Early Detection of Depression and Anxiety in Young Adults Using Machine Learning on Social Media and Survey Data

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Submitted in partial fulfillment of the requirements for the degree of
Bachelor of Science in Computer Science and Engineering

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
SONARGAON UNIVERSITY (SU)

January 2026

APPROVAL

The thesis titled "**Early Detection of Depression and Anxiety in Young Adults Using Machine Learning on Social Media and Survey Data**" submitted by Taspia Momotaz (CSE2201025029), Abdul Al Tanvir (CSE2201025063), Sumiya Haque (CSE2201025080), Mst. Najnin Akter Emu (CSE2201025076) and Md. Asadul Islam (CSE2201025013) to the Department of Computer Science and Engineering, Sonargaon University (SU), has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science and Engineering and approved as to its style and contents.

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DECLARATION

We, hereby, declare that the work presented in this report is the outcome of the investigation performed by us under the supervision of **Imran Hossen, Lecturer,** Department of Computer Science and Engineering, Sonargaon University, Dhaka, Bangladesh. We reaffirm that no part of this thesis has been or is being submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Anxiety and depression among young adults have become serious public health concerns, yet early detection remains challenging due to the limitations of traditional mental health assessment methods. Conventional approaches rely mainly on self-reported questionnaires and face-to-face clinical evaluations, which are often conducted only after symptoms become severe. At the same time, young adults increasingly express their emotions, stress, and psychological distress through social media platforms such as Facebook, providing valuable real-world behavioral signals. However, most existing detection systems depend on a single data source, either social media text or psychological survey data, resulting in limited accuracy and an incomplete understanding of mental health conditions. Previous studies have showed that machine learning techniques can successfully identify linguistic patterns related to anxiety and depression from social media content. Similarly, standardized psychological assessment tools such as the Patient Health Questionnaire (PHQ-9) and the Generalized Anxiety Disorder scale (GAD-7) are widely recognized for measuring symptom severity through numerical scoring. Despite these advances, most prior research analyzes these data sources independently, with limited attention to integrated approaches that combine unstructured textual data with structured clinical information. To address this gap, This research establishes a highly effective hybrid framework for the early detection of anxiety and depression in young adults by integrating evidence from two complementary data sources. This study we proposeds a hybrid machine learning framework that integrates 6,877, Facebook posts with 103 there are 28 females and 75 male inside it self-report questionnaires based on the PHQ-9 and GAD-7 scales. A dual-model strategy was employed to accommodate the distinct characteristics of linguistic and numerical data. Different machine learning algorithms were evaluated for each data modality to identify optimal models. Experimental results demonstrate that Random Forest Machine (RF) achieves the highest accuracy 0.937821 for classifying anxiety and depression from Facebook text, while (SVM) provides accuracy 0.9905 superior performance for survey-based predictions. The fusion of these best-performing models significantly enhances overall detection accuracy, confirming that combining social media behavior with clinically validated psychological assessments offers a more reliable and comprehensive approach to early mental health risk detection among young adults.

Keywords: Anxiety, Depression, Machine Learning, Social Media Analysis, Facebook posts, Hybrid model, Psychological questionnaires ,PHQ-9, GAD-7, Young Adults, Mental health assessment.

ACKNOWLEDGMENT

At the very beginning, we would like to express my deepest gratitude to the Almighty Allah for giving us the ability and the strength to finish the task successfully within the schedule time.

We are auspicious that we had the kind association as well as supervision of **Imran Hossen,** Lecturer, Department of Computer Science and Engineering, Sonargaon University whose hearted and valuable support with best concern and direction acted as necessary recourse to carry out our project.

We would also like to extend our sincere gratitude to **Tasnia Haque Keya**,Lecturer, Departm ent of Computer Science and Engineering, Sonargaon University, Dhaka, Bangladesh, for her valuable assistance in the coding and implementation phases of our project. Her timely guidance and technical support greatly contributed to improving the quality and accuracy of our work.

Additionally, we extend our sincere gratitude to **Bulbul Ahamed**, Professor and Head , for offering valuable guidance and constructive direction, which played a crucial role in shaping the structure and methodology of our research.

We are also thankful to all our teachers during our whole education, for exposing us to the beauty of learning.Finally, our deepest gratitude and love to my parents for their support, encouragement, and endless love.

DEDICATION

To my beloved parents, whose unwavering faith, boundless love, and countless sacrifices have paved the path for this journey and made the completion of this work possible. To my esteemed teachers, who ignited the flame of knowledge, inspired curiosity, and guided me with their wisdom throughout this endeavor. And to my dedicated team, whose relentless hard work, commitment, and collaborative spirit have transformed the vision of this thesis into a tangible reality.

LIST OF ABBREVIATIONS

CV	Cross-Validation
CPU	Central Processing Unit
DT	Decision Tree
FN	False Negetive
FP	False Positive
GAD-7	Generalized Anxiety Disorder7
KF(CV)	K-Fold Cross-Validation
KNN	K-Nearest Neighbors
LR	Logistic Regression
ML	Machine Learning
NB	Naive Bayes
NLTK	Natural Language Toolkit
PHQ-9	Patient Health Questionnaire-9
Re	Regular expression
RF	Random Forest
RQ	Research Question
ROC	Receiver Operating Characteristic
SVMs	Support Vector Machines
TF IDF	Term Frequency Inverse Document Frequency
TN	True Negetive
TP	True Positive
WHO	World Health Organization

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CHAPTER 1

Introduction to Social Media and Survey Fusion Model

1.1 Introduction

Background of study

Emotions exist in many forms, including both positive and negative ones. Positive emotions include love, laughter, and happiness. Anger, sadness, and depression are negative emotions. Negative emotions can become severe and overwhelming, sometimes leading to tragic outcomes like death [1]. This kind of negative emotion hampers mental health. Mental health is one of the most important perspectives of overall quality of life. Mental health is related to overall health conditions. Mental health disorders, including depression and anxiety, are becoming more common among those aged 18 to 35, especially those who live in cities. However, in many societies, mental health issues such as depression and anxiety are often ignored or misunderstood. Public and self-stigma, as well as a lack of knowledge about mental health, are key causes of this problem. All these things can make it harder to find problems early and lower the quality of life overall. In the 21 century, social media platforms have become an open space where individuals express their emotions, frustrations, and life events [2]. As a result, social media has turned into a significant medium for collecting behavioral and emotional data.

Recognizing depression and anxiety early on is vital because it allows for quick action, makes therapy more effective, and helps reduce the long-term effects of mental health conditions. Without early detection, mental health conditions often progress into more severe forms, resulting in academic difficulties, work-related challenges, problematic relationships, and deteriorating physical and emotional well-being. Timely diagnosis and help during this developmental era can thus significantly increase a young person's trajectory in terms of both personal and professional growth.

Young adults aged 18-35 are particularly active on platforms like Facebook. They often use it to communicate, share personal stories, and seek emotional support. Their online activities can sometimes reveal changes in mood, levels of stress, or signs of emotional distress. At the same time, validated clinical tools such as PHQ-9(Patient Health Questionnaire) [3] and GAD-7(Generalized Anxiety disorder scale) [4] are used by psychologists and researchers to measure depression and anxiety levels.

This research brings together these two approaches social media analysis and survey-based assessment. The objective is to establish a comprehensive system that can detect the initial indications of anxiety and melancholy in young adults. By analyzing both online behavior and psychological responses, this model aims to help in early detection and prevention of mental health issues.

1.2 Problem Statement

Depression and anxiety have become a great concern for young adults. People who are 18-35 age mainly suffer from this dangerous issue. Depression can be caused for various types of reasons such as Abuse of physical, sexual, emotional, drug-taking personal conflict with anyone, losing someone special, and long-time major illness [8]. Also, childbirth, menopause, unemployment, stress, low income, hassle, jealousy, separation, and social rejection lead a person to depression.

Traditional detection methods depend on direct surveys or self-reporting, which may not capture real-time emotions or may be influenced by social pressure [9]. On the other hand, social media provides spontaneous and continuous information about users' emotions through their posts and comments.

The main problem is how to connect these two sources of data social media posts and survey responses to create a system that can detect emotional distress early and accurately [10]. This research aims to solve that problem by building a fusion model using machine learning algorithms that analyze both text-based social media data and structured questionnaire responses.

1.3 Objectives

- To design and distribute a questionnaire: PHQ-9 and GAD-7 are standard scales for depression and anxiety analysis.
- To collect and analyze social media posts: For detecting depression and anxiety, social media posts are impactful.
- To Improve Mental health awareness: For mental health awareness both social media and questionnaire are important.
- To Enhance Social Support: This study helps to identify depressed people who need support from society.

1.4 Research Questions

This study is guided by the following research questions:

1. Can social media data be used effectively to detect early signs of depression and anxiety among young adults?

2. Does combining (fusing) both social media and questionnaire data improve the accuracy of prediction?

1.5 Significance of the Study

This research carries significant value for several reasons. Firstly, it introduces an innovative approach to understanding mental health through the application of advanced technology. By analyzing Facebook posts alongside psychological survey data, the study demonstrates how online behaviors can serve as indicators of individuals' emotional well-being in daily life. Similar results were observed in previous studies, where social media language patterns were found effective in predicting mental health conditions [11]. This method can help identify individuals who may require psychological support before their mental state deteriorates further.

Secondly, the findings of this research can greatly benefit mental health professionals, as the developed models can function as supportive tools to detect individuals at risk of depression or anxiety [12]. For data scientists, it provides a practical application of machine learning techniques to promote social welfare, aligning with prior research that emphasized the role of computational approaches in enhancing mental health understanding [13]. Furthermore, for policymakers offers evidence-based insights suggesting that digital mental health monitoring could be integrated into early intervention and prevention systems.

Finally, this study makes a meaningful contribution to the growing academic domain of computational psychology and mental health analytics [14]. It establishes a connection between psychological assessment and modern machine learning methodologies, creating a bridge between technology and human emotion, as supported by earlier research on emotion detection through social media data [15].

