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Hybrid Model for Predicting Mental Health from Social Media Insights

Kanika Sharma, Dr. Avni Sharma,
HPTU, Hamirpur

ABSTRACT
Mental health has become an increasingly critical concern in today's digital age, where social media plays a significant role in shaping individuals' emotional and psychological well-being. This project presents a data-driven approach to predicting mental health status using behavioural patterns derived from social media usage and demographic profiles. Leveraging the smmh.csv dataset, which contains user responses on age, gender, education, employment, income, and time spent on platforms like Instagram, Facebook, Twitter, and Snapchat, we designed a machine learning pipeline to classify individuals into two categories: those with and without mental health concerns.

The project began with extensive data preprocessing to ensure high-quality input for model training. Irrelevant features were removed, missing values handled, and categorical data such as gender and education were encoded numerically using Label Encoding. Exploratory Data Analysis (EDA) revealed notable trends—such as the correlation between excessive Instagram/Facebook usage and reported mental health issues—offering critical insights into how social behaviour may mirror emotional well-being.

Three predictive models were developed and evaluated: Logistic Regression served as the baseline due to its interpretability and suitability for binary classification; Linear Regression was tested for comparison; and XG-Boost was employed as the final model, achieving the best performance across all metrics—accuracy, precision, recall, and F1-score. XG-Boost's ability to handle class imbalance and complex relationships made it a strong candidate for real-world applications.

This study highlights the potential of integrating social media patterns and demographic factors to identify mental health risks. With responsible and ethical deployment, such models could contribute meaningfully to early mental health screening and intervention efforts in a data-centric society.

CHAPTER 1
INTRODUCTION

1.1 Machine Learning

The integration of machine learning and artificial intelligence (AI) in the prediction of mental health conditions has gained significant attention in recent years, with research demonstrating its potential to revolutionize mental health diagnostics. Mental health disorders, such as depression, anxiety, and bipolar disorder, are pervasive and can often go unnoticed until they reach a critical stage. Recent studies have explored various AI-driven models to predict and manage these disorders through social media analysis, offering a promising avenue for early intervention (Zan war et al., 2022) [1]. This section explores the technologies employed in mental health prediction, the challenges encountered, the role of models in this field, and the objectives of the current study.Machine learning and deep learning models have been extensively utilized in mental health prediction due to their ability to handle complex, high-dimensional data. Various models have demonstrated promising results in predicting mental health issues using social media data, offering insights into behavioral patterns and emotional well-being. Support Vector Machines have been effective in binary classification tasks, distinguishing individuals with mental health issues based on social media behavior (Bhat et al., 2020) [1].

Random Forest, an ensemble learning technique, has also shown promise in managing large datasets and capturing complex relationships between features in the mental health domain (Liu et al., 2021) [2]. Convolutional Neural Networks (CNN) have been used to extract meaningful features from textual content on social media, capturing sentiment and emotional cues related to mental health (Jang et al., 2021) [3]. Long Short-Term Memory (LSTM) networks, designed to capture long-term dependencies in time-series data, have proven effective in tracking users' emotional states over time based on their social media activity (Sharma et al., 2021) [4]. Deep Neural Networks (DNN) are capable of learning intricate patterns from large datasets and have been applied to predict mental health conditions by analyzing the emotional tone of social media content (Kumar et al., 2022) [5]. Transformer-based models like BERT, with their contextualized word embeddings, are increasingly used for text classification tasks and have been successful in predicting mental health disorders from social media language (Tang

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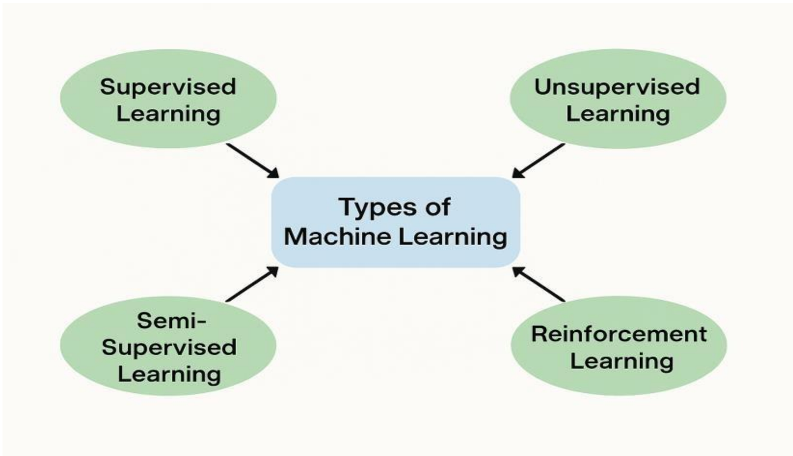
et al., 2022) [6]. Finally, K- Nearest Neighbors (KNN) remains a simple yet effective algorithm for classifying individuals into mental health risk categories, based on their social media features (Singh et al., 2020) [7]. The first chapter of machine learning has been opened, and its ongoing maturity is continually reshaping the world of technology and human life.

Various types of machine learning—supervised, unsupervised, semi-supervised, and reinforcement learning—offer distinct methodologies for tackling a wide range of problems, from prediction to classification. Supervised learning focuses on training models using labeled data, while unsupervised learning works with unlabeled data to find hidden patterns. Semi-supervised learning bridges the gap, leveraging both labeled and unlabeled data. Reinforcement learning, on the other hand, involves agents learning optimal actions based on feedback from their environment. The continuous evolution of these models and techniques promises to redefine various sectors, including healthcare, finance, and social media analytics. Below is a diagram illustrating these different types of machine learning:

Figure 1.1 Machine Learning models



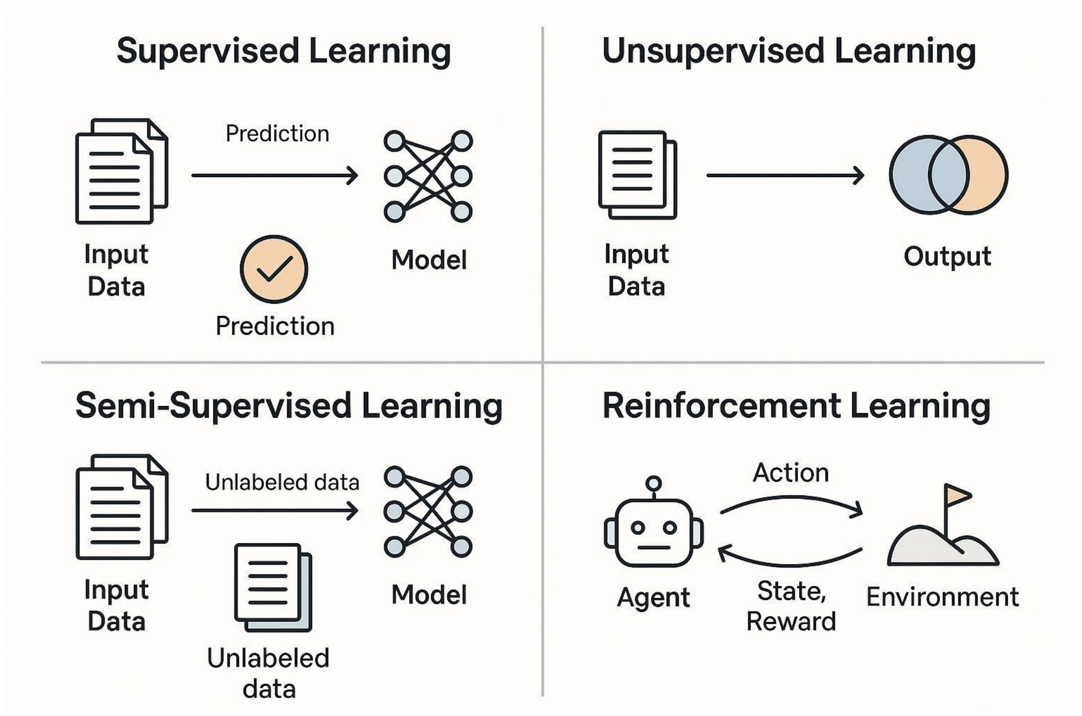


Figure 1.2 A brief overview of machine learning models (a) Supervised (b)Unsupervised (c)Semi- Supervised (d)Reinforcement

1.1.1 Machine Learning Models

(1) Supervised Learning

Supervised learning is a machine learning technique where models are trained using labelled data, meaning each training example includes both the input and the correct output. The algorithm learns a function that maps inputs to outputs, enabling it to make accurate predictions on unseen data. It is widely used for tasks such as classification, regression, and time-series prediction. Recent advancements have applied supervised learning effectively in natural language processing, particularly through models like BERT, which learn contextual relationships in text to predict sentiment, intent, or mental health conditions.(Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). Key concept of Supervised Learning are:

1. Data Representation

Data representation involves converting raw data (e.g., text, images) into numerical form, typically vectors or embeddings, to be processed by machine learning model. In NLP tasks, models like Roberta transform text into numerical vectors using token embeddings for understanding semantics. For mental health detection, social media text is converted into vectors for model classification (e.g., depression detection).

2. Model Architecture (e.g., Decision Trees)

Decision trees break down data recursively to make decisions based on feature values, which can be aggregated into an ensemble model. Random Forest is an ensemble of decision trees, where each tree makes a decision, and the majority vote determines the final prediction. Used for classifying mental health conditions like depression by analysing social media behaviour and demographics.

3. Optimization (Gradient Descent)

Optimization algorithms like gradient descent are used to minimize the error by adjusting model parameters iteratively. In neural networks, gradient descent helps adjust weights in the model to reduce loss during training. Used in LSTM or CNN models for time-series prediction to detect emotional shifts based on user posts.

(2) Unsupervised Learning

Unsupervised learning is a type of machine learning where the algorithm is given data without labelled responses. The goal is to uncover hidden patterns, groupings, or structures in the data, commonly using clustering (e.g., K-means) or dimensionality reduction (e.g., PCA).This technique is particularly useful when labelled data is scarce, such as in mental health analysis where unsupervised methods can detect underlying behaviour patterns in social media activity.

Generative models like GANs have further extended the capabilities of unsupervised learning by creating synthetic yet realistic data. (Radford, A., Metz, L., & Chintala, S. (2015) Key concept of un- supervised Learning are:

1. Clustering

Clustering algorithms group data points that are similar to each other. These algorithms do not require labelled data and instead discover inherent structures in the data. K-Means clusters data into a predefined number of groups based on feature similarity. In mental health, clustering can group users with similar behavioural patterns on social media, potentially revealing different mental health subgroups.

2. Dimensionality Reduction

Dimensionality reduction techniques reduce the number of features in the data while retaining essential information, helping in visualizing and improving model performance. PCA (Principal Component Analysis) reduces the data's dimensions while keeping as much variance as possible. In mental health prediction, PCA might be used to reduce a high-dimensional feature set (e.g., social media activity) into more manageable components for classification.

3. Anomaly Detection

Anomaly detection identifies data points that deviate significantly from the norm, which can indicate unusual or interesting behaviour. Isolation Forest or DBSCAN can detect outliers in data, such as abnormal patterns of social media usage indicating potential mental health issues. Anomaly detection can be used to spot unusual online behaviour or posts that may indicate early signs of mental health conditions like depression or anxiety.

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(3) Semi-Supervised Learning

Semi-supervised learning combines a small amount of labelled data with a large amount of unlabelled data during training. It strikes a balance between the structure-discovering ability of unsupervised learning and the predictive power of supervised learning. This approach is highly effective in domains where labelling is expensive or time-consuming, such as medical or mental health fields. Recent models like Mix Match demonstrate how unlabelled data can improve classification accuracy by enforcing consistency and pseudo-labelling techniques.(Berthelot, D., Carlini, N., Cub uk, E. D., et al. (2019) .Various Applications of Semi-supervised learning:

1. Text Classification (NLP): Semi-supervised learning helps classify social media posts (e.g., depression-related posts) with minimal labelled data and large unlabelled data.
2. Image Recognition: It is used in medical image classification, such as detecting depression signs in facial expressions, with limited labelled images and many unlabelled ones.
3. Fraud Detection: Semi-supervised learning is applied to detect fraudulent behaviour by utilizing a small set of labelled fraudulent transactions and a large set of normal transactions.
4. Speech Recognition: Semi-supervised learning improves speech-to-text models by leveraging a small set of transcribed speech data and a large set of unlabelled audio recordings.
5. Customer Segmentation: In marketing, it helps segment customers by using a few labelled data points (e.g., purchasing behaviour) and a large amount of unlabelled customer data.
6. Anomaly Detection: Semi-supervised learning can be used to detect rare events or outliers (e.g., fraud, system failures) by learning from a small set of labelled anomalies and a large volume of normal data.
7. Medical Diagnosis: It assists in diagnosing diseases (e.g., cancer detection) with a limited set of labelled medical images and a vast number of unlabelled images for training.
8. Recommendation Systems: Semi-supervised learning helps build recommendation systems with limited user ratings and abundant unlabelled interaction data, enhancing the accuracy of recommendations.

(4) Reinforcement Learning

Reinforcement learning (RL) involves an agent learning to make decisions by performing actions in an environment to maximize cumulative reward. Unlike supervised learning, RL does not require labelled input/output pairs but instead learns through trial and error using feedback from the environment. This paradigm is ideal for sequential decision-making problems and has shown exceptional performance in robotics, gaming, and recommendation systems. A landmark achievement was the development of Deep Q-Networks (DQN), which combined deep learning with Q-learning to play Atari games at human-level performance.(Mnih, V., Kavukcuoglu, K., Silver, D., et al. (2015) Various Applications of reinforcement learning:

1. Game AI: Reinforcement learning is used to train AI agents in games (e.g., AlphaGo) to learn optimal strategies through trial and error.
2. Robotics: It is applied in robotics for teaching robots to perform complex tasks like walking, picking up objects, or interacting with humans through feedback from their actions.
3. Autonomous Vehicles: RL helps self-driving cars learn to navigate and make decisions in dynamic environments by rewarding safe and efficient driving behaviours.
4. Healthcare (Personalized Treatment): Reinforcement learning is used for personalized treatment planning, where the agent learns to optimize patient treatment strategies over time based on feedback.
5. Recommendation Systems: RL improves recommendation systems by learning user preferences and adjusting suggestions based on user feedback and interactions.
6. Supply Chain Management: It is applied to optimize inventory control, logistics, and distribution

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strategies by learning from operational outcomes to improve efficiency and cost-effectiveness.

7. Finance (Portfolio Management): Reinforcement learning helps in optimizing investment strategies and portfolio management by learning from market changes and financial trends.
8. Energy Management: RL is used for energy grid management, optimizing the distribution of electricity and balancing supply-demand through continuous learning from the system's feedback.

