that digital behavior on social media serves as a significant indicator of depression risk.

In conclusion, this study demonstrates that combining social media activity data with demographic attributes and validated mental health screening tools can yield accurate and efficient depression detection models. The proposed approach not only addresses existing research gaps but also holds promise as a practical early detection tool to support mental health interventions, particularly among Gen-Z.

CONFLICT OF INTEREST

The authors declares that there is no conflict of interest between the authors or with research object in this paper.

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