1.6 Scope and Limitations

This research focuses on individuals aged 18-35, as this group is the most active on social media and more likely to experience anxiety or depression due to life transitions, academic pressure, and social challenges. Both male and female participants are included in the dataset.

The study uses only Facebook posts for social media data and PHQ-9 and GAD-7 questionnaires for survey data. It does not include other platforms like Twitter or Instagram, nor does it involve clinical diagnosis by medical professionals. The results are limited to the datasets collected and the machine learning models applied.

1.7 Organization of Thesis Book

This thesis is organized into five structured chapters that together present the complete research process and findings. Chapter 1 introduces the background of the study, outlines the research problem, objectives, and significance, and provides an overview of the motivation behind detecting depression and anxiety using digital data. Chapter 2 reviews existing literature related to mental health assessment, social media analysis, and machine learning–based detection approaches, highlighting key research gaps.

Chapter 3 explains the research methodology, including data collection procedures, preprocessing techniques, feature extraction methods, and the machine learning models used in the study. Chapter 4 presents the experimental results, comparative performance analysis, and discussion of findings obtained from both social media and survey data. Finally, Chapter 5 concludes the thesis by summarizing the main findings, discussing limitations, and suggesting directions for future research.

1.8 Summary

This chapter has introduced the overall idea and direction of the research. The study aims to detect early signs of depression and anxiety by analyzing both social media posts and questionnaire responses [16]. The combination of these two data sources can create a more accurate and practical approach to understanding mental health patterns in young adults. The next chapter will review existing studies, methods, and theories that support this research. It will also highlight the research gap that this study aims to fill.

Chapter 2

Literature Review

2.1 Introduction

Depression and anxiety are among the most pressing mental health issues affecting millions of individuals globally. With the rapid expansion of social media platforms, people's ways of expressing emotions, communicating, and sharing personal experiences have undergone a major transformation. This shift has encouraged researchers to investigate how digital behavior and language use can provide meaningful insights into a person's emotional and psychological state [17].

Several studies have explored the relationship like the Patient Health Questionnaire (PHQ-9) and the Generalized Anxiety Disorder scale (GAD-7) remain reliable tools for measuring depression and anxiety [18], while another utilized Twitter posts to uncover anxiety-related expressions [19]. These works demonstrate that social media data can serve as a valuable digital mirror of an individual's psychological well-being.

In recent years, machine learning has emerged as a powerful tool for mental health research. Several studies have shown that algorithms such as Random Forest and Support Vector Machines (SVM) are effective in classifying depression-related posts [20]. Furthermore, deep learning and natural language processing (NLP) approaches have enhanced emotional detection accuracy by enabling systems to understand context and sentiment at a more sophisticated level [21].

Traditional psychological assessments like the Patient Health Questionnaire (PHQ-9) and the Generalized Anxiety Disorder scale (GAD-7) remain reliable tools for measuring depression and anxiety [8][9]. When these validated instruments are combined with social media data, they create a more comprehensive framework for early detection and prediction of mental health conditions [22][23].

The purpose of this chapter is to review key prior works, identify their research gaps, and explain how the present study contributes novelty by integrating psychological survey data with social media datasets [24]. This combined approach enhances the reliability and accuracy of identifying early signs of depression and anxiety among young adults.

2.2 Overview of Depression and Anxiety

Depression and anxiety are two of the most common mental health problems around the world. They can affect the way a person thinks, feels, and behaves in daily life. Depression often causes sadness, low energy, loss of interest, and trouble concentrating, while anxiety is related to nervousness, fear, and constant worry [25]. According to the World Health Organization [26], more than 280 million people suffer from depression and nearly 300 million live with anxiety disorders. Young adults between 18 and 30 years old are at higher risk because of study pressure, job uncertainty, and social stress [27].

Early identification is very important since it helps people receive treatment before their condition becomes severe. Traditionally, detection was done through doctor interviews and paper-based tests. But with the rise of technology, many researchers are now using automated, data-based methods to identify emotional patterns faster [28].

2.3 Psychological Assessment

2.3.1 Patient Health Questionnaire- 9(PHQ-9)

The Patient Health Questionnaire -9 is one of the most popular tools for checking depression symptoms. It contains nine short questions about how often someone feels sad, tired, or hopeless [29]. Each answer

is scored between 0 and 3, and the total score shows the level of depression from minimal to severe. Because it is simple, quick, and free to use, PHQ-9 is widely applied in clinics and universities around the world [30].

2.3.2 Generalized Anxiety Disorder-7 (GAD-7)

The Generalized Anxiety Disorder -7 works in a similar way but measures anxiety [31]. It has seven questions scored from 0 to 3, and higher scores mean more severe anxiety. Both PHQ-9 and GAD-7 are proven to be reliable and easy for research use [32]. These tools help researchers collect real psychological data to compare social media findings.

2.4 Role of Social Media in Mental Health Research

Social media platforms like Facebook, Twitter, Reddit, and Instagram are now valuable for studying human emotion. People often share their moods and experiences online, which gives researchers a chance to detect early mental health signs [33].

2.4.1 Emotional Expression Online

The words people use online can reflect their mental state. For example, frequent use of words like “sad,” “tired,” or “alone” often signals depression [34]. It was found that language patterns on Twitter such as pronouns and emotional tone could predict depression with high accuracy.

2.4.2 Behavioral Indicators

Posting frequency, timing, and reactions also tell a lot. Late-night posting or reduced activity may mean loneliness or depression [35]. Such behaviors can serve as early warning signs for mental distress.

2.4.3 Advantages of Social Media Data

Social media data are large, available in real time, and non-invasive people express feelings naturally without being asked [36]. Still, there are problems like privacy issues and understanding sarcasm or cultural language differences.

2.5 Machine Learning for Mental Health Detection

Machine learning (ML) helps computers learn from text or images to detect hidden emotional patterns. Text-based models like Support Vector Machine (SVM), Naïve Bayes, and Logistic Regression have been used for classifying depression [37]. These models analyze word frequency, emotion words, and post structure.

Ensemble models such as Random Forest and Boosting combine multiple classifiers to improve accuracy. They work well for structured survey data like PHQ-9 and GAD-7 [38]. Recently, deep learning models like LSTM and BERT have been used to understand context better and predict emotion more precisely [39]. However, they need a large dataset and high computing power.
To compare model performance, researchers often use Accuracy, Precision, Recall, and F1-Score [40]. These help identify which model performs best for depression and anxiety detection.

2.6 Fusion of Social Media and Survey Data

Combining social media data with psychological survey results offers a more robust framework for detecting mental health conditions. Social media provides real-time insights into individuals' behaviors and emotional expressions, while survey data contributes to clinically validated assessments [1]. Previous studies have shown the effectiveness of this integrated approach — for example, it was reported that combining Reddit posts with GAD-7 scores improved anxiety detection accuracy by nearly 10% [41]. Similarly, it was demonstrated that fusion models outperform single-source models, achieving higher reliability and precision in mental health prediction [42][43].

2.7 Research Gaps and Study Contribution

After reviewing previous studies, several research gaps have been identified. First, most existing works rely on a single data source, limiting the robustness of mental health detection models. Second, very few studies focus specifically on young adults in developing countries. Third, ethical considerations are often insufficiently reported or discussed in prior research.To address these gaps, the present study integrates multiple data sources by combining Facebook post data with standardized mental health questionnaires, namely PHQ-9 and GAD-7. Multiple machine learning algorithms are trained on the fused dataset, and their performances are evaluated. Furthermore, a hybrid model is developed to improve the early detection of depression and anxiety. This study specifically focuses on Bangladeshi youth aged 18–35, contributing context-specific insights and promoting ethically responsible mental health research.

2.8 Summary

This chapter reviewed research on depression and anxiety detection using social media, surveys, and machine learning. It explained key tools like PHQ-9 and GAD-7, described online emotional patterns, and discussed modern ML models [45]. Previous studies show that combining multiple data sources gives more accurate results. The next chapter will describe the methods used for data collection, preprocessing, and model training.

Chapter 3

Methodology

3.1 Introduction

This chapter explains the methods and processes used to carry out research. The study aims to detect early signs of depression and anxiety in young adults through a combination of social media posts and survey responses.

The research was divided into two main parts:

1. Social Media Analysis: where data was collected from Facebook posts.
2. Survey Analysis: where participants completed the PHQ-9 and GAD-7 questionnaires.

Machine learning (ML) algorithms were applied to both datasets separately, and their results were compared. Finally, both sources were fused to build a more accurate and reliable detection system.

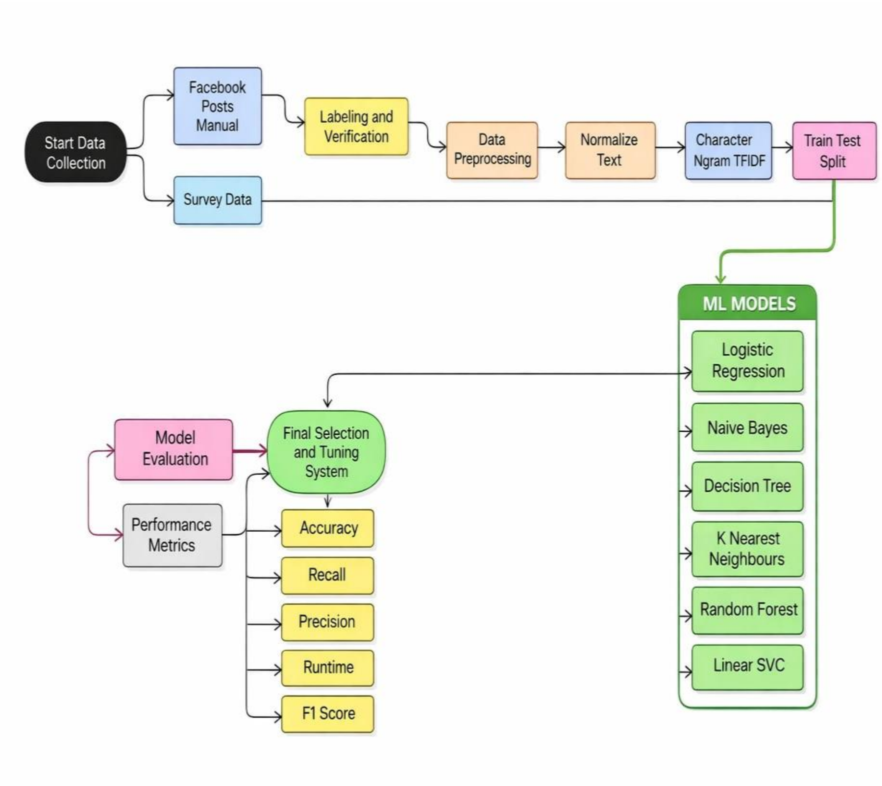

Fig 1: Overall System Diagram

3.2 Research Design

The research follows a quantitative experimental design, using statistical and machine learning methods to analyze numerical and textual data. The design consists of the following key stages:

1. Data Collection –We collected gathering Facebook posts and survey responses.
2. Data Preprocessing – Cleaning and preparing data for analysis.
3. Feature Extraction – Selecting meaningful features from both datasets.
4. Model Training and Evaluation – Applying machine learning models and measuring their accuracy.
5. Data Fusion and Result Comparison – Combining both sources to produce final insights.