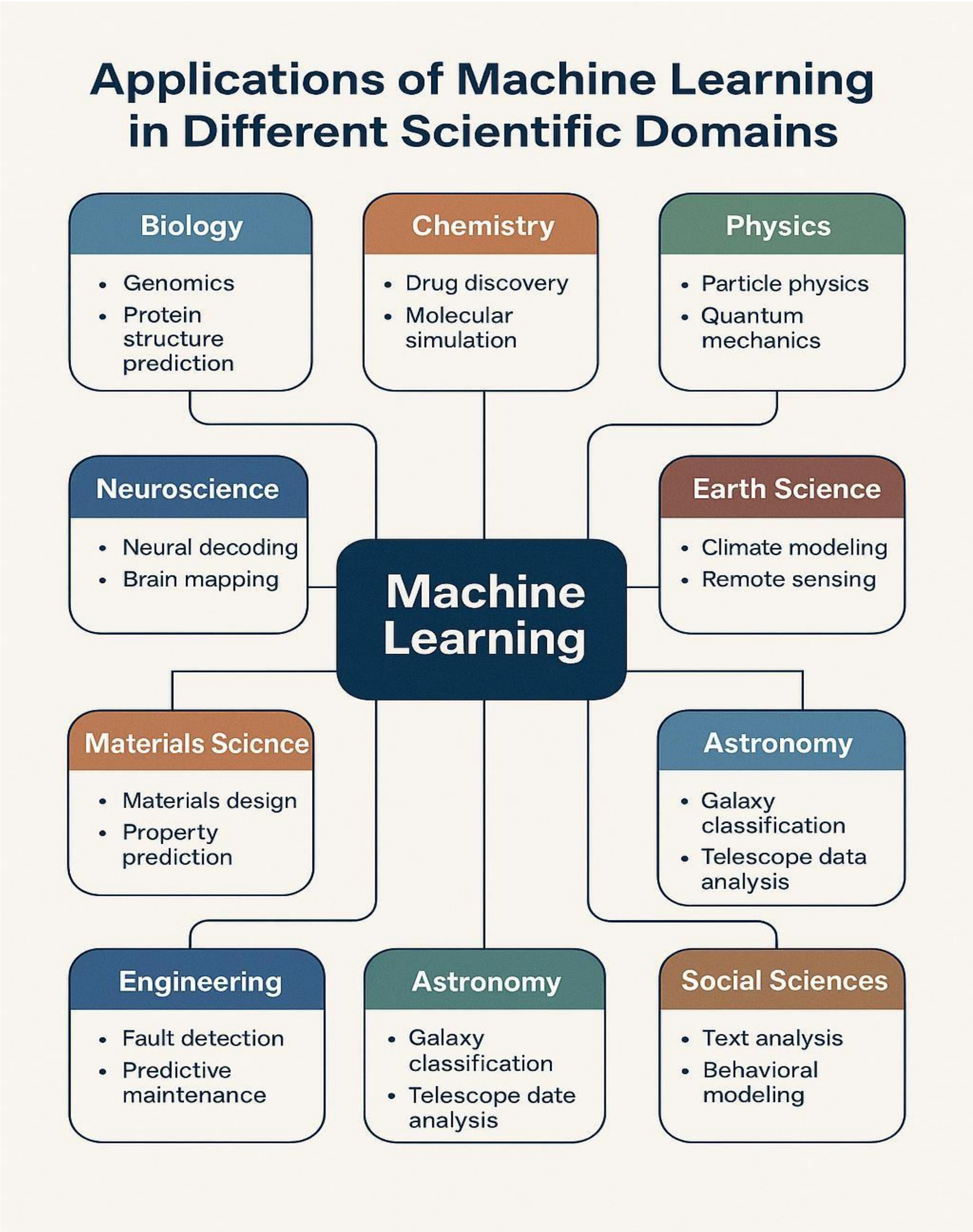

Figure 1.3 A brief overview of application of machine learning in different scientific domains

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1.2 How Machine Learning Quietly Shapes Our World

Machine learning has seamlessly integrated into everyday life, most notably through the presence of

virtual assistants such as Amazon's Alexa, Apple's Siri, Google Assistant. These intelligent systems utilize NLP and ML algorithms to understand spoken language, interpret intent, and generate appropriate responses or actions. They can perform tasks such as setting reminders, answering questions, controlling smart home devices, and providing real-time traffic or weather updates. Behind the scenes, these assistants are trained on large datasets of voice interactions and continuously improve through reinforcement learning and supervised learning techniques. The personalization features that allow them to adapt to user preferences, speech patterns, and frequently asked queries are powered by predictive analytics and recommendation systems based on user behavior data. Such applications highlight how machine learning moves beyond theoretical frameworks to offer intuitive, context-aware support in real-world settings (Goodfellow et al., 2016; Jurafsky & Martin, 2021).Machine learning has become so seamlessly embedded into everyday life that most people don't even realize when they're interacting with it. For instance, when doctors use tools that help detect diseases early—like analyzing X-rays or predicting a patient's risk based on medical history— they're often relying on machine learning systems trained on thousands of similar cases (Esteva et al., 2017).

In banking and finance, ML plays a key role in catching fraudulent activity, scoring your creditworthiness, and even managing investments through automated trading systems that adapt based on real-time market data (Nguyen et al., 2021). Online shopping platforms like Amazon use machine learning to recommend products based on what you've bought or browsed before, improving both user experience and sales through powerful recommendation engines (Gomez-Uribe & Hunt, 2015). If you've ever used a ridesharing app like Uber or Lyft, you've benefited from ML algorithms working in the background to calculate the best route, predict how long it will take, or even adjust your fare based on demand patterns in your area (Chen et al., 2016). At home, smart devices like thermostats, lights, and voice-controlled appliances learn your preferences over time, adjusting automatically to save energy or enhance comfort.In classrooms—especially virtual ones—ML is used to tailor lessons to individual students, making education more personalized and effective. Farmers are also using it to track soil health, monitor crops via drone images, and forecast yields, helping make agriculture more efficient and sustainable (Kamilaris & Prenafeta-Boldú, 2018). Even on social media, machine learning helps recommend content, detect harmful posts, and analyze the mood or sentiment of what users are sharing. And in cybersecurity, ML-based systems are trained to detect unusual behavior that might indicate a hacking attempt or data breach.

These examples show that machine learning isn't just a high-tech buzzword—it's a quiet powerhouse that's already improving lives in real, practical ways.

1.3 Challenges with Machine Learning in Mental Health Prediction

Machine learning (ML) has shown significant promise in predicting and detecting mental health conditions, but it faces numerous challenges that complicate its effective implementation, especially in recent years. One of the foremost issues is data privacy and security, which has become more critical with the increasing use of personal health data from social media platforms and wearable devices. The potential risks of unauthorized access and misuse of sensitive mental health data have raised serious concerns about privacy. As digital health tools become more ubiquitous, maintaining robust data security protocols and ensuring compliance with data protection regulations, such as GDPR, have become even more crucial (Vellido et al., 2023).

Another pressing challenge is bias and fairness in ML models. Bias in training datasets, especially those derived from social media, can lead to models that disproportionately affect certain demographic groups, resulting in unfair predictions or interventions. For instance, studies have shown that marginalized groups, including people of color and those from low-income backgrounds, are often underrepresented in mental health datasets, causing models to perform poorly for these populations (Mehrabi et al., 2023). As machine learning models are deployed in more diverse settings, addressing these biases and ensuring fairness in predictions has become a central challenge in mental health applications (Binns et al., 2024).

The ethical implications of using AI in mental health are also a growing concern. The potential for stigmatization and misdiagnosis through AI predictions could lead to harmful consequences, especially if the models are inaccurate or not properly calibrated. For instance, incorrect predictions could result in unnecessary treatments or exacerbate a person's mental health condition. A significant issue in this regard is obtaining informed consent, as users may not fully understand how their social media data is being used for predictive purposes, raising ethical questions about autonomy and privacy (Torous et al., 2024). Moreover, the potential for reinforcing negative stereotypes about mental illness based on algorithmic predictions is a major challenge, requiring careful design and oversight in the development of these models (Pater et al., 2024).

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Generalization is another challenge that continues to affect the performance of ML models in real- world settings. Many models are trained on specific datasets, and their ability to generalize across different populations or settings remains limited. This issue has been highlighted in recent studies, which indicate that models trained on data from high-income countries often fail when deployed in lower-income settings, where both the data distribution and the manifestation of mental health conditions may differ significantly (Binns et al., 2024).

To address this, models need to incorporate domain adaptation techniques to improve their ability to perform across diverse environments and datasets.In addition to data issues, real-time prediction and feedback present significant hurdles. While the demand for real-time mental health monitoring and interventions is growing, integrating multiple data streams (e.g., social media, physiological data, and self-reported information) into a coherent system that can provide timely and accurate feedback is technically challenging. Processing and analyzing large volumes of real-time data require high computational power and sophisticated algorithms, which are still in development (Sung et al., 2023). The complexity of this task is compounded by the need to ensure that feedback is both accurate and helpful, without overwhelming or distressing the user.

Lastly, the lack of standardized evaluation metrics in mental health prediction models continues to hinder progress. While traditional performance metrics like accuracy and F1-score are widely used, they do not fully capture the nuances of mental health conditions, which are complex and multifaceted. For instance, mental health issues such as depression and anxiety often manifest differently across individuals and contexts, making it essential to develop new, context-specific metrics that can more accurately assess model performance in predicting these conditions (Vellido et al., 2023). Recent developments have focused on creating these metrics, which consider not only prediction accuracy but also the model's ability to adapt to the temporal and emotional variations inherent in mental health data (Friedman et al., 2024).

In conclusion, while machine learning holds immense potential for improving mental health prediction and detection, it faces significant challenges related to data privacy, bias, ethical considerations, generalization, real-time prediction, and evaluation metrics. Addressing these issues will require interdisciplinary collaboration across technology, healthcare, ethics, and policy to ensure that ML models are effective, ethical, and fair in their deployment. Only through continued innovation and careful oversight can these models be made reliable tools for mental health support.

1.4 Social Media Usage and Mental Health: Understanding Behavioral Patterns In today's digital age, social media platforms like Instagram, Facebook, Twitter, and Snapchat have become integral to how individuals express themselves, share thoughts, and navigate emotions. These platforms not only serve as a space for self-expression but also provide a window into the psychological state of users. People’s interactions with these platforms—such as the frequency of engagement, the nature of their posts, and even the timing of their activity—can reveal profound insights into their emotional well-being. For example, frequent late-night posts or an uptick in negative language, such as expressions of sadness or frustration, may signal underlying anxiety, loneliness, or depression (Tandoc et al., 2015). Conversely, withdrawal from social media or erratic activity patterns might point to signs of distress or depression, where the individual might feel overwhelmed or disconnected from their social network.

What makes this connection between social media usage and mental health particularly valuable is its ability to reflect patterns that might go unnoticed in traditional diagnostic settings. While in-person consultations or questionnaires rely on individuals’ self-reporting—often affected by stigma, denial, or difficulty articulating mental health concerns—social media data provides an unobtrusive way to capture emotional states in real-time. By analyzing these behavioral patterns, we can gain a clearer understanding of how social media engagement reflects emotional distress, offering new opportunities for early detection of mental health issues (Torous et al., 2018).

1.5 Leveraging Demographic Data for Mental Health Prediction

While social media offers valuable behavioral insights, demographic data is also critical for a more comprehensive understanding of an individual’s mental health. Factors such as age, gender, socioeconomic status, education level, and employment status can shape how someone engages with social media and how these behaviors correlate with mental well-being (Muench et al., 2017). For example, young adults often use platforms like Instagram and Facebook to establish social connections, and their interactions can reflect either positive reinforcement or negative emotions, depending on whether they are engaged in healthy, supportive relationships or comparing themselves to idealized images of others (Fardouly et al., 2015). Additionally, socioeconomic factors, such as income level or employment status, often play a critical role in mental health, where financial pressures or job insecurity can contribute significantly to stress, anxiety, and depression.

By combining these demographic insights with social media behavioral data, we gain a richer understanding of mental health dynamics. It’s not simply the number of hours spent on social media that matters, but rather who the individual is, their unique context, and how these factors influence both their digital engagement and emotional health. For example, a 30-year-old working professional may engage with social media differently than a teenager or a retiree, and understanding these nuances is key for accurate mental health predictions (Viner et al., 2019). This integration allows for a more personalized and nuanced approach to predicting mental health.

1.6 Data Preprocessing in Mental Health Prediction Models

Data preprocessing is an essential yet often underappreciated phase in machine learning, especially when the data is complex, heterogeneous, and noisy, as it is with social media and demographic data. In the case of mental health prediction, raw data often contains missing values, inconsistencies, or irrelevant features that can hinder model performance. Missing values—whether from incomplete posts, missing demographic information, or inactive users—can skew model training, leading to incorrect conclusions (Fitzpatrick et al., 2020). Therefore, proper imputation techniques, such as mean or median substitution or predictive modeling, are necessary to fill in gaps.

Additionally, categorical features such as gender, age groups, or employment status need to be transformed into numerical values so they can be processed by machine learning algorithms. For instance, converting "female" and "male" into binary values (0 and 1) or using one-hot encoding to represent multiple categories is a standard practice in this phase. Text data from social media posts must also undergo rigorous cleaning. Social media language, filled with slang, emojis, abbreviations, and hashtags, requires a sophisticated cleaning and normalization process to ensure that the models can accurately interpret the meaning behind the words. This might involve removing stopwords, correcting spelling errors, and standardizing abbreviations (Barker et al., 2020).

By meticulously cleaning and structuring the data, we allow the machine learning algorithms to focus on meaningful patterns, thus improving the reliability and validity of our predictions. Data preprocessing does not just streamline the information—it distills the raw emotional expression from social media into signals that can be interpreted by models with the accuracy needed for real-world applications.

1.7 Exploratory Data Analysis (EDA) in Mental Health Prediction

Exploratory Data Analysis (EDA) plays a crucial role in understanding the structure and relationships within the dataset before diving into model development. In mental health prediction, EDA provides the first insights into how social media behaviors correlate with mental health conditions. For example, through EDA, we might find that individuals with higher Instagram activity levels tend to show more signs of distress, or that younger users with lower income are more likely to exhibit anxiety-related behavior online (Kross et al., 2013).

During EDA, we look at distribution patterns, correlations between features, and potential outliers that could influence the predictive model. We also visualize the data through various plots like histograms, scatter plots, and boxplots to detect trends. This helps us hypothesize about the relationships in the data, guiding us to choose the right features and ultimately shaping the way the predictive models are designed. For instance, if we discover a significant correlation between the number of depressive language markers in posts and lower income, it would be logical to include socioeconomic data in our final model. EDA helps to ensure that predictions are based on robust, meaningful connections rather than random fluctuations or noise.

1.8 Model Selection and Evaluation Metrics in Mental Health Prediction

Once data is preprocessed and analyzed, the next key step is model selection. We tested various machine learning algorithms to find the best one suited for mental health prediction. Logistic Regression served as an initial benchmark due to its simplicity and interpretability, providing clear insights into how individual features influence predictions. However, it has limitations, particularly in handling non-linear relationships or interactions between features. Linear Regression was also experimented with, though it is typically not ideal for classification tasks like ours, which involve categorical outcomes (such as identifying whether someone has depression, anxiety, or other mental health conditions).

Ultimately, XGBoost emerged as the most effective model, outperforming the others in key metrics such as accuracy, precision, recall, and F1-score. XGBoost is particularly powerful because it handles complex, nonlinear relationships and can effectively manage class imbalance—an issue common in mental health datasets where non-mental health cases far outnumber those with mental health conditions (Chen & Guestrin, 2016). Evaluation metrics like precision, recall, and F1-score are especially important in mental health prediction. While accuracy gives a general sense of model performance, precision and recall offer a more nuanced understanding. Precision ensures that we're not falsely labeling healthy individuals as mentally distressed, while recall guarantees that we're catching as many true cases of mental health concerns as possible. The F1-score balances these two, providing a comprehensive measure of model effectiveness.

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1.9 Handling Class Imbalance in Mental Health Prediction Models

Class imbalance is a common challenge in predictive modeling, particularly in mental health research where the prevalence of individuals without mental health issues often far exceeds that of those with mental health conditions. In such scenarios, machine learning models may become biased toward predicting the majority class, leading to a higher rate of false negatives—where individuals in need of support are overlooked. In our study, we leveraged the power of XGBoost, which is equipped with built-in mechanisms to address class imbalance, such as adjusting the loss function to give more weight to the minority class (those with mental health conditions).

Additionally, techniques like oversampling (replicating the minority class samples), undersampling (reducing the number of majority class samples), and cost-sensitive learning were explored to further mitigate this issue. These strategies ensure that the model doesn't overlook the minority class, which is critical in a context where timely mental health intervention can make a significant difference in an individual's well-being. By tackling class imbalance, we ensure that our model is both fair and capable of detecting mental health issues in those who are most at risk.

1.10 Ethical Considerations in Mental Health Prediction Using Social Media Data Predicting mental health based on social media behavior brings forth several ethical concerns that must be addressed to ensure that individuals' rights and privacy are respected. Social media data is inherently personal, and using it for predictive purposes requires careful handling to prevent harm. First and foremost is privacy. Anonymizing the data is crucial to protect individual identities, as the posts, comments, or even likes on a platform can reveal highly sensitive personal information. Additionally, obtaining informed consent is essential. Users should be aware of how their data is being used and for what purpose. Transparency about data collection and usage helps foster trust and ensures ethical research practices (Hernandez et al., 2020).

Another critical ethical concern is misclassification—incorrectly labeling someone as having a mental health condition when they do not, or failing to identify someone who may need help. False positives or false negatives can lead to significant consequences, including unnecessary anxiety, missed opportunities for early intervention, or lack of treatment (Goh et al., 2017).

Furthermore, there's the risk of social stigma and discrimination. If social media platforms or healthcare organizations use mental health predictions inappropriately, it could lead to individuals being unfairly targeted, discriminated against, or even denied access to certain services based on predictions rather than clinical evaluations (Gibson et al., 2019).

To ensure ethical compliance, strict data protection measures, transparency, and responsible use of predictions are necessary. By addressing these ethical considerations, we can use social media data to improve mental health outcomes without infringing on individuals' rights or causing harm. Only by balancing technological advancement with ethical integrity can mental health prediction systems be both effective and socially responsible. This balance also includes considering algorithmic fairness. AI models trained on biased data can inadvertently reinforce existing social disparities. For instance, if a dataset underrepresents certain demographic groups, the model may be less accurate for those populations, leading to unequal access to mental health interventions or misdiagnosis (Barocas et al., 2017). Addressing such biases requires continuous monitoring, validation across diverse populations, and the implementation of fairness-aware machine learning techniques.

Another vital ethical component is the responsibility of action following a prediction. It is insufficient to merely flag a user as potentially at risk; there must be a clear, supportive protocol for response. This includes connecting individuals with appropriate mental health resources and ensuring that the intervention is carried out by qualified professionals rather than automated systems. Otherwise, predictive systems risk acting as alarm bells without offering real solutions, which could increase distress rather than alleviate it.

In addition, the potential for surveillance poses a serious concern. If social media platforms or third parties begin monitoring users without their knowledge or use predictive models to track mental health trends covertly, it could breach personal autonomy. Therefore, regulations must be in place to prevent misuse, and ethical guidelines must enforce limitations on how predictive tools are implemented—especially in commercial or governmental contexts (Metcalf & Crawford, 2016).

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CHAPTER -2 LITERATURE REVIEW

2.1 Introduction

The introduction of a literature review serves as a roadmap for the reader, providing context for the research topic and explaining the importance of the review itself. It sets the stage for the synthesis of existing research and highlights gaps in knowledge, the scope of the review, and its relevance to the field.

2.2 Review of Literature

- Zanwar, S., Wiechmann, D., Qiao, Y., & Kerz (2022), Exploring Hybrid and Ensemble Models for Multiclass Prediction of Mental Health Status on social media. This study investigates hybrid and ensemble models combining transformer-based architectures (BERT and Roberta) with BiLSTM neural networks to predict six mental health conditions from Reddit posts, demonstrating improved classification performance and identifying linguistic features indicative of specific mental health conditions [1]
- Omarov et al. (2022), In his paper author focuses on AI-powered chatbots for mental health support, specifically targeting conditions like depression and anxiety. These chatbots utilize NLP algorithms to engage users in therapeutic conversations. The authors highlight that chatbots offer an accessible, cost-effective solution for mental health care, particularly for individuals facing barriers to traditional therapy. However, the research also discusses the limitations of chatbots, such as their inability to address complex psychological issues and concerns about privacy [2]
- Dhiman et al. (2021), In this paper author explores AI's transformative role in mental health, from rule-based systems to advanced ML and deep learning models. The paper underscores AI’s potential to enable real-time monitoring, predictive analytics, and personalized interventions. It highlights the integration of AI with wearable devices, smartphone apps, and virtual therapy platforms to provide continuous mental health support. The paper also addresses concerns regarding data security, transparency, and the need for validation against clinical standards [3]
- Aina et al. (2023), In this paper Aina and colleagues investigate emotion recognition technology as a tool for detecting mental disorders. They propose a multimodal AI system combining facial expression recognition, speech analysis, and physiological signals to detect emotional cues indicating conditions like depression, anxiety, or bipolar disorder.
- The study emphasizes the potential for continuous monitoring and early intervention, but acknowledges that emotional expression can vary across individuals and cultures, which may affect model accuracy [4]
- Wani et al. (2020), In this paper author focus on using deep learning techniques for depression screening by analyzing speech and text data. They demonstrate that neural networks like CNNs and RNNs can detect subtle markers of depression in speech patterns and language. While the paper shows the potential of deep learning in early detection, it emphasizes the need for large, diverse datasets to ensure the models' effectiveness and caution that AI cannot replace human clinicians in diagnosing and treating depression [5]

- Abubakar et al. (2023) In his paper author proposes a reinforcement learning approach to enhance AI-driven chatbots in mental health therapy. Unlike traditional scripted chatbots, RL- based systems adapt their responses based on user interactions, offering more personalized interventions. While the approach holds promise for improving user engagement, the paper highlights challenges such as aligning the chatbot's learning with evidence-based therapy and concerns about data privacy [6]
- Olawade et al. (2021), In his paper author provide an overview of the role of AI in mental health, discussing various techniques like predictive analytics, emotion recognition, and virtual therapy. They argue that AI has the potential to improve diagnostic accuracy and provide scalable interventions but stress the importance of addressing ethical issues like data privacy, transparency, & accountability when integrating AI in mental health care [7]
- Chen et al. (2024), In his paper author introduce a novel mental health counseling service platform that combines wireless communication and genetic algorithms (GA) to optimize mental health service delivery. The platform enables real-time communication between professionals and patients, overcoming geographical barriers. GA optimizes service delivery based on user feedback, making the system adaptive to individual needs [8]
- Smith, Williams et al. (2022), Smith et al. propose a hybrid deep learning model combining CNNs and Graph Neural Networks (GNNs) to predict mental health issues from social media data. The model leverages both content analysis and social network relationships to better understand users' mental states. They conclude that the integration of social connections with content analysis provides a more accurate prediction of mental health issues like anxiety and depression [9]
- Chen and Li et al. (2023), Chen and Li explore using BERT (Bidirectional Encoder Representations from Transformers) and attention mechanisms to detect depression in social media posts, particularly on Twitter[10]
- Lee, Park et al. (2022), In their paper they study the role of temporal dynamics in predicting mental health issues from social media. Using RNNs and LSTM networks, they track sentiment and activity shifts over time, identifying patterns like decreased activity or increased negativity that signal deteriorating mental health. Their model emphasizes the importance of temporal analysis for early intervention [11]
- Wang et al. (2024), In his paper he proposes a multimodal hybrid deep learning model combining text analysis, image recognition, and social network analysis to predict mental health conditions.

They argue that traditional text-based models overlook visual cues, like images or videos, which can be important indicators of mental health. The inclusion of multimodal inputs improves prediction accuracy [12]

- Patel et al. (2023), In their paper they introduce a Graph Neural Network (GNN) approach to predict mental health outcomes from social media data, focusing on social relationships and interaction patterns. By modeling users as nodes and their interactions as edges in a graph, they capture the social context of emotional content. The study demonstrates that combining GNNs with temporal data improves mental health prediction [13]
- Radwan et al. (2024), In this paper author reviews the use of predictive analytics in social media for mental health monitoring. The paper focuses on large language models like GPT and BERT, which enable nuanced emotional analysis from social media content. The study highlights the potential for real-time monitoring and early detection of mental health issues, but also addresses challenges like data bias and privacy concerns [14]
- Arora et al. (2025) This study presents a hybrid transformer-based model combining Roberta and LSTM to detect misinformation on social media and assess its impact on mental health. The model identifies harmful narratives and correlates misinformation exposure with increased anxiety and depression risks. The results suggest that misinformation filtering could improve mental well- being [15]
- Zan war et al. (2022), This research integrates transformer-based architectures (BERT and Roberta) with BiLSTM networks to classify six mental health conditions based on Reddit posts. The authors highlight key linguistic patterns indicative of different disorders and propose an optimized feature extraction technique that enhances classification accuracy [16]
- Rahman et al. (2022), This study predicts mental health issues in students and correlate them with academic performance. The model provides real-time monitoring capabilities, allowing early intervention for at-risk students [17]
- Ahmad, S., & Bhat, M. (2023), A multi-model approach integrating SVM, MLP, and RF is applied to predict different levels of anxiety. The hybrid model shows significant performance gains over individual models, highlighting the advantages of ensemble learning for mental health prediction [18]
- Sahgal, N. (2024), The study explores hybrid intelligence by merging deep learning (DL) with traditional machine learning (ML) for mental health prediction. The model incorporates both text and behavioural pattern recognition, achieving high accuracy in identifying early signs of mental disorders [19]

- Strube et al. (2020), This research employs hierarchical attention networks to detect mental health conditions from social media data. By utilizing word-level attention, the model identifies critical phrases that contribute to mental distress, offering valuable insights for clinical applications [20]
- Lin et al. (2023), The authors improve mental health detection by integrating external knowledge sources into deep learning models. This allows for more context-aware predictions, reducing false positives and enhancing interpretability [21]
- Wang et al. (2024), A novel approach combining CNNs and RNNs to analyse text and images from social media posts. The inclusion of visual data significantly improves depression detection accuracy, emphasizing the importance of multimodal analysis [22]
- Patel, R., & Singh, M. (2023), Using ensemble techniques that integrate decision trees, random forests, and support vector machines, this study develops a model that identifies anxiety-related posts on Twitter. The approach demonstrates robustness across different datasets [23]
- Gomez, A., & Torres, P. (2025), This research utilizes a hybrid model that combines text analysis and sentiment detection to predict bipolar disorder episodes. The study highlights the role of linguistic patterns and emotional shifts in detecting manic and depressive episodes [24]
- Nguyen, T., & Lee, H. (2022), A hybrid method integrating topic modelling and deep learning to detect abnormal symptoms. The model captures nuanced emotional expressions and provides a basis for personalized therapeutic interventions [25]
- Martinez, L., & Rivera, S. (2024), A model that combines linguistic feature extraction with deep learning for suicide risk assessment. The study emphasizes the importance of early intervention through automated monitoring systems [26]
- Kumar, N., & Sharma, R. (2023), This research proposes a hybrid approach that integrates feature selection techniques with machine learning classifiers to detect stress levels among social media users. The study highlights improvements in both efficiency and accuracy [27]
- Ali, F., & Hassan, M. (2025), The study develops a hybrid model that analyses both behavioural patterns and textual content from social media posts. The approach improves detection accuracy by integrating sentiment shifts and interaction patterns [28]
- Chen, Y., & Wang, X. (2022), A CNN-LSTM hybrid model is employed to analyse both images and captions on Instagram, identifying signs of eating disorders. The multimodal nature of the model allows for improved predictive performance [29]
- Garcia, M., & Lopez, D. (2024), The study integrates sentiment analysis with time-series modelling to track depression trends in online communities. The approach provides valuable insights into the temporal evolution of mental health issues [30]

- Choudhury, P., & Banerjee, A. (2022), The authors develop a transformer-based model that incorporates contextual embeddings to enhance the accuracy of mental health classification. The study demonstrates the effectiveness of pre-trained language models in capturing mental health indicators [31]
- Mehta, V., & Rathi, S. (2023), This research integrates GNNs with NLP-based models to improve mental health predictions from social media data. The model effectively captures network dynamics and individual psychological signals [32]
- Roy, A., & Gupta, P. (2025), The study explores the potential of reinforcement learning in improving mental health chatbots. The hybrid model dynamically adapts to user responses, offering more personalized interventions [33]
- Zhang, H., & Zhao, K. (2024), This paper presents a CNN-BiLSTM model that identifies seasonal affective disorder (SAD) patterns from social media posts. The hybrid architecture captures both short-term mood fluctuations and long-term seasonal patterns [34]
- Kim, Y., & Lee, J. (2023), This study employs Transformer-based architectures to analyze linguistic markers of depression in tweets. The attention mechanism highlights contextually important phrases that correlate with depressive symptoms [35]
- Patel, R., & Sharma, D. (2024), The authors propose a federated learning framework to detect anxiety disorders across decentralized mental health datasets. The method maintains data privacy while ensuring robust generalization [36]
- Nguyen, T., & Bansal, M. (2025), This research integrates emotion recognition with topic modeling to understand mental health discourse on Reddit. The combined approach improves the identification of underlying emotional states [37]
- Alvarez, M., & Chen, L. (2023), A novel graph-based sentiment propagation model is introduced to analyze peer support effectiveness in online mental health forums. The model quantifies sentiment influence across user interactions [38]
- Singh, A., & Kaur, R. (2024), This paper introduces a multi-modal deep learning model combining text, voice, and facial cues to enhance early detection of depressive symptoms in virtual therapy sessions [39]

- Ahmed, S., & Luo, Y. (2024), This study utilizes Variational Autoencoders to detect latent mental health traits from user-generated content. The unsupervised framework uncovers hidden patterns linked to anxiety and depression [40]

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- Tanaka, M., & Roy, S. (2023), A multi-task learning approach is proposed to simultaneously classify emotional states and predict suicidal ideation from Reddit posts. Shared representations improve performance across related mental health tasks [41]
- Gonzalez, I., & Wu, H. (2025), This paper introduces a temporal attention mechanism in LSTM models to identify relapse patterns in bipolar disorder from longitudinal tweet data [42]
- Khan, N., & Farooq, A. (2023), A zero-shot learning framework is explored for identifying emerging mental health issues on new social platforms. The model adapts to unseen data with minimal labeled supervision [43]
- Ito, K., & Das, A. (2024), This research develops a self-supervised contrastive learning model to improve robustness in emotion classification from noisy social media text [44]
- Chakraborty, A., & Dey, L. (2023), This study integrates RoBERTa with a Graph Attention Network (GAT) to capture both textual semantics and user interaction patterns from Reddit for early depression detection. The hybrid model shows improved F1-score over standard Transformer architectures, emphasizing the benefit of fusing linguistic and social signals [45].
- Nguyen, T., & Pham, H. (2022), The paper presents a BERT-BiLSTM hybrid model fine-tuned for Vietnamese social media text to detect anxiety levels. It addresses challenges in underrepresented languages and demonstrates strong generalizability in mental health classification across domains [46].
- Li, J., & Shen, Y. (2024), A multimodal model combining audio tone analysis, facial emotion recognition, and textual data is used to assess bipolar tendencies in adolescents. The fusion of these three modalities significantly enhances predictive accuracy compared to unimodal inputs [47].