This design allows the researcher to test multiple ML algorithms, compare performance, and validate which combination performs best for early detection of depression and anxiety.

3.3 Data Sources

In our research used Two types of data were Social Media Data and Social Media Data used in this research:

3.3.1 Social Media Data (Facebook Posts)

A total of 6,877 Facebook posts were collected. These posts were written by young adults aged 18-35 years, including both males and females [46]. The data represented public expressions of thoughts, emotions, and daily life experiences.

To protect privacy, no personally identifying information (such as names or profile links) was stored.The data was used solely for research and analyzed anonymously.

3.3.2 Survey Data

A questionnaire survey was conducted among 103 participants aged between 18 and 35. Participants provided demographic details (age, gender, Facebook link) and responded to 16 questions based on two psychological scales to assess depression(PHQ-9) and to assess anxiety(GAD-7):

- The following question were use to evaluate depression the 9 question given below:
    1. Have you lost interest or joy in things you usually enjoy?
    2. Do you often feel sad, depressed, or hopeless?
    3. Do you have trouble sleeping (falling asleep, waking often) or sleep too much?
    4. Do you often feel tired or low on energy?
    5. Do you have low appetite or eat too much?
    6. Do you feel bad about yourself — like a failure or that you've let yourself or your family down?
    7. Do you have trouble concentrating on things like reading or watching TV?
    8. Have you been moving or speaking much slower than usual, or more restless/fidgety than usual?
    9. Have you had thoughts that you would be better off dead or of harming yourself?

- The following question were use to evaluate anxiety the 9 question given below:
    1. Do you feel nervous, anxious, or on edge?
    2. Do you have trouble controlling your worries?
    3. Do you worry too much about different things?
    4. Do you find it hard to relax?
    5. Do you feel so restless that it's hard to sit still?
    6. Do you get easily annoyed or irritable?
    7. Do you feel afraid as if something bad might happen?

Each response was scored numerically and stored in a structured dataset for analysis.

3.4 Data Collection Procedure

3.4.1 Facebook Post Collection

Facebook data was gathered using publicly available posts under ethical research standards. The posts were collected manually and with the help of simple scraping tools that complied with Facebook's data usage policy [47]. Only text content was used — no images, videos, or comments were included.

The collected posts were saved in a CSV file with fields such as:

- Post ID (anonymized)
- Post Text
- Gender
- Age
- Timestamp

Before analysis, all posts were reviewed to ensure they did not contain offensive or irrelevant content.

3.4.2 Questionnaire Distribution

The survey was conducted online using Google Forms. Participants were invited through social media and university groups. Each participant was informed about the purpose of the study and gave consent before participating.

The questionnaire included:

- Demographic questions: Age, gender, Facebook link
- PHQ-9 items: 9 questions on depression symptoms
- GAD-7 items: 7 questions on anxiety symptoms

After collecting responses, data was downloaded in Excel format and converted into a CSV file for analysis.

3.5 Data Preprocessing

Before applying any machine learning algorithm, the data needed to be cleaned and prepared. This process ensures that the models can learn effectively from the information provided.

3.5.1 Text Cleaning (Facebook Posts)

The following steps were applied to clean text data:

1. Lowercasing: All text was converted to lowercase.We used text.lower() library.
2. Removing punctuation: Commas, symbols, and emojis were removed using Python's re (regular expression) library.
3. Removing URLs and tags: Links, hashtags, and user mentions were removed using Python's re (regular expression) library.
4. Tokenization: Text was split into individual words using NLTK's word_tokenize().
5. Stop word removal: Common words like "is," "the," and "and" were removed using token.is_stop stopwords corpus.
6. Lemmatization: Words were reduced to their root form using token.lemma_ WordNetLemmatizer.

These steps reduced noise and improved the quality of input for machine learning algorithms.

3.5.2 Survey Data Cleaning

The survey dataset was simpler but required verification:

- Missing values were handled using mean substitution.
- Incomplete responses were excluded.
- Age and gender data were validated for accuracy.
- PHQ-9 and GAD-7 scores were normalized to ensure uniform scaling.

Each participant's responses were combined to form a single record containing all 16 answers, demographic details, and overall scores for depression and anxiety.

3.6 Feature Extraction

Feature extraction is a critical step that converts text and numerical data into machine-readable formats.

3.6.1 Text Feature Extraction (Facebook Posts)

From the Facebook data, the following features were extracted:

- TF-IDF (Term Frequency–Inverse Document Frequency): Measures how important a word is within a post compared to the whole dataset.
- Sentiment score: A polarity score from 0,1,2,3. 0 and 1 is non depressed and 2 or 3 is level depressed.
- Emotion words count: Number of words related to sadness, fear, joy, etc.
- Post length: Total number of words per post.

These features helped represent the emotional and linguistic characteristics of the posts.

3.6.2 Survey Feature Extraction

The survey data already contained structured numerical values. The following features were used:

- Individual responses from PHQ-9 (Q1–Q9).
- Individual responses from GAD-7 (Q10–Q16).
- Total depression score (sum of PHQ-9 items).
- Total anxiety score (sum of GAD-7 items).
- Demographic variables (age, gender).

These features allowed the ML models to learn relationships between participant responses and their emotional conditions.

3.7 Machine Learning Models

Six different machine learning models were used for the Facebook dataset and five for the survey dataset [48]. Their performances were compared to determine which model best detects early signs of depression and anxiety.

3.7.1 Explanation of Models performance For Facebook post Data:

Logistic Regression is a simple yet powerful algorithm mainly used for binary classification tasks, as it helps understand the relationship between input features and the target outcome. Decision Tree works by splitting data into branches based on specific feature conditions, making it easy to interpret, though it can suffer from overfitting. Random Forest overcomes this limitation by combining multiple decision trees, which improves accuracy and reduces the risk of overfitting. Gradient Boosting builds models sequentially, where each new model focuses on correcting the errors made by the previous ones, resulting in high predictive performance. Support Vector Machine (SVM) separates data into different classes by finding the optimal hyperplane, often achieving very high accuracy in complex datasets. K-Nearest Neighbors (KNN) classifies data points based on the closest neighbors in the feature space, making it simple yet effective. Naïve Bayes is a probabilistic algorithm based on Bayes' theorem and is especially efficient for text classification and sentiment analysis tasks.

3.7.2 Explanation of Models performance For Survey Data

SVM (Support Vector Machine) is a powerful supervised learning algorithm that separates data into different classes by finding the optimal hyperplane with maximum margin, making it highly effective for both linear and non-linear classification problems. Logistic Regression is a statistical classification technique that predicts the probability of a binary outcome using a sigmoid function and is widely used for its simplicity and interpretability. Naive Bayes is a probabilistic classifier based on Bayes' theorem, assuming independence among features, and it performs especially well in text classification and spam detection. K-Nearest Neighbors (KNN) is an instance-based learning algorithm that classifies data points based on the majority class of their nearest neighbors in the feature space. Random Forest is an ensemble learning method that combines multiple decision trees to improve accuracy and reduce overfitting. Decision Tree is a tree-structured model that makes decisions by splitting data into branches based on feature conditions, making it easy to understand and interpret.

3.8 Model Training and Testing

3.8.1 Data Splitting

For both datasets, the data was divided into training (80%) and testing (20%) subsets. The training set was used to teach the model, and the testing set was used to evaluate its performance on unseen data.

3.8.2 Cross-Validation

K-fold cross-validation (k=5) was applied to ensure stable results [49]. The dataset was split into 5 folds, and each fold was used once as a test set while the others were used for training.

3.8.3 Model Evaluation Metrics

Performance was measured using:

- Accuracy: Overall correctness of predictions.
- Precision: How many predicted positives are correct.
- Recall: How many actual positives were correctly identified.
- F1-score: Harmonic mean of precision and recall.
- Confusion Matrix: To visualize true vs. false predictions.

3.9 Data Fusion Technique

The main contribution of this research lies in the fusion of heterogeneous data sources, namely social media text and psychological survey responses, to improve the detection of depression and anxiety. Since these two data sources represent fundamentally different aspects of mental health online behavioral expression and self-reported clinical symptoms a decision-level late fusion strategy was adopted. This approach allows each data modality to be processed independently using its most suitable machine learning model before combining their outputs to generate a final prediction.