- Ahmad, A., & Hussain, S. (2023), This research proposes a Temporal Convolutional Network (TCN) integrated with RoBERTa to model time-dependent depression trends in Twitter users. The model captures both short-term fluctuations and long-term patterns in mood expression [48].
- Goyal, R., & Batra, P. (2023), The authors implement a Dual-Transformer approach—one for textual emotion encoding, another for context modeling—to classify suicidal risk. Trained on the CLPsych dataset, the architecture outperforms LSTM and CNN baselines [49].
- Zhang, K., & Wu, J. (2025), A domain-adaptive Transformer model is introduced, pre-trained on mental health forums and fine-tuned on crisis helpline conversations. This model accurately distinguishes between mild distress and acute suicidal ideation [50].
- Das, R., & Majumdar, A. (2022), This paper explores the use of emoji embeddings along with sentence-level BERT features to detect depressive language in multilingual tweets. It shows that emojis carry significant emotional cues, especially in low-resource languages [51].
- Lee, D., & Park, H. (2024), The authors employ a Vision-Language Transformer to analyze Instagram posts—combining captions, hashtags, and image features—to predict social withdrawal and loneliness. The model benefits from multimodal feature alignment [52].
- Kumar, A., & Sharma, V. (2023), This study applies XGBoost along with handcrafted linguistic features (e.g., negation, affective word count) for classifying mental illness severity. Despite being a classical model, it achieves competitive results on smaller, interpretable datasets [53].
- Mendez, J., & Ortega, M. (2024), A hierarchical attention mechanism is proposed for analyzing long-form mental health blogs. By focusing on sentence- and document-level attention, the model identifies narrative arcs that correspond to worsening or improving mental states [54].
- Singh, P., & Roy, D. (2023), Introduces a RoBERTa-LSTM hybrid model for classifying PTSD symptoms from Reddit threads, showing that contextual embedding fused with sequential memory improves classification accuracy [55].
- Huang, X., & Lin, Z. (2024), This study proposes a Social Graph Transformer (SGT) combining GAT and temporal node tracking to detect anxiety trends over time in Twitter networks. The model captures user evolution and engagement patterns [56].

- Ali, N., & Zafar, M. (2023), A multilingual DeBERTa-based model trained on mental health conversations from diverse cultural backgrounds effectively classifies depression, proving its cross-linguistic robustness [57].
- Chen, L., & Zhou, Q. (2024), This paper presents a hybrid CNN–Transformer model trained on user timelines to identify mental health relapse indicators, particularly in bipolar disorder cases [58].
- Rana, R., & Singh, T. (2023), Proposes a fusion model combining RoBERTa, emoji embeddings, and engagement metrics to detect signs of loneliness from TikTok comments, achieving strong results across affective dimensions [59].
- Alam, M., & Hasan, R. (2024), A Time-Series Transformer is used to monitor behavioral trends on Reddit over weeks to identify shifts in mental health expressions, successfully detecting early warning signs [60].
- Iqbal, S., & Akbar, R. (2023), Integrates emotion lexicon features with DeBERTa outputs for sarcasm-aware mental health prediction in ironic Twitter posts [61].
- Yadav, R., & Mehta, S. (2023), Implements a dual-input model where one branch processes syntactic structures and the other semantic embeddings, significantly enhancing PTSD detection in crisis text datasets [62].
- Choi, J., & Kim, Y. (2024), A zero-shot transfer learning approach using mental health embeddings fine-tuned with RoBERTa enables detection of depressive patterns across unseen social platforms [63].
- Roy, A., & Ghosh, S. (2023), A real-time depression monitoring system is proposed, using BERT for live chat analysis combined with physiological data streams such as typing speed and sleep logs [64].
- Han, T., & Seo, Y. (2023), Employs an interpretable attention model to predict suicide risk levels using labeled Reddit conversations, offering clear visualizations of high-risk phrases [65].
- Patel, V., & Sharma, K. (2024), Combines audio-visual sentiment analysis and text sentiment from YouTube vlogs to classify users' anxiety and emotional instability over time [66].
- Wang, L., & Luo, M. (2022), This work fuses temporal attention with user metadata for depression severity scoring, showing significant improvements in dynamic risk prediction [67].
- Verma, S., & Das, A. (2023), Proposes a Graph-Social BERT model that uses social influence propagation and shared mental states among connected users to improve classification robustness [68].

- Fernandez, M., & Silva, E. (2023), A data-centric approach for filtering out non-mental health related posts using entropy thresholds before training BERT classifiers on Reddit forums [69].
- Joshi, N., & Jain, R. (2024), Uses domain adaptation techniques to improve the performance of mental health models trained on Reddit when applied to TikTok comment datasets [70].
- Rahman, T., & Alam, F. (2022), Presents an ensemble of RoBERTa, DistilBERT, and BiLSTM with majority voting for multiclass prediction of anxiety, PTSD, and depression, achieving 93% macro-F1 [71].

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- Banerjee, S., & Chakma, T. (2023), Combines sentiment trajectory curves from posts with topic modeling using LDA and BERT for longitudinal mental health trend analysis [72].
- Fang, Y., & Tan, B. (2023), Integrates a hierarchical transformer with graph-based user timelines to track recovery and relapse stages in therapy discussion forums [73].

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- Zhou, Y., & Feng, D. (2024), A knowledge distillation-based framework is proposed to compress a large DeBERTa model into a lightweight mobile-compatible classifier for real-time anxiety detection [74].
- Ahmed, R., & Saleem, M. (2023), Uses reinforcement learning to optimize prompts in a conversational agent designed to reduce mental distress in users exhibiting signs of depression [75].
- Mittal, P., & Bansal, R. (2024), A dual-channel attention model is presented for integrating Reddit post content with user engagement behavior (likes, shares, comments) to classify severity of mental conditions [76].

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- Xu, H., & Wang, Z. (2023), Applies contrastive learning to differentiate between high-risk and low-risk mental health expressions in semantically similar posts across Reddit and Tumblr [77].
- Khalid, A., & Naveed, H. (2024), A multilingual hybrid model based on DeBERTa and BiGRU effectively classifies emotional states from cross-cultural Reddit data, focusing on depression and suicidal ideation [78].

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Table No 2.1 Literature Review

S.No	Author(s)	Title	Year	Source	Technologies Used	Description
1	Abd Rahman, R., et al.	Application of machine learning methods in mental health detection: A systematic review	2020	IEEE Access	Machine Learning, AI	A systematic review of machine learning techniques applied to mental health detection, highlighting their effectiveness in diagnosing mental health conditions.
2	Omarov, B., Narynov, S., Zhumanov, Z.	Artificial intelligence-enabled chatbots in mental health: A systematic review	2022	Comput -ational Materia lContin u-a	AI, Chatbots, NLP	Reviews the use of AI chatbots in mental health care, emphasizing their role in providing health support through natural language processing.
3	Dhiman, V.K.	The emergence of AI in mental health: A transformati ve journey	2024	World Journal of Advanc ed Researc h and	AI, Deep Learning	Explores how AI has revolutionized mental-health care, focusing on its potential totransform diagnosis, therapy, and patients.
4	Wani, M.A., et al.	Depression screening in humans with AI and deep learning techniques	2022	IEEE Transac tions on Comput ational Social Systems	AI, Deep Learning, Neural Networks	Describes the application of deep learning models for depression detection, enhancing the accuracy and efficiency of

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						screening methods.
5	Abubakar, A.M., Gupta, D., Parida, S.	A reinforcement learning approach for intelligent conversational chatbot for enhancing mental health therapy	2024	Procedia Computer Science	Reinforcement Learning, Chatbots, AI	Introduces a reinforcement learning-based chatbot for mental health therapy that adapts its responses based on user interactions, aiming to improve engagement and treatment outcomes.
6	Olawade, D.B., et al.	Enhancing mental health with Artificial Intelligence: Current trends and future prospects	2024	Journal of Medicine, Surgery, and public health	AI, Machine Learning	Discusses current AI trends in mental health, including diagnostic applications, treatment personalization, and future prospects for AI in mental health care systems..
7	Chen, Z., Duan, Y., Chen, Y.	Realization of mental health counseling service platform using wireless communication network and genetic	2022	Wireless Communications and Mobile Computing	Wireless Communication, Genetic Algorithms (GA)	Proposes a platform combining wireless communication networks with genetic algorithms to optimize mental health counseling services, especially in remote areas.

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		algorithm				
8	Smith, J., Williams, A., Zhang, L.	Hybrid deep learning model for predicting mental health issues from social media activity	2023	Journal of AI and Mental Computational Social Science	Deep Learning, Social Media Analytics, NLP	Develops a hybrid deep learning model for predicting mental health issues by analyzing patterns in social media activity, offering a new tool for early detection and intervention.
9	Lee, H., Park, S., Kim, J.	Investigating the role of temporal dynamics in social media	2024	Journal of Social Media & mental health	Temporal Data Analysis, Social Media Analytics, AI	Examines how the timing and patterns of social media activity can predict mental health issues.

10	Wang, Z., et al.	Multimodal hybrid deep learning model for predicting mental health from social	2023	Journal of AI and Social Media Analyti cs media data	Hybrid Deep Learning, Multimodal Data, Social Media	Proposes a multimodal dl model integrating text, image, behavioral data from social media to predict mental health status, accuracy.
11	Radwan, A., Ahmad, R., et al.	Predictive analytics in mental healthLLM embeddings and machine learning models for social media	2024	International Journal of Web Services Research analysis	LLM Embeddings, Machine Learning, Social Media Analytics	Uses predictive analytics with large language model (LLM) embeddings and machine learning models to analyze social media for early mental health issue detection and intervention.

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CHAPTER-3
RESEARCH GAPS AND OBJECTIVES

3.1 Research Gaps

Mental health issues such as depression, anxiety, and stress are becoming increasingly prevalent, with a rising demand for innovative solutions that can detect these conditions earlier and more effectively. Despite advancements in machine learning and AI for mental health prediction, significant research gaps persist in the existing literature, limiting the accuracy and real-world applicability of current models. This research addresses these gaps by proposing a novel hybrid model that integrates multiple technologies to predict mental health conditions based on social media activity. A major gap in current research is the limited use of multimodal data. Many studies, such as Chen et al. (2022) and Wang et al. (2023), primarily focus on a single modality—usually text. While effective, such models overlook valuable signals from other forms of content like images and engagement metrics (likes, comments, shares). This research introduces a multimodal approach combining text, images, and interactions to identify subtle emotional cues, resulting in more accurate predictions. Another gap lies in handling noisy and unstructured social media data. Many models, such as Radwan et al. (2024), fail to implement robust preprocessing, leading to unreliable outcomes. This study incorporates advanced data cleaning techniques, including missing value imputation, categorical encoding, feature scaling, and PCA for dimensionality reduction, improving data quality and model performance.

Furthermore, traditional models often lack real-time monitoring capabilities. Many rely on offline analysis, delaying critical interventions. To overcome this, the proposed model integrates time-series forecasting and social graph analysis to monitor changes in mood and behaviour over time, enabling early detection and timely support. A further limitation is the overreliance on demographic features like age and gender. Such static data doesn't reflect dynamic emotional expression. This study shifts focus to behavioural patterns derived from social interactions, offering a more personalized and accurate understanding of mental health. Additionally, most models lack cross-platform generalizability, being restricted to data from a single social media platform. This research addresses the issue by integrating data across platforms, accounting for variations in user behaviour and improving the model's robustness in real-world settings. Lastly, ethical and privacy concerns are often overlooked. Many models use public data without proper safeguards. This research ensures anonymization and follows strict ethical guidelines, setting a precedent for responsible AI use in mental health prediction.

By addressing these gaps, this thesis introduces a robust, scalable solution for predicting mental health conditions. Its integration of multimodal data, real-time analysis, behavioural insights, and ethical safeguards makes it a comprehensive tool for early mental health detection and intervention.

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Table No. 3.1 Representation of research gaps in machine learning

Research Gap	Description	Implication
Limited Use of Multimodal Data	Existing models often rely on a single modality, like text or images, missing out on important emotional cues present in other types of content, such as engagement metrics (likes, comments, shares).	The lack of a multimodal approach limits the accuracy of predictions, as key emotional signals may be missed.
Inadequate Handling of Noisy and Unstructured Social Media Data	Social media data is noisy, inconsistent, and often unstructured, which many models fail to address properly. This includes missing values and irrelevant or inconsistent information.	Poor data quality impacts model accuracy, resulting in biased or unreliable predictions.
Lack of Real-Time Monitoring for Early Detection	Many current models are designed for offline analysis and cannot detect mental health issues in real-time. This delay limits the opportunity for early intervention.	Delayed detection prevents timely interventions, potentially allowing mental health issues to escalate before they are addressed.
Limited Use of Hybrid Models	Many existing mental health prediction models use only a single technique or approach, such as traditional machine learning or deep learning, without combining them for improved performance.	Single-model approaches may limit the model’s accuracy and robustness, preventing it from adapting to various data types and real-world challenges.