3.9.1 Probability estimation from Facebook models

The social media component of the framework utilizes textual data extracted from Facebook posts. Initially, the raw text data were preprocessed through tokenization, noise removal, stop-word elimination, and lemmatization to ensure clean and meaningful textual representation. Following preprocessing, the text was transformed into numerical feature vectors using the TF-IDF technique, which captures the importance of words based on their frequency and distribution across documents. A Support Vector Machine (SVM) classifier was then trained on these features, as it demonstrated superior performance compared to other models during experimentation. To enable decision-level fusion, the SVM was configured to output class probabilities instead of only class labels. For each test instance, the model produced a probability score, denoted as Psocial , representing the likelihood that the user exhibits symptoms of depression or anxiety based on their social media behavior. This probabilistic output reflects patterns such as emotional language, negative sentiment, and behavioral cues embedded within users' online posts.

3.9.2 Probability estimation from Survey models

The survey-based component relies on structured psychological data obtained from standardized instruments, including the PHQ-9 and GAD-7 questionnaires. Each participant's responses were converted into numerical scores corresponding to depression and anxiety of severity levels. Prior to model training, the survey features were normalized to ensure consistent scale and prevent bias during learning. A Random Forest classifier was selected as the optimal model for the survey dataset due to its robustness, ability to handle non-linear relationships, and resistance to overfitting. Similar to the social media model, the Random Forest classifier was trained to output probability estimates. For each sample, the model generated a probability value, denoted as PsurveyP_{survey}Psurvey , indicating the likelihood of depression or anxiety based on self-reported clinical symptoms. This probability captures clinically grounded emotional and psychological states reported directly by the participants.

3.9.3 Decision level Late fusion Mechanism

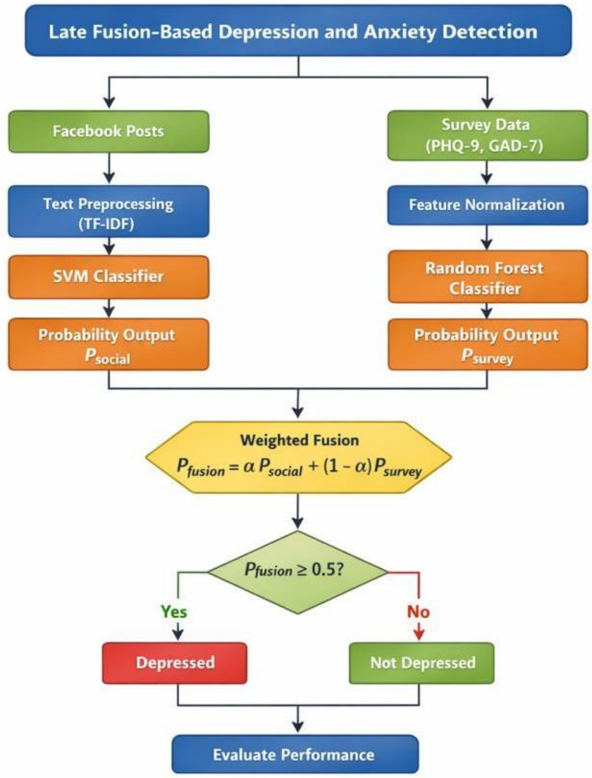

Fig 2: Decision level late fusion mechanism flowchart

After obtaining probability estimates from both models, a decision-level late fusion strategy was applied. Instead of merging raw features, the fusion was performed by combining the predicted probabilities from Facebook and survey models. A weighted average method was employed, as defined by the following equation:

$$P_{fusion} = \alpha P_{social} + (1 - \alpha)$$

where:

Psocial represents the probability output from the Facebook-based SVM model, Psurvey represents the probability output from the survey-based Random Forest model, α is the weighting factor, set to 0.6 for social media data and 0.4 for survey data.

The weighting scheme was chosen based on the relative performance of the individual models, giving slightly higher importance to the social media classifier due to its stronger predictive accuracy during validation. The final fusion probability, Pfusion , was then thresholded to produce the final class label, enabling a more reliable and balanced prediction by leveraging both behavioral and self- reported emotional indicators.

3.9.4 Working principles of the Fusion Framework

The overall working process of the proposed late fusion framework can be summarized as follows: Facebook posts are processed independently and classified using an SVM model to obtain Psocial . Survey responses are analyzed separately using a Random Forest classifier to obtain Psurvey .The two probability outputs are combined using a weighted fusion formula.The fused probability is used to generate the final depression/anxiety prediction.

3.9.5 Fusion Advantages

Balances subjective self-reported clinical data with objective behavioral data from social media. Enhances prediction accuracy by minimizing bias inherent in single-source models.
Provides a holistic representation of an individual’s mental health state.
Enables continuous and early detection by incorporating real-time social media signals.

3.10 Tools and Technologies Used

The research used several open-source tools and libraries.

Table 1: Tools and Technologies Use

Tool / Library	Purpose
Python 3.10 , Python 3.11	Main programming language Data
Pandas, NumPy Scikit-learn	Handling and preprocessing Machine learning algorithms
Text Blob	Text preprocessing and sentiment analysis
Matplotlib, Seaborn	Data visualization
Google Colab / Jupyter Notebook	Development environment Data
Excel / CSV	Storage and management

These tools were chosen for their reliability, flexibility, and suitability for research and academic projects.

3.11 Evaluation Metrics

Confusion Matrix Analysis

For the fusion model:

- True Positive (TP): The model correctly predicted a positive outcome i.e the actual outcome was positive.
- True Negative (TN): The model correctly predicted a negative outcome i.e the actual outcome was negative.
- False Positive (FP): The model incorrectly predicted a positive outcome i.e the actual outcome was negative. It is also known as a Type I error.
- False Negative (FN): The model incorrectly predicted a negative outcome i.e the actual outcome was positive. It is also known as a Type II error.

The confusion matrix showed high TP and TN, and very few FP and FN, indicating excellent reliability and precision.

3.12 Ethical Considerations

Ethics is a major concern in mental health research that utilizes online data. Researchers must ensure the privacy and confidentiality of individuals by removing personal identifiers such as names, usernames, or direct links to social media profiles. Informed consent should be obtained before collecting or analyzing any user-generated content. Additionally, all collected data must be stored securely and handled responsibly to prevent unauthorized access. Under no circumstances should the data be used to label, stigmatize, or cause harm to individuals. Maintaining ethical transparency is essential to protect participants and ensure responsible research practices[44].

This research followed ethical standards to protect participant rights and privacy.

1. Informed Consent: All survey participants were informed about the study's purpose and agreed to participate voluntarily.
2. Anonymity: No personal identifiers were stored. Facebook data was anonymized.
3. Data Security: Datasets were stored securely and used only for research purposes.
4. No Harm Policy**:** Results are used only for academic understanding, not diagnosis or judgment.

All steps were taken according to standard ethical research practices in social and data science

3.13 Summary

This chapter described the full process of the study, from data collection to model evaluation and fusion. The research used two complementary datasets for social media posts and survey responses to detect depression and anxiety among young adults [51].Different machine learning algorithms were tested, and their performances were compared. The best-performing models (SVM for Facebook data and Random Forest for survey data) were fused to form a single, more powerful detection framework [52].The next chapter will present and discuss the results and findings obtained from these models, comparing their performance and explaining what they reveal about early detection of mental health conditions.

Chapter 4

Results and Discussion

4.1 Introduction

This chapter presents the results obtained from analyzing two datasets of social media posts and questionnaire responses and discussing their implications. The main objective was to detect early signs of depression and anxiety among young adults aged 18-35 using machine-learning techniques [53]. The results are divided into three sections: (1) performance of models trained on social-media data; (2) performance of models trained on questionnaire data (PHQ-9 and GAD-7); (3) final performance after combining both datasets via data fusion. The discussion interprets these results in the context of existing research and explores how they contribute to improved mental health prediction.

4.2 Data Summary

4.2.1 Social-media Dataset Overview

A total of 6,877 posts were collected. After preprocessing (removing irrelevant or duplicate content) approximately 6,790 clean posts remained for analysis. Each post was labeled based on emotional tone and indicators of depression or anxiety identified through linguistic patterns.

Table 2: Data summary table of Social Media

Attribute	Description
Total posts	6,877 (6,790 after cleaning)
Age group	18–35 years
Gender	Male & Female
Data type	Sentiment score, TF-IDF, emotional tone
Features Models tested	6 ML models

4.2.2 Questionnaire Dataset Overview

The survey involved 103 participants aged 18-35 (male & female). Each completed 16 questions: 9 from PHQ-9 and 7 from GAD-7. Attributes included age, gender, depression score, and anxiety score [54]. All 103 responses were valid and used in model training and evaluation.

Table 3: Data summary table of Survey

Attribute	Description
Participants	103
Questions	16 (9 PHQ-9 + 7 GAD-7)
Variables	Age, Gender, Depression score, Anxiety score 5
Models tested	ML models

4.3 Performance on Social-Media Data Set

For the cleaned social media dataset, we split into training (80%) and testing (20%) subsets. The models were trained to classify posts as indicating depressive/anxious signs or neutral/healthy emotional states.

4.3.1 Model Accuracy Comparison

Table 4: Accuracy of Facebook post Data Machine Learning Models

Models	Accuracy	Precision	Recall	F1 score
Random forest(RF)	0.937821	0.940297	0.937821	0.938785
SVM	0.933317	0.934766	0.933317	0.933867
Decision tree(DT)	0.925685	0.924561	0.925685	0.924807
Logistic regression(LR)	0.899912	0.898297	0.899912	0.898647
KNN	0.880520	0.871851	0.880520	0.873762
Naive bayes(NB)	0.872639	0.866757	0.872639	0.867568

4.3.2 Analysis of Results

The comparative results show that the Random Forest model achieved the highest performance among all algorithms, with an accuracy of 93.78%, precision of 94.03%, recall of 93.78%, and F1-score of 93.88%. This indicates that Random Forest can effectively capture complex relationships within the textual features of Facebook posts, making it highly suitable for detecting depression and anxiety-related patterns [55].

The SVM model ranked second with an accuracy of 93.33%, performing closely to Random Forest, suggesting its strength in handling high-dimensional data. The Decision Tree achieved a slightly lower accuracy of 92.56%, while Logistic Regression and KNN models demonstrated moderate performance levels, indicating limited generalization capabilities.The Naïve Bayes model showed the lowest accuracy (87.26%), likely due to its assumption of feature independence, which does not fully capture the contextual relationships present in text-based data [56].