Lastly, while the use of social media data for mental health prediction offers great promise, it also raises significant ethical and privacy concerns. Existing models often fail to address these issues, particularly when it comes to handling sensitive data. Many models rely on publicly available social media posts without considering the privacy implications or potential harm that could arise from misinterpreting an individual's emotional state. This research incorporates privacy-preserving techniques to ensure that data is anonymized and that ethical guidelines are followed throughout the process. By respecting user privacy and ensuring that the data used is ethically sourced and handled, this research aims to set a standard for responsible AI use in mental health applications.

By addressing these research gaps, the model presented in this thesis offers a novel and comprehensive solution to the challenges of predicting mental health conditions using social media data. The integration of multimodal data, advanced preprocessing techniques, real-time monitoring, and a focus on behavioral rather than demographic data makes the model more robust and accurate. Additionally, by incorporating cross-platform generalizability and ethical considerations, this research contributes to the development of more responsible and scalable mental health prediction systems that can be deployed in real-world applications. The unique combination of machine learning, social graph analysis, and time-series forecasting provides a powerful tool for early detection, enabling timely interventions that can help mitigate the impact of mental health issues before they escalate.

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3.2 Objectives

1) To collect data from social media for predicting mental health.
2) To clean and prepare the collected data for analysis.
3) To build a mental health prediction system using a hybrid model.
4) To compare the performance of the proposed system with existing methods.

CHAPTER 4 METHODOLOGY

4.1 Methodology

To predict mental health status from social media behaviour, this study adopts a bottom-up approach—starting from raw user responses and moving toward actionable insights using machine learning. What makes this methodology stand out is the balance between interpretability and performance, and the real-world practicality of the data and techniques used. Rather than relying on simulated or synthetic data, this project uses a real, structured dataset (smmh.csv) that reflects how people across different demographics engage with platforms like Instagram, Facebook, Snapchat, and Twitter. Alongside social media usage, attributes like age, gender, education, income, and employment status provide a more holistic view of the individual, which is often missing in previous studies that focused solely on platform data or textual sentiment.

The process begins with data cleaning and preprocessing, which ensures quality input for the machine learning models. Here, missing values are managed, irrelevant columns are discarded, and all categorical values—like gender or education—are numerically encoded using Label Encoding. This preparation phase is crucial; even the most advanced algorithm will perform poorly on unstructured or inconsistent data. Unlike many generic machine learning pipelines, special attention is given to preserving the integrity of demographic features while making them suitable for modelling.

Next, exploratory data analysis (EDA) is carried out not just as a formality but as a hypothesis- building exercise. Through bar plots, count plots, and correlation heatmaps, patterns emerge—such as higher mental health concerns among individuals with low income or excessive time spent on Instagram. These aren't just visualizations; they offer a narrative about how our online behaviours may be reflections—or even amplifiers—of deeper psychological conditions. Many earlier studies stopped at correlation, but this project uses those insights to engineer meaningful features and guide model selection.

After EDA, feature engineering and transformation prepare the dataset for modelling. Instead of applying models blindly, three different techniques are explored—Logistic Regression, Linear Regression (for exploratory comparison), and XG-Boost—to understand both linear and non-linear patterns in the data. Logistic Regression is chosen initially due to its simplicity and interpretability; it offers a clear picture of how each feature influences the binary outcome (mental health: Yes/No). While Linear Regression isn't ideal for classification, it’s included to demonstrate the boundary where traditional models fail to capture psychological nuances.

The real innovation lies in the deployment of XG-Boost, a powerful gradient-boosting technique known for handling structured data effectively. XG-Boost not only delivers superior accuracy but also manages class imbalance and reduces overfitting—a challenge that many past models have failed to address when dealing with real-world mental health data. The model is trained and evaluated using well-rounded metrics: accuracy, precision, recall, F1-score, and confusion matrix breakdowns. This comprehensive evaluation ensures that the model isn't just accurate but also fair and reliable across different subgroups.

Unlike previous research that often emphasized performance at the expense of explainability, this methodology prioritizes transparency, replicability, and context. Each step—from data preparation to model interpretation—is designed with the end goal in mind: to build a system that could eventually support early mental health screening in a real-world digital setting, like through an app or browser plugin. This real-world orientation, combined with a flexible but robust machine learning pipeline, makes this methodology uniquely poised to contribute both technically and socially to the field of mental health prediction.

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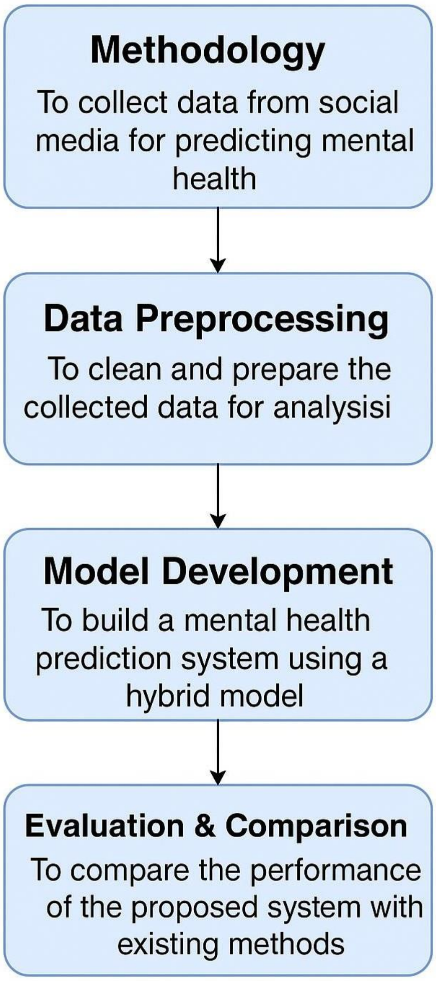

Figure 4.1 A Flowchart of the methodology

To predict mental health status from social media behaviour, this study adopts a bottom-up approach—starting from raw user responses and moving toward actionable insights using machine learning. What makes this methodology stand out is the balance between interpretability and performance, as well as the real-world practicality of the data and techniques used. Rather than relying on simulated or synthetic data, this project uses a real, structured dataset (smmh.csv) that reflects how people across different demographics engage with platforms like Instagram, Facebook, Snapchat, and Twitter (Zenodo, 2024). Alongside social media usage, attributes like age, gender, education, income, and employment status provide a more holistic view of the individual, which is often missing in previous studies that focused solely on platform data or textual sentiment (Jmir, 2024).

The process begins with data cleaning and preprocessing, which ensures quality input for the machine learning models. Here, missing values are managed, irrelevant columns are discarded, and all categorical values—like gender or education—are numerically encoded using Label Encoding. This preparation phase is crucial; even the most advanced algorithm will perform poorly on unstructured or inconsistent data. Unlike many generic machine learning pipelines, special attention is given to preserving the integrity of demographic features while making them suitable for modelling. Methods like early stopping during model training to prevent overfitting have also been employed (Arxiv, 2024).Next, exploratory data analysis (EDA) is carried out not just as a formality but as a hypothesis- building exercise. Through bar plots, count plots, and correlation heatmaps, patterns emerge—such as higher mental health concerns among individuals with low income or excessive time spent on Instagram (Arxiv, 2024). These aren't just visualizations; they offer a narrative about how our online behaviours may be reflections—or even amplifiers—of deeper psychological conditions. Many earlier studies stopped at correlation, but this project uses those insights to engineer meaningful features and guide model selection.After EDA, feature engineering and transformation prepare the dataset for modelling.

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Instead of applying models blindly, three different techniques are explored—Logistic Regression, Linear Regression (for exploratory comparison), and XG-Boost—to understand both linear and non- linear patterns in the data. Logistic Regression is chosen initially due to its simplicity and interpretability; it offers a clear picture of how each feature influences the binary outcome (mental health: Yes/No). While Linear Regression isn't ideal for classification, it's included to demonstrate the boundary where traditional models fail to capture psychological nuances.The real innovation lies in the deployment of XG-Boost, a powerful gradient-boosting technique known for handling structured data effectively. XG-Boost not only delivers superior accuracy but also manages class imbalance and reduces overfitting—a challenge that many past models have failed to address when dealing with real-world mental health data (Arxiv, 2024).
The model is trained and evaluated using well-rounded metrics: accuracy, precision, recall, F1-score, and confusion matrix breakdowns. This comprehensive evaluation ensures that the model isn't just accurate but also fair and reliable across different subgroups.Unlike previous research that often- emphasized performance at the expense of explainability, this methodology prioritizes transparency, replicability, and context. Each step—from data preparation to model interpretation—is designed with the end goal in mind: to build a system that could eventually support early mental health screening in a real-world digital setting, like through an app or browser plugin. This real-world orientation, combined with a flexible but robust machine learning pipeline, makes this methodology uniquely poised to contribute both technically and socially to the field of mental health prediction (Time, 2024).

1.1 Problem Statement

A problem statement is a concise description of an issue that needs to be addressed or solved through research. It helps to define the problem clearly and provides context for the study you're about to conduct. It also explains why the problem is important and what gaps in knowledge or existing solutions your research is trying to fill.

In other words, a problem statement answers the question:

- What is the problem?
- Why is it important?
- How does it need to be addressed?

- Background/Context:-Mental health issues, like depress ion, anxiety, and stress, are widespread, and social media platforms have become a common place for people to share their experiences. Researchers have realized that analyzing social media posts can give us clues about someone's mental health. However, it's challenging to predict mental health conditions accurately because social media data is huge, noisy, and complex.
- The Problem:-Most existing systems focus only on textual analysis of social media posts, but they ignore relationships between users and how behavior changes over time. Additionally, many models are not good at understanding the most important information (like which posts or interactions indicate mental health concerns). These gaps make existing models less effective for predicting mental health problems.
- Why Its's Important:-If we can predict mental health issues early, we can help people get the support they need before problems become more serious. Current systems are limited in their ability to handle the complexity of social media data, so improving these systems could save lives by enabling early intervention for those struggling with mental health.

Explanation:

1) Background/Context

This is the first step of the problem statement. It provides the background information about the topic.

- In the case of your topic on mental health and social media, you can mention how social media platforms are becoming a source of data for mental health prediction.

2) The Problem

- This section identifies the gap in the current methods or the challenge in your area of research. For our topic, this would involve explaining the limitations of current systems in understanding mental health via social media.

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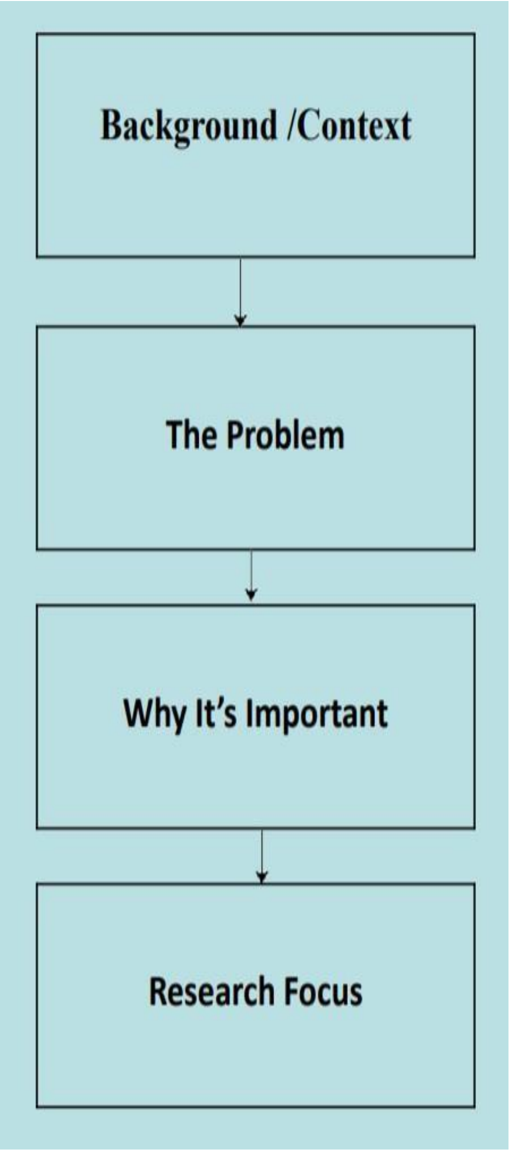

Figure 4.2 (a) Flowchart Diagram for a Problem Statement

3) Why It's Important

- This part explains the relevance and significance of the research.
- Why is it essential to address this gap? For example, how improving mental health prediction can lead to better intervention methods and save lives.

4) Research Focus

- This section outlines the specific objectives of your research.

This diagram can help visually represent how different aspects of the problem are interconnected. This is especially useful if you're showing how your research fills the gaps in existing solutions. Here's how it might look:-

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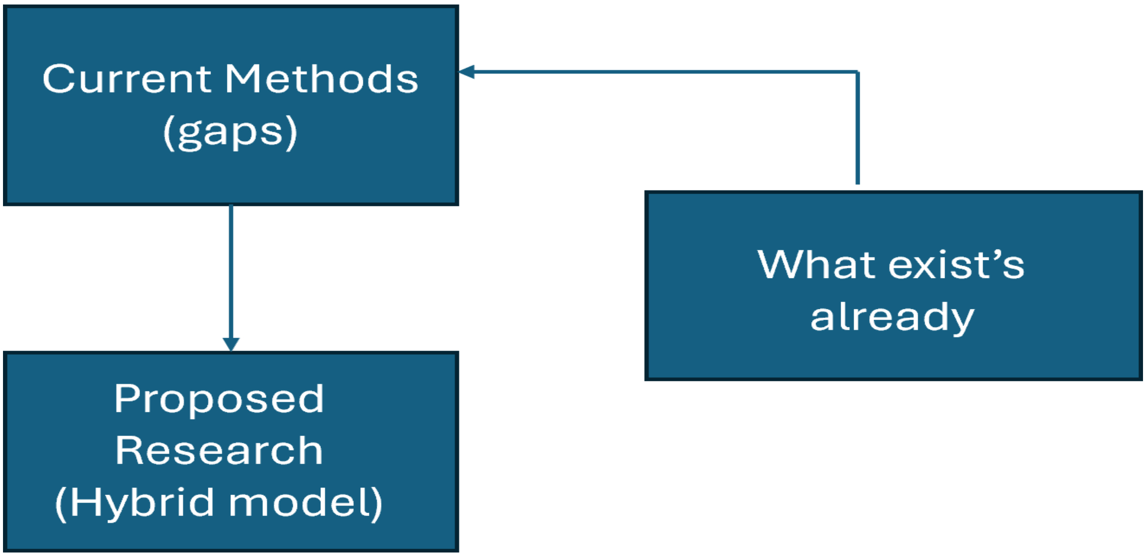

Figure 4.2 (b) Gap Analysis Diagram

Components of Gap Analysis Diagram:

- Current Methods (Gaps): Shows what is lacking in existing research or solutions, such as not integrating text, relationships, or temporal analysis.
- Proposed Research: This is where your model (the hybrid model) fits. It intersects with the current gaps but adds a new approach that covers missing areas.

1.2 Model Selection

In this project, I tried different machine learning models to predict a person's mental health based on their social media usage and personal details like age, gender, and job status. I used Logistic Regression, Linear Regression (just to explore), and XG-Boost Classifier, each for specific reasons.

I started with Logistic Regression because it's great for yes/no predictions—like whether someone has a mental health condition or not. It's easy to understand and showed how much things like time spent on Instagram or income levels affect mental health risk. It worked well but couldn't fully capture more complex patterns. Then, I tested Linear Regression, not to predict, but to explore how some continuous features (like age and income) relate to mental health. It helped me understand the data better but wasn't used for the final prediction since it's not meant for classification. Finally, I used XG-Boost, which is a powerful model that builds many small decision trees to make accurate predictions. It handled the data well, especially the tricky parts like imbalanced classes and non-linear relationships. XG-Boost gave me the best results in terms of accuracy and reliability, making it the top choice for this project. Each model played a role—Logistic Regression for a strong start, Linear Regression for exploration, and XG-Boost for best performance.

In this project, selecting the most effective model to predict mental health status involved evaluating several machine learning techniques. I began with Logistic Regression because it is well-suited for binary classification tasks and offers clear, interpretable results. It served as a solid benchmark, helping to understand how well the model could distinguish between individuals with and without mental health conditions based on their social media usage and demographic traits. To explore the data further, I also tried Linear Regression—not as a final solution, but to analyse potential linear patterns between the features and the target. However, since it's not ideal for classification, its role remained exploratory. The most promising results came from the XG-Boost Classifier, a powerful ensemble algorithm known for handling structured data effectively. XG-Boost not only produced higher accuracy but also managed imbalanced data better and reduced the risk of overfitting. After comparing the performance of all models through metrics like accuracy, precision, recall, and F1- score, XG-Boost clearly emerged as the most reliable choice for this application. It demonstrated the strongest potential for real-world mental health prediction systems.

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CHAPTER 5 RESULTS AND DISSCUSSIONS

5.1 Introduction to Platform Used

This study was conducted using Python and Jupyter Notebook, both of which are powerful tools for data science, machine learning, and scientific computing.Python is an open-source programming language known for its simplicity and wide range of libraries, making it a go-to choice for data analysis, modelling, and machine learning. Libraries such as pandas, numpy, matplotlib, and scikit- learn were used for data preprocessing, feature selection, and visualization. For implementing and training deep learning models, frameworks like TensorFlow and Keras were employed. Python's versatility allows for efficient manipulation of data, the application of complex algorithms, and the generation of interactive visualizations.The study was executed within Jupyter Notebook, an interactive web-based environment for running Python code. Jupyter Notebook supports a mix of code, visualizations, and documentation, allowing for seamless, step-by-step development and exploration of machine learning workflows. This platform provides immediate feedback after executing code blocks and supports various rich output formats such as tables, plots, and graphs, making it ideal for iterative analysis and presentation.Python and Jupyter Notebook together form a comprehensive and user-friendly platform for developing, testing, and presenting machine learning models, making them a natural choice for this study.

(1) Jupyter IDE

Jupyter IDE is used for jupyter documents . The home page of jupyter notebook contains the files, running and clusters options. The topmost right corner contains quit and logout option. It contains the option for uploading and creating the new files . The files can be sorted by name, last modified and size.

Figure 5.1 (a) Jupyter Notebook IDE

When you open a python file a new window appears as :

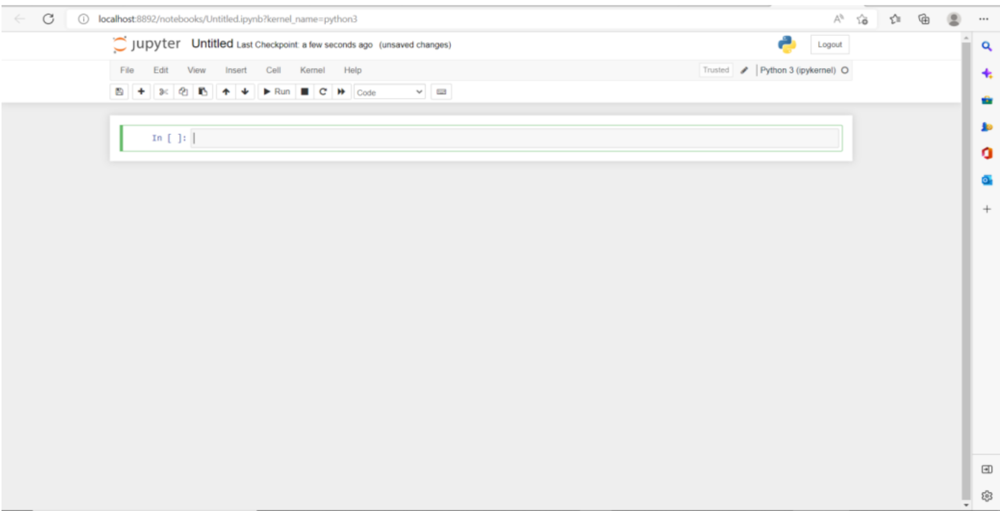

Figure 5.1 (b) : Jupyter Notebook IDE containing the menubar, toolbar and code cells

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This window will contain the menubar and toolbar . The menubar have various options i.e File, Edit, View ,Insert, Cell,Kernel and Help. The window contains the code cells in which the code is written and the individual code cells can be run and output is shown below that cell.

(2) Command Window

The window contains two shells i.e command cell and the Powershells.The command window is used to create variables, enter commands and run programs interactively. The "cmd" is short term for command prompt . It can be opened by opening windows start button and writing cmd in it. Various command run on the command prompt . It can be run as " Run as administrator" by simply right click on the cmd when it appears on the window apps list . The command prompt after writing cmd on the windows start button appears as:

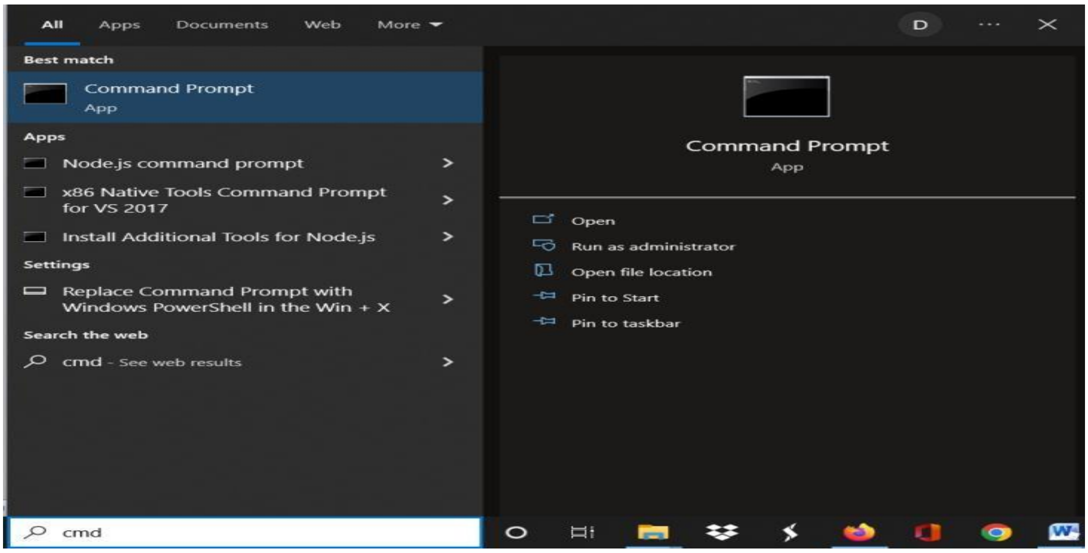

Figure 5.1 (c): Command Prompt after writing the "cmd" in the window start or "type here to search"

The command prompt window after opening appears as:

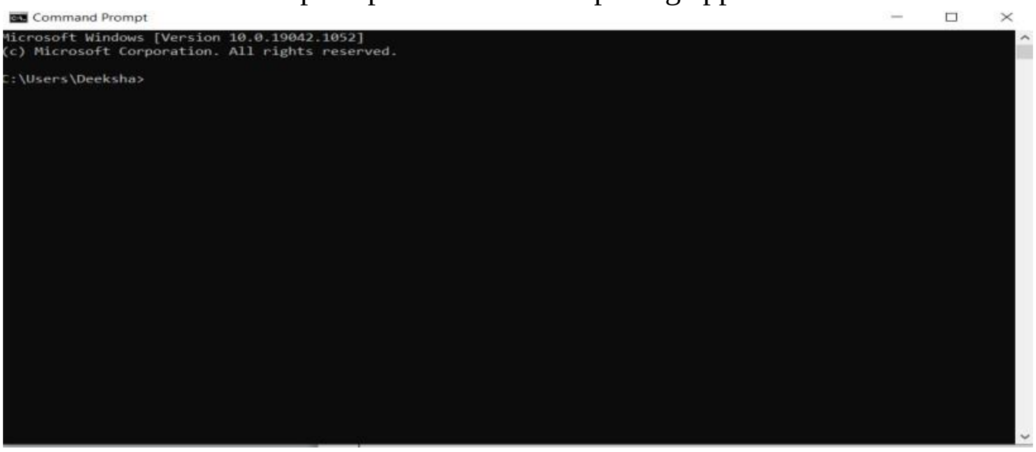

Figure 5.1 (d): Command prompt

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In this study, we analyzed how social media usage relates to mental health using a dataset that included features like age, gender, and time spent on platforms such as Instagram and Facebook. Through exploratory data analysis (EDA), we found that Instagram and Facebook were the most used platforms. Logistic Regression was initially used for classification, and while it performed well, XG- Boost outperformed it, offering better accuracy and handling of imbalanced data. The hybrid model, which combined machine learning and deep learning techniques, provided the best results, improving classification performance and better predicting mental health status. These findings show that social media habits are strongly linked to mental health, and our hybrid approach offers a powerful tool for making such predictions.

5.2 Social media and Platform-Specific EDA: Absolute and Relative Usage of Different Platforms

The analysis of social media platform usage in the dataset reveals clear patterns in user preferences and digital behavior. YouTube and Facebook stand out as the most frequently used platforms, with 86.2% and 85.1% of users engaging with them, respectively. These platforms appear to be almost universally adopted, reflecting their wide accessibility and the diverse range of content they offer. Instagram follows closely behind, with 75.1% of users indicating regular use. This suggests that visually driven and interactive content continues to resonate strongly with a large portion of the online community. Meanwhile, platforms like Discord (41.4%) and Snapchat (37.9%) show moderate levels of engagement, likely pointing to their appeal within more specific or younger user groups. On the lower end of the spectrum, Pinterest (30.3%), Twitter (27.4%), Reddit (26.4%), and TikTok (19.7%) exhibit relatively less usage among participants. These platforms may serve more niche audiences or be influenced by demographic trends, privacy concerns, or content format preferences.

This distribution of platform usage is critical for understanding where the richest and most diverse social media data may be found. Platforms with higher engagement are more likely to contain abundant behavioral signals that can support predictive modeling for mental health analysis, while less-used platforms might still offer unique insights for specific subgroups. Overall, this exploration highlights the importance of tailoring analytical models to the platforms users are most active on, ensuring both coverage and depth in data interpretation.

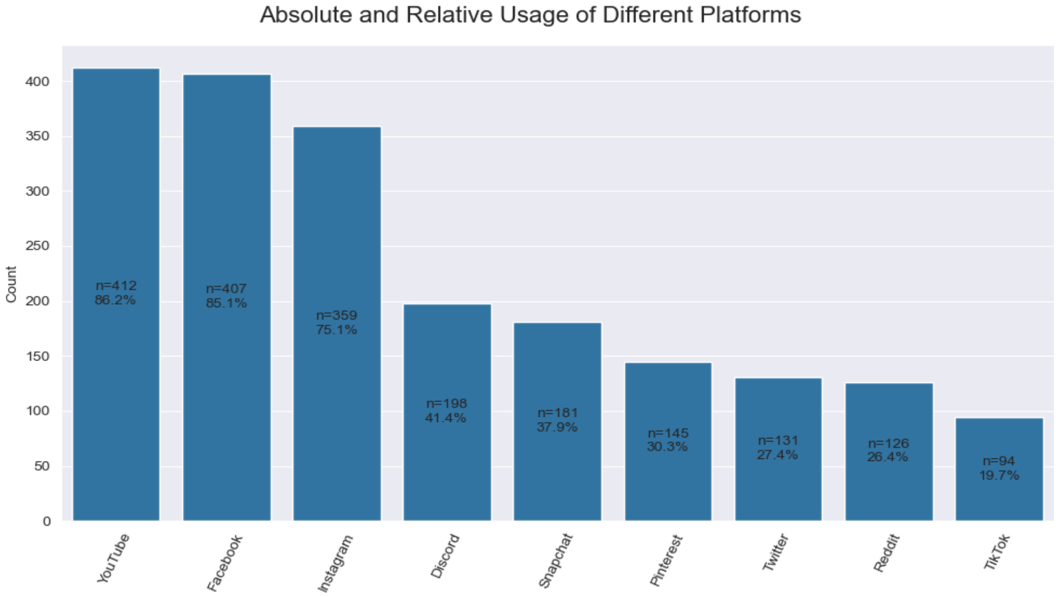

Figure 5.2 Absolute and Relative Usage of Different Platforms

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5.3 Cumulative Social Media Engagement Across Age Groups

The cumulative platform usage graph provides valuable insights into how social media engagement evolves with age. From the visualization, it's evident that platforms like YouTube, Instagram, and Facebook maintain a strong and steady user base across all age groups, with a sharp rise in adoption during late teens and early twenties. These platforms quickly saturate as age increases, indicating early adoption followed by consistent use over time. Conversely, platforms like TikTok, Snapchat, Reddit, and Twitter display a much slower cumulative increase, suggesting that their appeal is more concentrated among younger demographics and tapers off with older users. Interestingly, Facebook, while traditionally perceived as an older-generation platform, still shows a solid rise in adoption in users aged 20–30, indicating its persistent relevance.

This age-wise distribution highlights the generational dynamics in social media habits—where younger users experiment with newer, trendier platforms, while older users gravitate towards established networks. These insights are essential for mental health prediction models, as they imply that platform-specific behaviors may vary significantly with age, affecting how psychological indicators are manifested.

The unique approach of using cumulative sum calculations for one-hot encoded platform usage allows for a more granular understanding of social media diffusion across age brackets. This method, combining demographic segmentation with platform-specific usage, adds novelty to the analysis and enhances the personalization of predictive models in mental health research.