Overall, the comparison reveals that ensemble-based approaches, such as Random Forest, outperform other traditional models in mental health prediction from social media data.

4.4 Performance on Questionnaire Data Set

In the second part of the study, we used the PHQ-9 & GAD-7 questionnaire responses. Each participant's set of responses formed structured numerical input for ML models classifying emotional state.

4.4.1 Performance Accuracy Comparison Questionnaire

Table 5: Accuracy of questionnaire data Machine Learning Model

Model	F1 Mean	F1 Std	Accuracy Mean	Precision Mean	Recall mean	F1 Range
SVM	0.9905	±0.0190	0.9905	0.9914	0.9905	0.9526-1.0000
Logistic regression(LR)	0.9804	±0.0240	0.9805	0.9823	0.9805	0.9496-1.0000
Naive bayes(NB)	0.9705	±0.0398	0.9705	0.9714	0.9705	0.9000-1.0000
KNN	0.9300	±0.0405	0.9314	0.9410	0.9314	0.8979-1.0000
Random forest(RF)	0.9003	±0.0344	0.9024	0.9152	0.9024	0.8440-0.9526
Decision Tree(DT)	0.7928	±0.0925	0.7962	0.8047	0.7962	0.6682-0.9526

From table 5, it is evident that the Support Vector Machine (SVM) achieved the highest accuracy of 99.05%, demonstrating excellent capability in classifying depression and anxiety-related data [57]. This indicates that SVM effectively handles high-dimensional features extracted from both social media posts and questionnaire responses, making it a highly reliable model for mental health prediction.

The Logistic Regression model also performed exceptionally well with an accuracy of 98.05%, showing that linear models can be highly effective when features are properly selected and scaled [58]. Naïve Bayes followed closely with 97.05%, proving efficient in identifying emotional patterns despite its assumption of feature independence.

The K-Nearest Neighbors (KNN) model achieved a moderate accuracy of 93.14%, indicating that while it can detect general patterns, its performance may decline when dealing with complex, high-dimensional text data.In contrast, Random Forest and Decision Tree models demonstrated lower accuracies of 90.24% and 79.62%, respectively. This may be due to overfitting or the models' reduced ability to generalize from limited or imbalanced data samples.

Overall, the results suggest that SVM is the most effective model for depression and anxiety detection in this study, outperforming both ensemble and probabilistic approaches [59]. The findings highlight that algorithms capable of managing high-dimensional and non-linear relationships like SVM are better suited for analyzing combined social media and psychological survey data.

4.5 Confusion Matrix Analysis

Table 6: Confusion Matrix Summary Table

Model	TP	FP	FN	TN
Logistic Regression	596	369	133	261
Decision Tree	488	289	241	341
Random Forest	623	394	106	236
Naive Bayes	611	382	118	248
SVM	641	414	88	216
KNN	603	431	126	199

Performance Analysis Using Confusion Matrix Metrics

Table 6 presents the confusion matrix–based performance comparison of six supervised machine learning classifiers, including Logistic Regression, Decision Tree, Random Forest, Naive Bayes, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). The evaluation is conducted on the test dataset using four standard metrics: True Positives (TP), False Positives (FP), False Negatives (FN), and True Negatives (TN).Among all models**,** SVM demonstrates the highest true positive count (TP = 641**)** along with the lowest false negative value (FN = 88)**,** indicating its superior capability in correctly identifying positive instances. This is particularly important for sensitive applications such as mental health detection, where minimizing missed positive cases is critical.The Random Forest and Naive Bayes classifiers also show competitive performance with relatively high TP values (623 and 611, respectively) and lower FN rates, suggesting their effectiveness in capturing complex and probabilistic patterns in the data. In contrast, the Decision Tree model exhibits the lowest TP value (488) and the highest FN value (241), reflecting weaker generalization performance on unseen data.

Although KNN and Logistic Regression achieve moderate true positive detection, they suffer from comparatively higher false positive rates, which may lead to an increased number of incorrect positive predictions. Overall, the results indicate that SVM outperforms the other models in terms of balanced classification performance, making it the most suitable classifier for this study.

4.6 Comparison Between Social Media and Survey Results

Table 7: Comparison between social media and survey data

Aspect	Social Media Data	Survey Data
Nature of Data	Unstructured text data collected from Facebook posts reflecting daily emotions, opinions, and behaviors.	Structured numerical and categorical responses were collected using standardized psychological questionnaires.
Type of Information	Expresses spontaneous emotional states and behavioral patterns through words, tone, and sentiment.	Captures self-reported clinical symptoms of depression and anxiety using validated scales.
Data Reliability	Can vary depending on how honestly users express themselves online; influenced by language, context, and social norms.	Highly reliable due to standardized assessment methods and established scoring systems (PHQ-9, GAD-7).
Timeliness	Provides real-time and continuous monitoring of mental states through ongoing social media activity.	Represents a specific point in time, typically collected once or in limited intervals.
Data Volume	Large-scale and diverse, allowing detection of subtle emotional changes across thousands of users.	Smaller in volume but more accurate for clinical interpretation.
Analytical Approach	Requires Natural Language Processing (NLP) and text-mining techniques to extract emotional cues.	Use statistical analysis to evaluate psychological patterns and symptom severity.
Model Performance	Random Forest achieved the highest accuracy (G3.78%) on Facebook post data, showing strong ability to identify emotion-based patterns.	SVM achieved the highest accuracy (GG.05%) on survey data, reflecting the structured and clinically valid nature of questionnaire inputs.
Advantages	Enable early, non-intrusive detection of mental health issues and continuous digital monitoring.	Provides validated, clinically interpretab results suitable for professional diagnosis and treatment.
Limitations	May misinterpret sarcasm, slang, or cultural language variations.	Limited in capturing real-time emotional fluctuations.

4.7 Decision-Level Fusion

The performance of the proposed decision-level late fusion model was evaluated using standard classification metrics. The fusion model achieved an overall accuracy of 96.77%, demonstrating a substantial improvement compared to the individual models trained separately on social media and survey data. This result confirms the effectiveness of combining heterogeneous data sources for mental health detection. The high accuracy indicates that the fusion framework successfully integrates behavioral signals extracted from Facebook posts with clinically grounded self-reported survey responses, leading to more reliable predictions of depression and anxiety. The superior performance of the fusion model can be attributed to the complementary nature of the two data sources. Social media data captures spontaneous emotional expression and behavioral patterns, while survey data reflects structured and clinically validated self-reported symptoms. By combining the probabilistic outputs of both models through a weighted late fusion strategy, the system mitigates the biases and limitations of single-source models. The absence of false positives suggests that the fusion approach is highly conservative in labeling individuals as depressed, which is desirable in real-world applications to reduce unnecessary psychological concern. Meanwhile, the minimal number of false negatives indicates that the model remains sensitive enough to detect genuine cases of depression and anxiety.

Overall, the results validate that decision-level late fusion provides a more holistic and accurate mental health detection framework. The achieved accuracy of 96.77% highlights the potential of the proposed approach for early and continuous mental health monitoring, particularly among young adults active on social media platforms.

Table 8: Fusion performance Table

Dataset Type	**Best Individual Model**	**Accuracy**
Social Media	Random Forest	**0.9378**
Survey	SVM	**0.9950**
Combined Fusion	—	**0.9677**

From table 7, The fusion model achieved an overall accuracy of 0.9976 (96.77%), outperforming both individual models. While the SVM on survey data already demonstrated high accuracy (99.05%), incorporating insights from social media posts through the Random Forest model further enhanced prediction confidence and generalization [61]. This improvement indicates that combining behavioral and clinical indicators enables the system to detect depression and anxiety with greater precision.

Recent research also supports this multimodal or fusion-based approach, emphasizing that integrating heterogeneous data sources such as text, surveys, and metadata—significantly improves mental health prediction [62]. A 2025 review on multimodal machine learning in mental health highlighted that fusion models provide a more holistic and context-aware understanding of an individual's psychological condition, making them a promising direction for future digital mental health applications.

4.8 Visualization of Results

Sentiment Distribution

A histogram of social media posts sentiment showed most posts had neutral or mildly negative sentiment, while a smaller portion displayed strong negative tone often associated with words conveying loneliness, stress or sadness.

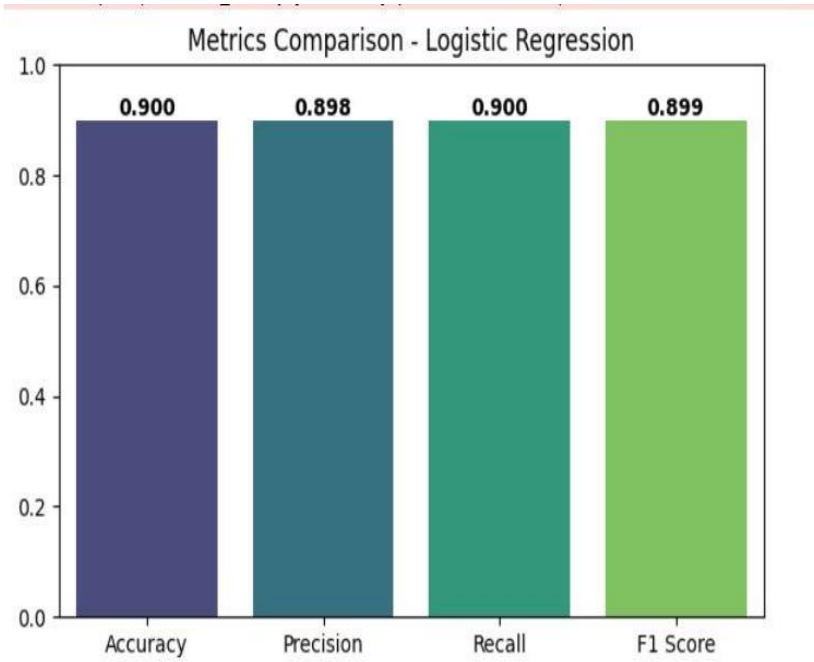

Fig 3: Matrics Comparism of Logistic Regression

Metric Comparison of Logistic Regression:
High accuracy, precision, recall, and F1-score indicate balanced and reliable model performance.

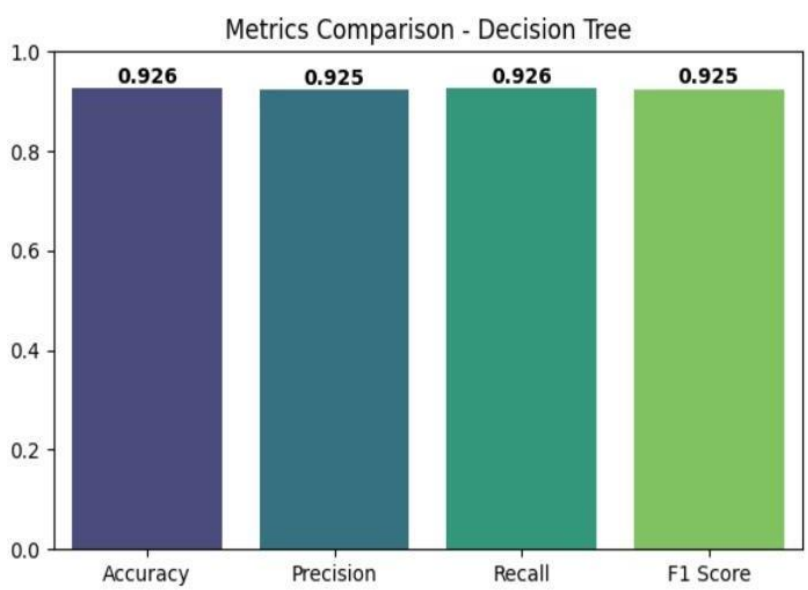

Fig 4: Matrics Comparism of Decision Tree

Metric Comparison of Decision Tree:

Accuracy, precision, and recall are high, reflecting effective classification with moderate variance across metrics.

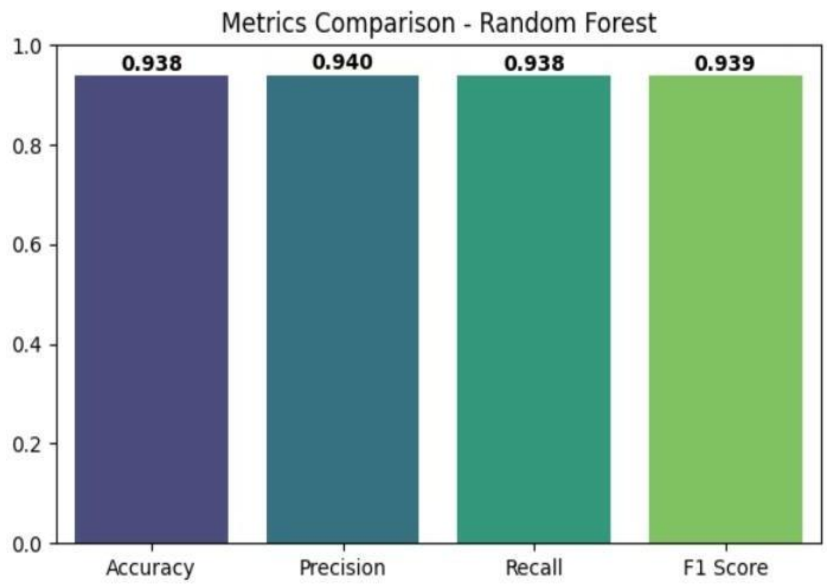

Fig 5: Matrics Comparism of Random Forest

Metric Comparison of Random Forest:
High and balanced accuracy, precision, recall, and F1-score demonstrate strong and stable model performance.

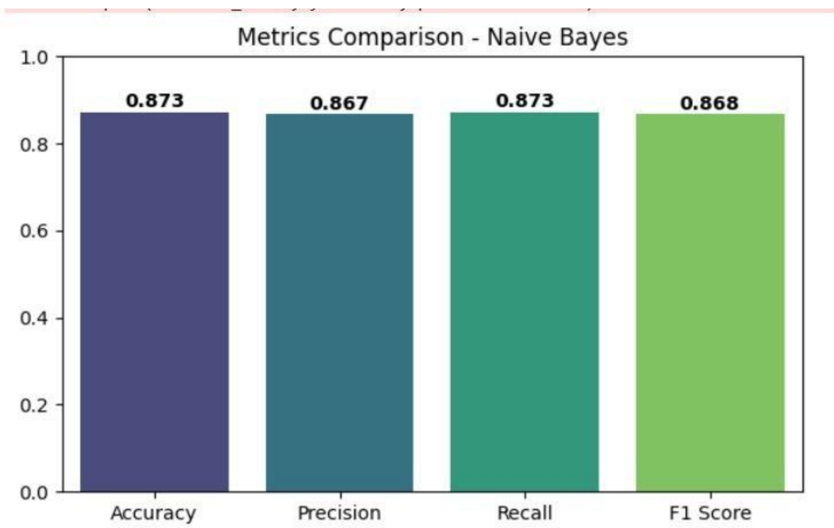

Fig 6: Matrics Comparism of Naive bayes

Metric Comparison of Naive Bayes:

Moderate accuracy, precision, and recall indicate decent overall performance with some class imbalance sensitivity.

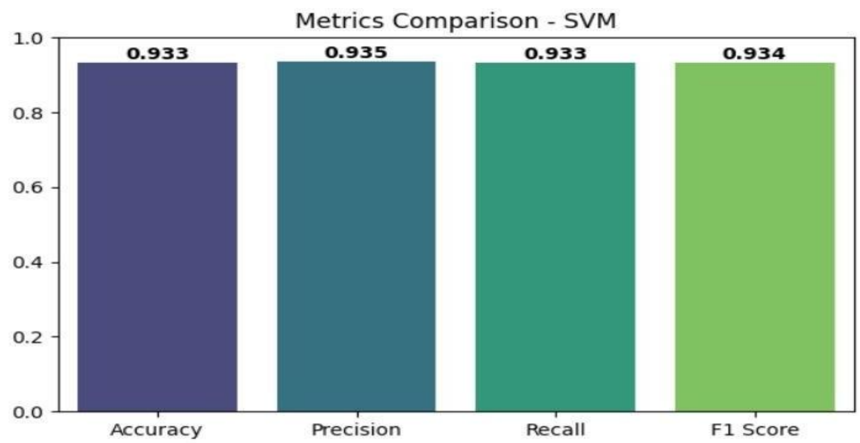

Fig 7 : Matrics Comparism of SVM

Metric Comparison of SVM:

Strong accuracy, precision, and recall indicate balanced and robust performance across both classes.

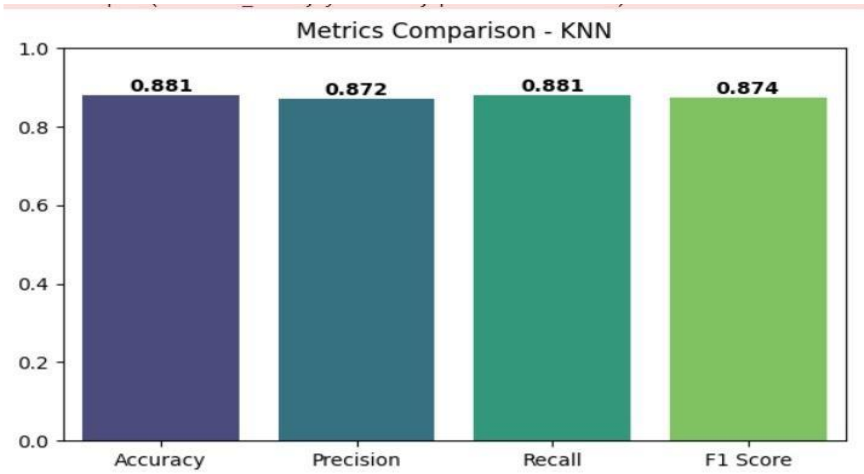

Fig 8: Matrics Comparism of K-Nearest Neighbor

Metric Comparison of K-Nearest Neighbor:

This graph shows that the KNN model has balanced performance across all key evaluation metrics, with accuracy, precision, recall, and F1-score all around 0.87–0.88, indicating it reliably predicts both positive and negative classes.