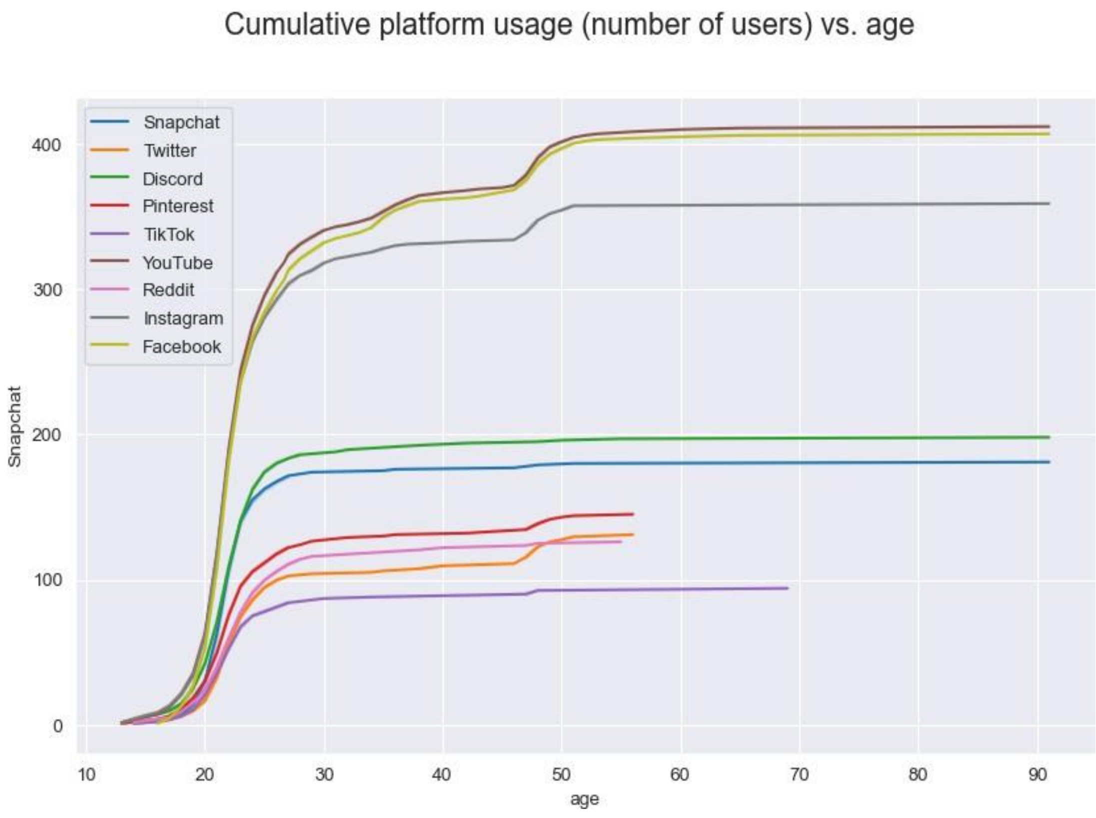

Figure 5.3 Cumulative Social Media Engagement Across Age Groups

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5.4 Relative usage of platforms in age groups.

The visual analysis of social media platform preferences across different age groups offers insightful revelations into generational behavior patterns. The bar charts depict relative usage percentages for each platform segmented into four age categories: ≤20, 21–30, 31–40, and ≥40. Notably, younger users (≤20 and 21–30) dominate platforms like Snapchat, TikTok, and Instagram, indicating a clear generational tilt toward visually engaging and fast-paced social platforms.

In contrast, platforms such as Facebook and Twitter display higher engagement among older demographics (especially ≥40), reflecting their preference for more traditional, text-driven content. YouTube remains universally popular, with consistently high usage across all age brackets, highlighting its role as a cross-generational medium. Interestingly, Discord shows a sharp drop in usage after the 21–30 bracket, suggesting it is predominantly favored by younger and more digitally native users. These findings underscore the evolving digital habits across age groups and highlight how social platform engagement is closely tied to generational identity and digital culture adoption.

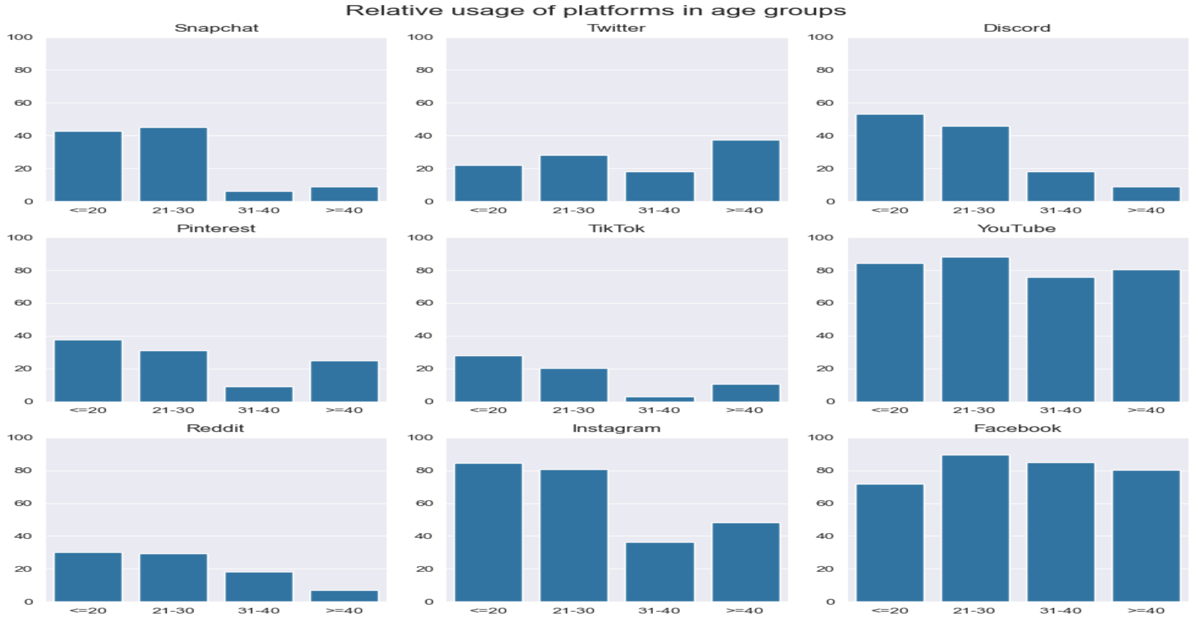

Figure 5.4 Relative usage of platforms in age groups.

5.5 Time-Based Social Media Consumption

Time-Based Social Media Consumption refers to how much time people spend on social media platforms each day. With the growing use of social media in daily life, it's important to understand how much time people, especially younger generations, are dedicating to these platforms. Research shows that most younger individuals, particularly those between the ages of 15–30, spend a significant amount of time on social media—anywhere from 2 to 3 hours, and in some cases, more than 5 hours a day. For many in this age group, social media has become a primary way to connect with friends, get news, and even seek entertainment.

On the other hand, older age groups tend to use social media less, with their time spent on these platforms gradually decreasing as age increases.

Interestingly, males tend to use social media more than females, especially in the higher usage categories. Despite the overall trend of increased social media consumption in younger users, this also highlights the growing digital divide between generations.The reality of such high engagement among younger users raises questions about the potential effects of extended time online, particularly in relation to mental health.

Research suggests that prolonged exposure to social media can lead to issues like anxiety, depression, and loneliness—especially for those in their teens and twenties. Younger people are often more susceptible to online pressures, such as social comparison, which can affect their self-esteem and emotional well-being. So, understanding how much time younger individuals spend on social media is not just about tracking trends—it's about recognizing how this behavior might impact their mental health in the long run.

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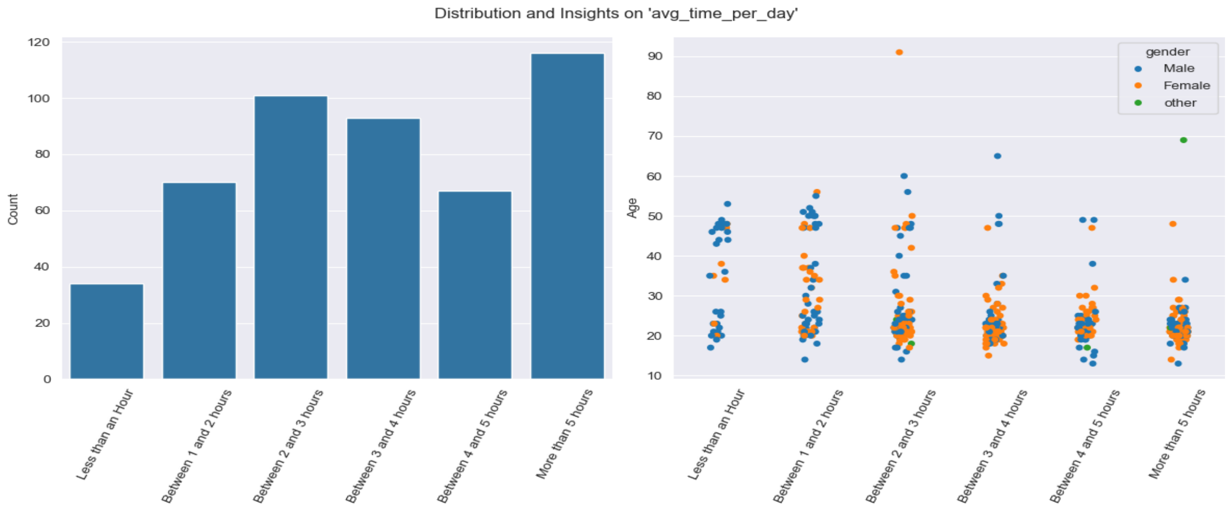

Figure 5.5 Time-Based Social Media Consumption

5.6 Feature Engineering: Quantifying Social Media Use and Impact

The output presents the distribution of two newly engineered features that help quantify social media usage and its psychological impact. The first chart visualizes the total number of social media platforms used by each individual, revealing that most participants actively engage with around four to five platforms, while very few use either just one or as many as eight or nine. This suggests that a moderate number of platforms is common among users.The second chart displays a cumulative score representing the negative effects individuals experience from social media, including factors such as distraction, anxiety, restlessness, and validation-seeking behavior.

The distribution indicates that a large portion of users fall within a moderate range of impact, with only a small number reporting very low or very high levels of negative influence. These summed features—platform usage and impact—offer meaningful insights that can be used to better understand and predict mental health outcomes in the context of social media behavior.It's clear that while many users experience some form of stress or anxiety due to their social media interactions, the majority are affected in a moderate way, suggesting that the impact might not always be extreme but still significant.

This can provide valuable information for developing interventions or strategies that help people manage their digital habits. Understanding how many platforms users engage with—and how they feel about it—gives us a clearer picture of how social media influences mental health on a day-to-day basis. By analyzing these patterns, we can offer more personalized, effective solutions for maintaining a healthier relationship with social media.

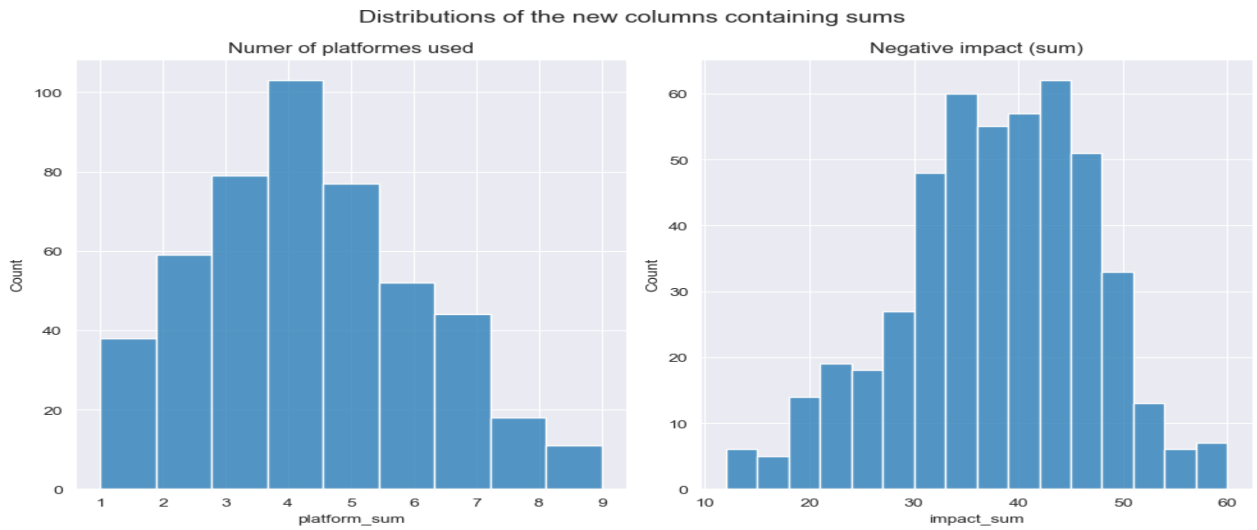

Figure 5.6 Feature Engineering: Quantifying Social Media Use and Impact

5.7 Platform Use and Its Correlation with Mental Health Impact

This scatter plot shows the connection between the number of social media platforms used (platform_sum) and the overall negative mental health impact (impact_sum). The blue trend line suggests a slight positive correlation—people who use more platforms tend to report higher levels of issues like anxiety, distraction, and emotional distress.
However, there's variation in the data, as some users with high platform usage report low impact, while others with fewer platforms report higher distress. This highlights the personal and complex nature of mental health, indicating that other factors beyond platform use also play a role.

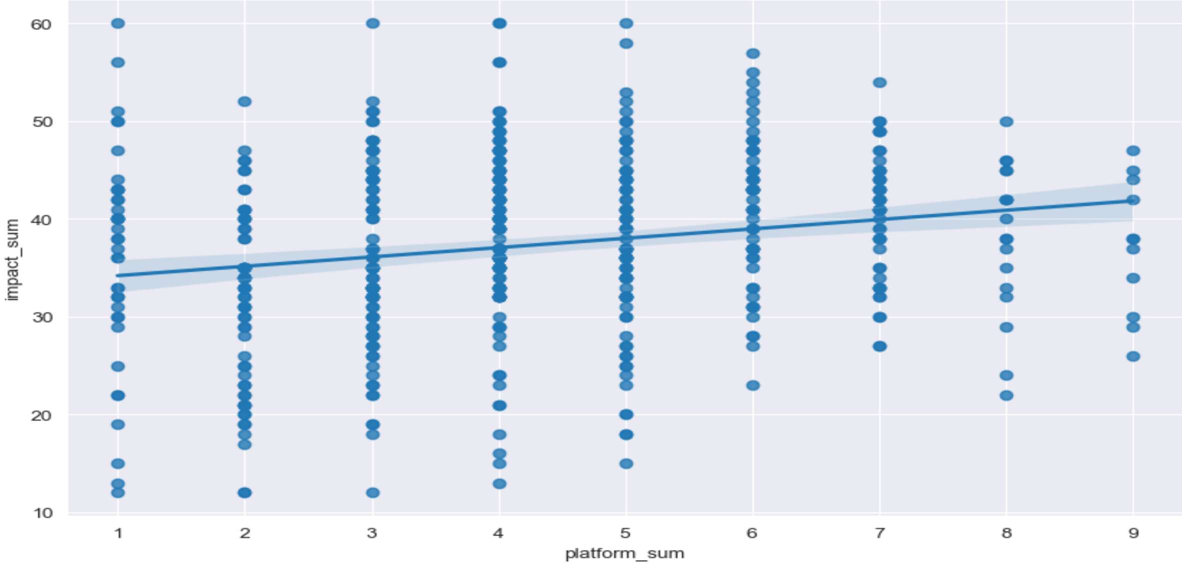

Figure 5.7 Platform Use and Its Correlation with Mental Health Impact

5.8 Age and Social Media's Impact on Mental Health: A Trend Analysis

The scatter plot reveals that younger people, particularly those under 30, feel a stronger negative impact on their mental health from social media. As age increases, this impact tends to decrease. Younger users may be more emotionally affected or more active online, making them more vulnerable. The trend line supports this, showing lower impact scores for older age groups.