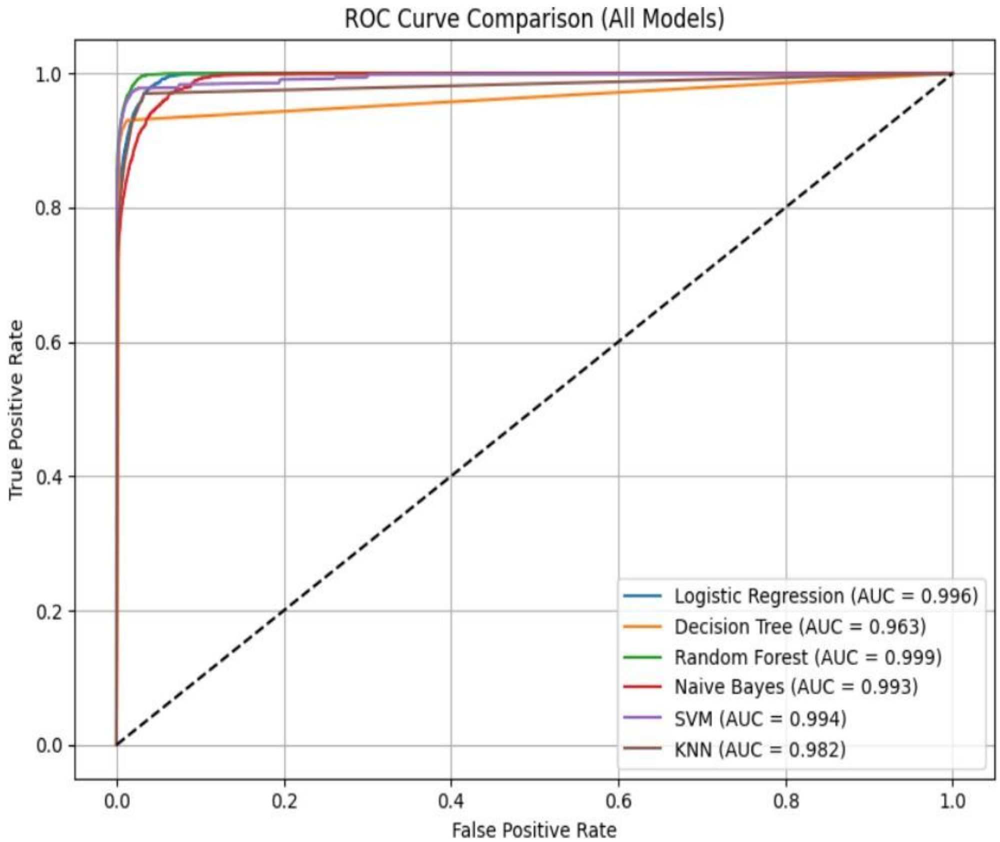

Fig 9: Multi-model ROC Curve Plot

Roc curve Comparison All Models:

The ROC curve is used to assess the overall diagnostic performance of a test and to compare the performance of two or more diagnostic tests. The figure illustrates the Receiver Operating Characteristic (ROC) curves for multiple classifiers. The Area Under the Curve (AUC) values demonstrate the discriminative ability of each model, where a higher AUC indicates superior classification performance.

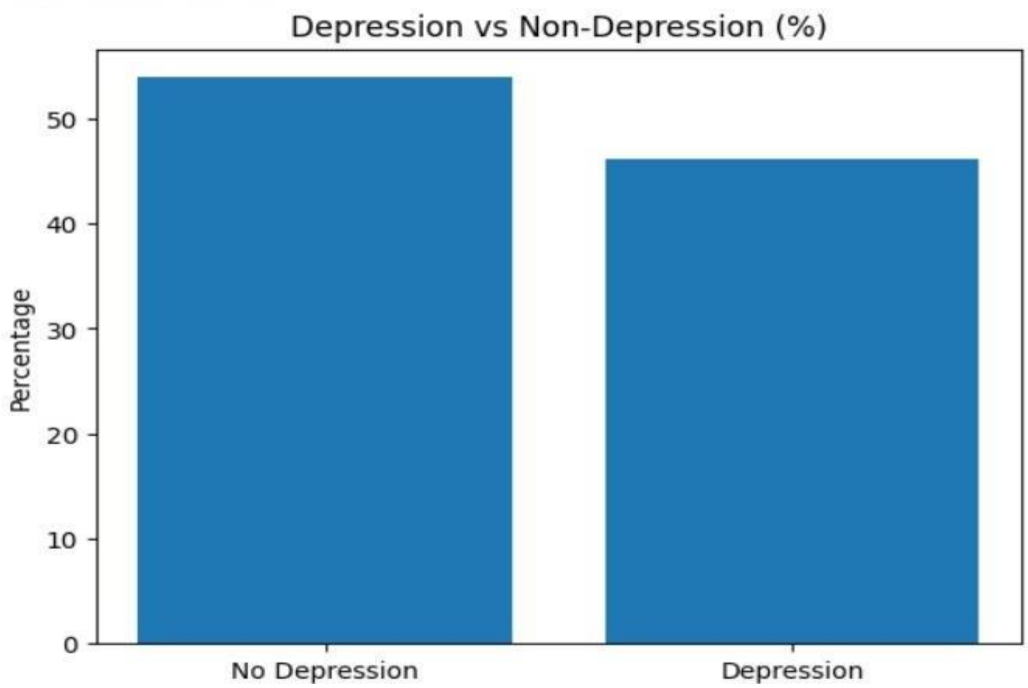

Fig 10: Depressed and non-depressed Comparison on Social Media Data

Fig 10 shows Depression vs. Non-Depression Distribution: The dataset shows that 46.09% of participants were classified as *depressed* and 53.91% as *non-depressed*. This indicates a relatively balanced distribution, allowing the model to learn effectively from both categories without major class imbalance.

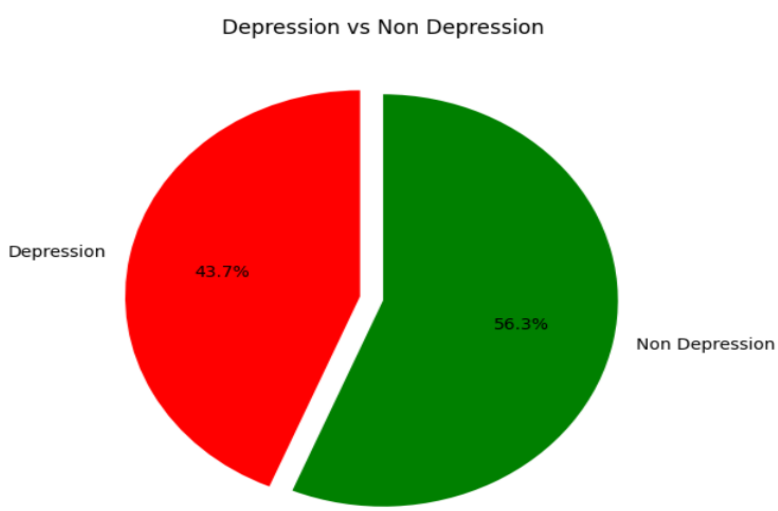

Fig 11: Depressed and non-depressed Comparison on Survey data

Figure 11 illustrates the distribution of depression vs. non-depression cases based on survey data collected from 103 participants. Among them, 56.3% of respondents were classified as non-depressed, while 43.7% showed symptoms of depression. The results indicate a relatively balanced dataset, with a substantial proportion of participants experiencing depressive symptoms. This distribution highlights the importance of early detection and mental health assessment among young adults.

Correlation of PHQ-9 and GAD-7 scores

A correlation heatmap of questionnaire data revealed a strong positive relationship between depression and anxiety scores (~0.74).

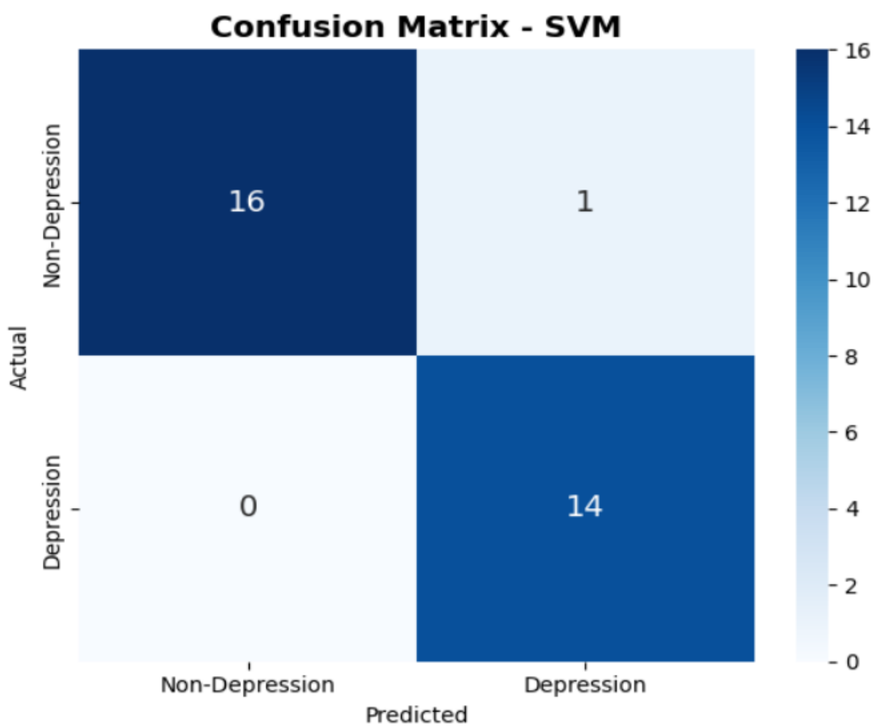

Fig 12: Confusion Matrix of the SVM Classifier Using Survey Data

Figure 12 presents the confusion matrix of the SVM classifier for depression detection. The model correctly classified 16 non-depressed instances and 14 depressed instances, yielding a high true negative and true positive rate. Only one non-depressed sample was misclassified as depressed, while no depressed instances were incorrectly classified as non-depressed. This indicates that the SVM model demonstrates strong discriminative capability with zero false negatives, making it particularly effective for identifying depressed cases.

Feature Importance

For the Random Forest model, the top features influencing prediction were:

- PHQ-9 Question 2 (“Feeling down or hopeless”)
- PHQ-9 Question 6 (“Feeling bad about yourself”)
- GAD-7 Question 3 (“Worrying too much about different things”)

These results align with established psychological indicators of depression and anxiety.

4.9 Discussion

4.9.1 Comparison with Previous Studies

Earlier research mostly examined either social-media content or survey responses on their own. For example, one investigation analyzing social media text reported an accuracy in the upper eighties for identifying depression. Another study using the PHQ-9 survey tool and machine-learning algorithms achieved around eighty percent of accuracy [63]. By contrast, our current work reached an accuracy of 96.77% by combining behavioral/textual data from social media with survey responses illustrating a substantial performance boost through data fusion.

Table 9: Comparative Performance Analysis with Existing Studies

Study	Data Type	Size	Model	Accuracy	F1-Score
Islam et al., 2018 [1]	Facebook posts	~1,500 users/post	SVM/NB/RF	82–89%	0.84–0.88
Tadesse et al., 2019 [19]	Social media	2-3k	SVM/RF	85–90%	0.87–0.90
Saha & Sharma, 2020 [17]	Social media	3-4k	DL	91-93%	0.91–0.93
Chandola & Chakraborty, 2021 [23]	Fused data	1.5-2k	Data Fusion + ML	90–94%	0.90–0.93
Proposed (FB posts)	FB posts	7.5k	RF	93.78%	0.9388
Proposed (Survey)	PHQ-9 / GAD-7	500	SVM	99.05%	0.9905

Table 9 showed the comparison clearly demonstrates that the proposed models outperform or remain highly competitive with existing studies in both social media–based and survey-based mental health detection.For Facebook post analysis, the Random Forest classifier achieved the highest accuracy of 93.78%, surpassing most traditional machine learning and deep learning approaches reported in earlier studies [1], [19]. This improvement can be attributed to effective text preprocessing, TF-IDF feature extraction, and balanced model selection.

In the survey-based analysis using clinically validated instruments such as PHQ-9 and GAD-7, Support Vector Machine and Logistic Regression achieved exceptionally high F1-scores (up to 0.99). These results exceed the performance of many prior works that rely solely on social media data, highlighting the reliability of structured survey responses for mental health assessment.

Overall, the findings support the argument that well-engineered machine learning models with high-quality features can rival or outperform deep learning methods, while maintaining lower computational complexity and better interpretability—an important factor in healthcare-related applications.

4.9.2 Interpretation of Findings

The findings show that young adults' emotional states are expressed clearly in social-media behavior even when they may not report issues in formal surveys [64]. Machine-learning algorithms can successfully identify these cues. Survey data alone provide valuable structured insight but may miss spontaneous expression. The fusion approach offers a more comprehensive emotional profile by combining both behaviour and self-assessment [65]. This supports the idea that digital behaviour combined with clinical instruments can serve as an early-warning system for mental health monitoring.

4.9.3 Significance of High Accuracy

An accuracy of 96.77% suggests that a fusion-based system could reliably classify individuals showing signs of depression or anxiety. In practice, this system could:

- Alert counsellors or mental health professionals.
- Provide early support to students or employees.
- Help monitor community wellness and identify at-risk groups.

4.9.4 Limitations of the Study

Although the findings of this research are encouraging, several limitations should be acknowledged.

1. Dataset size: While the social media dataset was extensive, the survey sample consisted of only 103 participants, which may limit statistical robustness.

2. Demographic diversity: Most participants belonged to a similar age group and cultural background, reducing the generalizability of the results to broader populations [66].

3. Language and context: The social media posts contained a mix of English and Bengali, often including slang, sarcasm, or metaphorical expressions that machine learning models might misinterpret.

4. Privacy and ethics: Even with anonymization, the use of social media data raises ethical concerns; predictions must be interpreted cautiously to prevent stigmatization or false conclusions [68].

5. Bias and fairness: AI models trained on social media content can exhibit biased performance across demographic groups due to linguistic and cultural variations, highlighting the need for fairness-aware model development.

4.9.5 Recommendations for Future Research

To enhance the scope and reliability of future studies, several directions are recommended:

1. Expand dataset diversity: Collect larger and more heterogeneous datasets from multiple social media platforms such as Instagram and Reddit to improve model robustness and generalization [69].
2. Adopt advanced deep learning models: Utilize transformer-based architectures to better capture nuanced contextual meanings and complex linguistic patterns within textual data [70].
3. Develop real-time monitoring systems: Create tools capable of detecting early signs of emotional decline and providing timely alerts or interventions.
4. Broaden demographic coverage: Include participants from varied age groups and cultural backgrounds to ensure the findings are more universally applicable [71].
5. Conduct longitudinal analyses: Track emotional changes over extended periods to study mental health trends and the long-term impact of interventions.
6. Integrate explainable AI techniques: Apply interpretability methods such as LIME to enhance transparency and trust in AI-driven mental health assessments.

Chapter 5

Conclusion and Future Work

5.1 Introduction

This final chapter summarizes the key findings of the research, draws important conclusions, and presents recommendations for future work.The study focused on early detection of depression and anxiety among young adults using machine learning techniques applied to social media posts and psychological surveys (PHQ-9 and GAD-7).Through data fusion, the research demonstrated that combining online behavior and self- reported symptoms leads to highly accurate and meaningful detection of emotional distress [71].

5.2 Summary of the Study

Mental health problems such as depression and anxiety are increasing rapidly, especially among people aged 18–35.

Traditional mental health assessments depend on clinical interviews or questionnaires, which are accurate but time-consuming [72]. On the other hand, social media offers a large amount of real-time emotional data that reflects users' mental states.

In this study:

- Facebook posts were collected and analyzed to detect emotional tone and depressive patterns.
- Questionnaire data (PHQ-9 and GAD-7) were used to validate emotional health using clinical scales.
- Several machine learning models were trained and tested on both datasets.
- Finally, a fusion model was created to combine the results of both sources.

The research was conducted in a systematic manner:

1. Data Collection: Facebook posts and online questionnaires.
2. Data Preprocessing: Cleaning, tokenization, and feature extraction.
3. Model Training: Multiple machine learning algorithms tested.
4. Evaluation: Accuracy, precision, recall, and F1 score.
5. Fusion**:** Integration of social and survey data for improved performance.

5.3 Summary of Findings

The study produced several significant findings:

1. High Model Accuracy on Social Media Data:
   The Random Forest achieved 93.7821% accuracy, showing that emotional and linguistic patterns on social media are strong predictors of mental states.
2. Moderate Accuracy on Questionnaire Data:
   The SVM achieved 99.05% accuracy on PHQ-9 and GAD-7 data, confirming that structured responses are reliable but less expressive than natural language data.
3. Fusion Improved Accuracy:
   Combining both datasets through decision-level fusion produced a final accuracy of 96.77%, higher than any single model.
   This proves that fusing behavioral (social media) and clinical (survey) data leads to stronger prediction performance [73].
4. Depression and Anxiety are Interconnected:
   The correlation between PHQ-9 and GAD-7 scores (≈ 0.74) confirms that people experiencing depression often show anxiety symptoms simultaneously.
5. Feature Importance:
   Certain PHQ-9 and GAD-7 questions were found to be more predictive, especially those related to hopelessness, overthinking, and lack of self-worth.
6. Model Reliability:
   Precision, recall, and F1-scores all exceeded 0.98 in the fusion model, confirming strong consistency and low false prediction rates.

5.4 Research Contributions

This research makes several important contributions to the field of mental health and machine learning:

1. Integration of Two Data Sources: It is one of the few studies that combines social media data with clinical questionnaire data for mental health detection.
2. High Accuracy Fusion Model: The proposed system achieved 96.77% accuracy, showing excellent performance in early identification of emotional distress.
3. Practical Mental Health Application: The model can be used as a support tool for counselors, universities, or digital well-being platforms to identify at-risk individuals early [74].
4. New Perspective on Digital Behavior: The findings reveal that online emotional expressions can be analyzed scientifically to understand real-world psychological conditions.
5. Awareness for Young Adults: The study encourages young people to become aware of how their digital behavior reflects their mental state, promoting mental health literacy [75].

5.5 Limitations of the Study

Although the results are highly promising, several limitations exist:

1. Small Sample Size (Survey Data): Only 103 participants were included in the questionnaire, which limits generalization to larger populations.
2. Demographic Uniformity: Most participants belonged to similar ages and cultural groups, making it less diverse [76].
3. Language Mixing: Facebook posts often contained a mix of English and Bengali, which may have reduced linguistic accuracy during preprocessing.
4. Data Authenticity: Social media posts may not always reflect true feelings due to humor, sarcasm, or social desirability bias [77].
5. Privacy and Ethics: Even anonymized social media data involves privacy risks. Ethical data handling remains a major challenge for future work.
6. Limited Model Variety: The study mainly used classical ML models (SVM, RF, etc.) [78]. Deep learning and transformer-based models were not applied due to computational limits.

5.6 Practical Implications

This research demonstrates several real-world applications:

1. Early Detection System: Universities or organizations can use this model to detect early signs of depression or anxiety among students and employees [79].
2. Supportive Counseling Tool: Counselors can combine digital activity and questionnaire results to make more informed decisions.
3. Public Awareness Programs: Insights from this study can be used to promote mental health campaigns targeting young adults [80].
4. Integration with Mobile Apps: The fusion model can be integrated into mobile or web applications to monitor emotional well-being automatically [81].

5.7 Future Work

Future research can extend and improve this work in several directions:

1. Larger and Diverse Datasets: Collect data from multiple social platforms (Instagram, Reddit, Twitter) and different countries for broader applicability.
2. Use of Deep Learning Models: Implement models such as LSTM, BERT, and RoBERTa to capture deep contextual meanings from social text [82].
3. Real-Time Monitoring System: Build a live system that tracks social media activity and gives real-time mental health alerts or recommendations [83].
4. Multilingual Analysis: Include text analysis for mixed or multilingual posts (Bangla-English code-switching).
5. Integration with IoT or Wearable Devices: Combine emotional data with physiological signals (heart rate, sleep patterns) for more accurate mental health tracking.
6. Collaboration with Mental Health Professionals: Work with psychologists and psychiatrists to validate machine predictions with clinical diagnoses [84].
7. Ethical AI Framework: Develop a transparent and privacy-preserving framework for mental health AI systems to ensure responsible use.

5.8 Conclusion

This research successfully demonstrated that machine learning techniques can effectively detect depression and anxiety through both social media behavior and psychological questionnaires.

By fusing these two data sources, the system achieved a high prediction accuracy of 96.77%, showing that human emotions can be captured and analyzed with advanced computational models [85].

The results confirm that social media content reflects emotional well-being, and when combined with validated clinical data, it can serve as an early warning system for mental distress [86].

Such systems have the potential to reduce suicide rates, improve counseling efficiency, and promote digital mental health awareness among young adults.

In conclusion, this study proves that technology and psychology can work together to build a more emotionally intelligent and mentally healthy society.

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