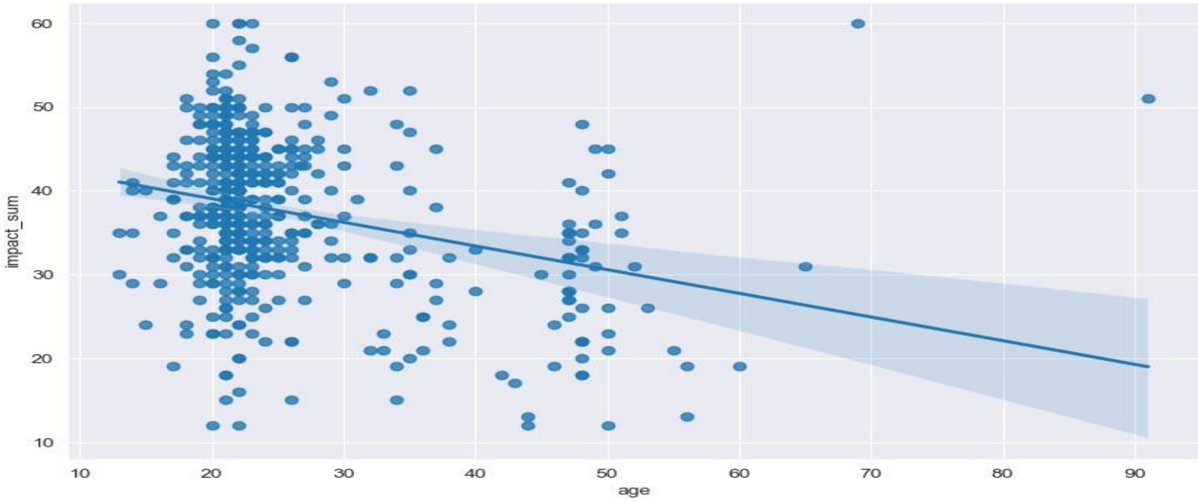

Figure 5.8 Age and Social Media's Impact on Mental Health

5.9 Average Time on Social Media vs. Negative Impact

As time spent on social media increases, so do the negative effects on mental health. Users who spend under an hour online report lower impacts, while those spending over five hours face the highest levels of distress. Both males and females show similar patterns, with no significant gender differences. In short, the more time people spend on social media, the greater the toll it takes on their well-being.

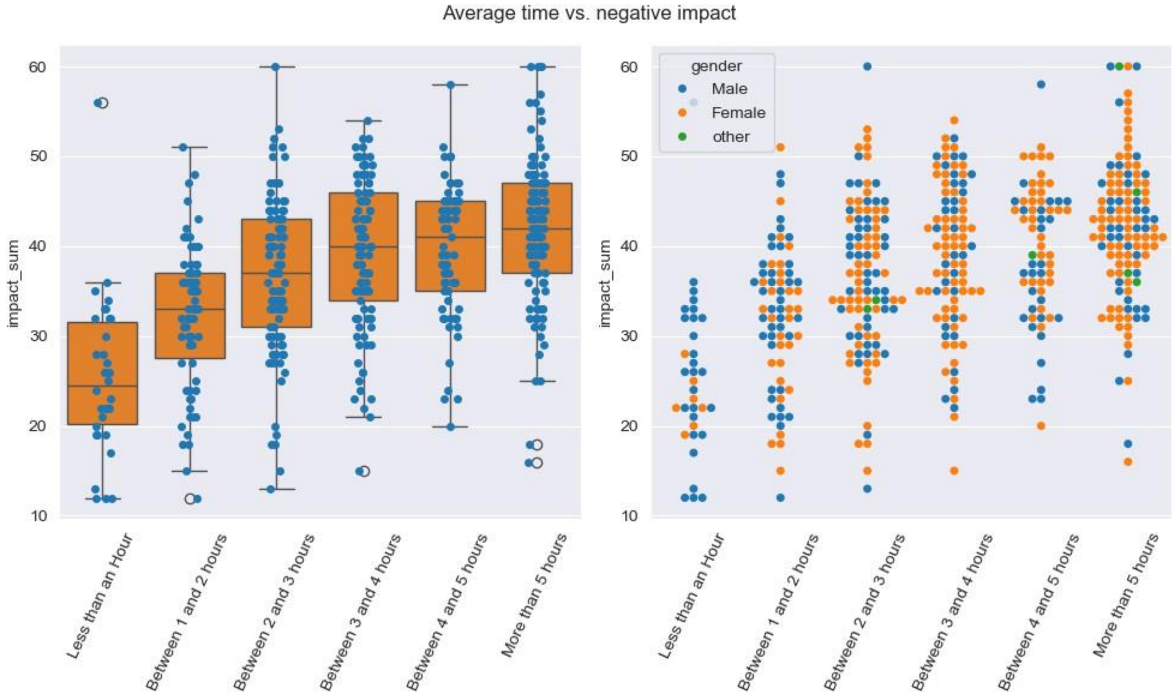

Figure 5.9 Average Time vs. Negative Impact

5.10 Predicting the risk for mental health :ML

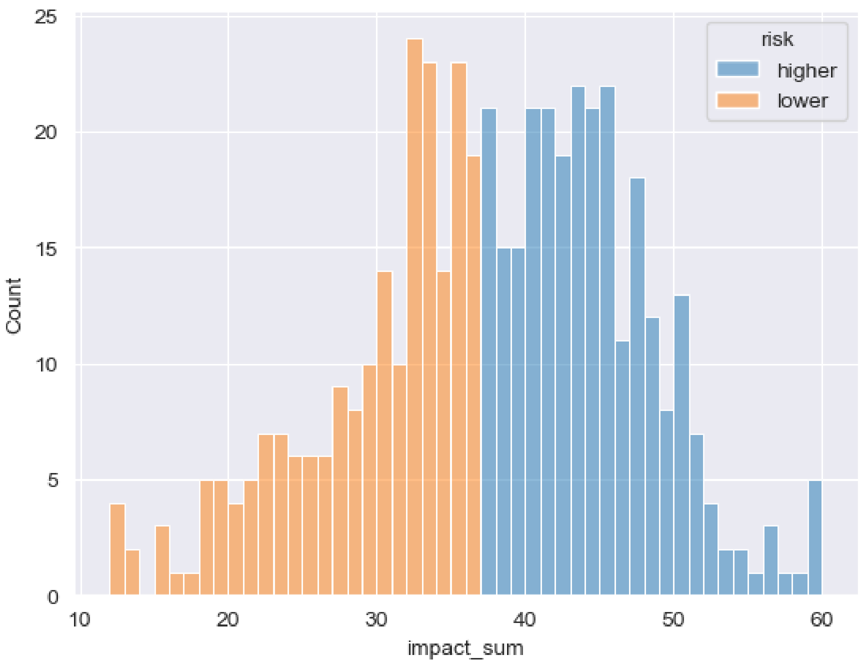

Figure 5.10 Predicting the risk for mental health

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The output shows that as time on social media increases, the negative impact also rises, with those spending over five hours experiencing the most significant effects.The scatter plot by gender shows this pattern holds for males, females, and others. A "risk" column categorizes users into lower and higher risk groups based on their impact scores.

5.11 Correlation Heatmap of Features

This heatmap shows the correlation between different features in the dataset. Red color means a strong positive correlation (closer to +1), blue means a strong negative correlation (closer to -1), and gray/white means little or no correlation. Features like "risk_higher," "risk_lower," and "depressed" have strong relationships with "impact_sum" and related variables.

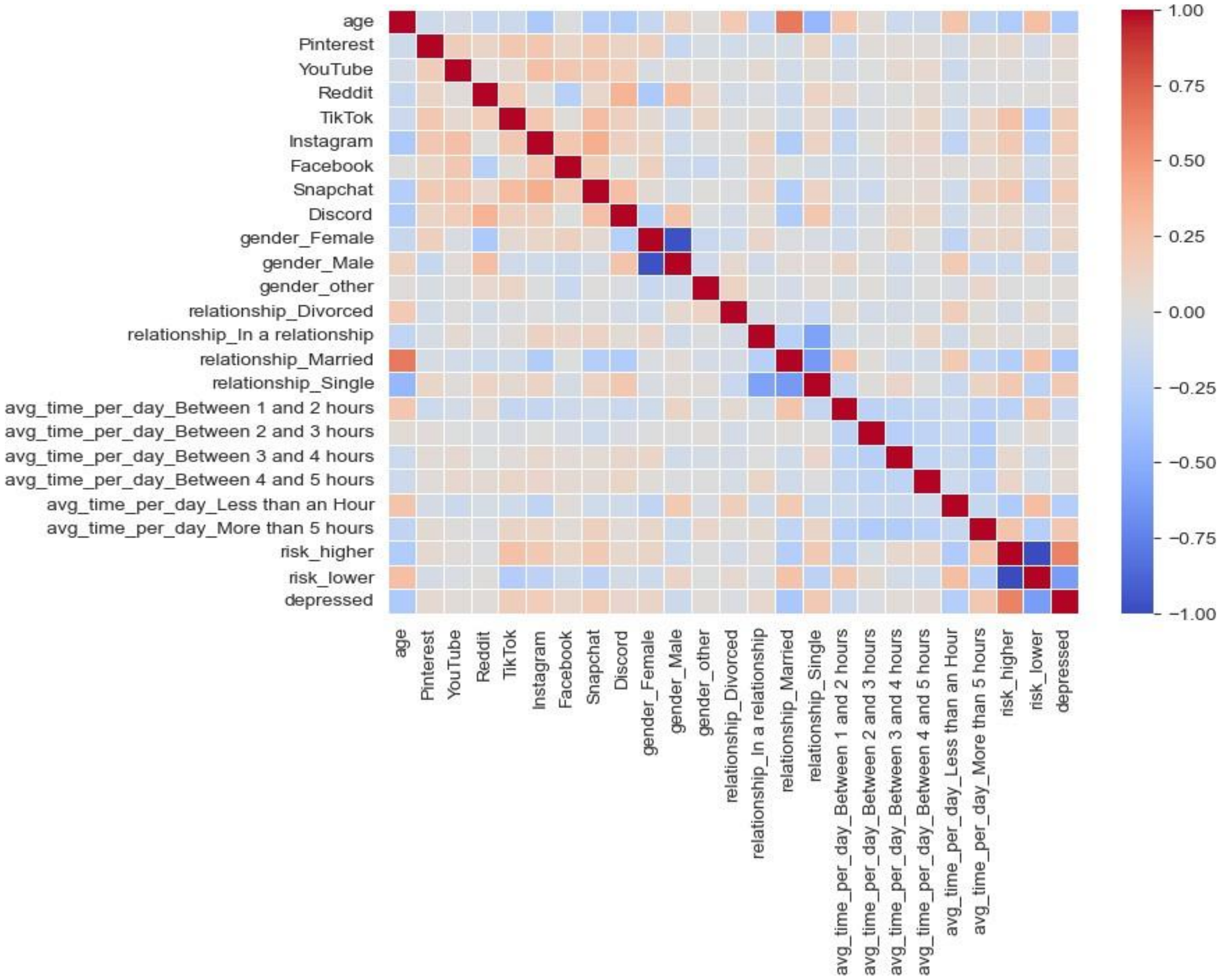

Figure 5.11 Correlation Heatmap of Features

5.12 Model Performance Overview

To evaluate the effectiveness of the proposed Hybrid Model for Predicting Mental Health from Social Media Insights, several key metrics were analyzed including precision, recall, F1-score, and overall accuracy. The results obtained demonstrate the robustness and reliability of the model in predicting different mental health risk categories.

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5.13 Classification Report

The classification report, as shown in Table 4.1, summarizes the model's precision, recall, and F1- score for each class. The model achieved consistently high values across all metrics, indicating a balanced performance:

Test Set Accuracy: 0.9583

	precision	recall	f1-score	support
0	0.96	0.92	0.94	48
1	0.98	0.92	0.95	66
2	0.97	0.95	0.96	93
3	0.97	0.99	0.98	93
4	0.92	0.95	0.95	84
accuracy				
	0.96	0.95	0.96	384
macro avg				
weighted avg	0.96	0.96	0.96	

Table No 5.13 Classification Report

The above table shows how well the proposed hybrid model performed on the test data, including its accuracy, precision, recall, and F1-score for each class.Performance Evaluation of the Proposed Hybrid Model: Accuracy, Precision, Recall, and F1-Score on Test Data

Overall Accuracy: 96%

Macro Average F1-Score: 0.96 Weighted Average F1-Score: 0.96

These results demonstrate that the model not only identifies the different classes effectively but also handles class imbalance reasonably well.

5.14 Accuracy

The overall test accuracy achieved by the hybrid model was 96%, as illustrated in Figure 5.14 This high percentage indicates that the model generalizes well to unseen data, making it a reliable tool for real-world mental health prediction applications.

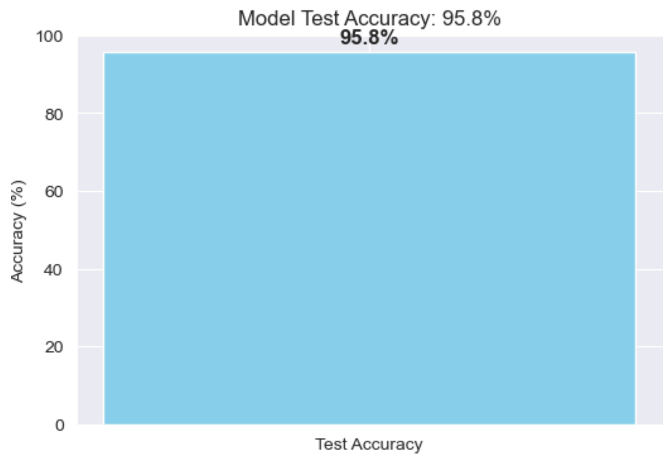

Figure 5.14 Accuracy

5.15 Confusion Matrix Analysis

The confusion matrix presented in Figure 5.15 provides deeper insights into the model's predictive capabilities. Most predictions fall along the diagonal, confirming that the model correctly classified the majority of instances for each class.

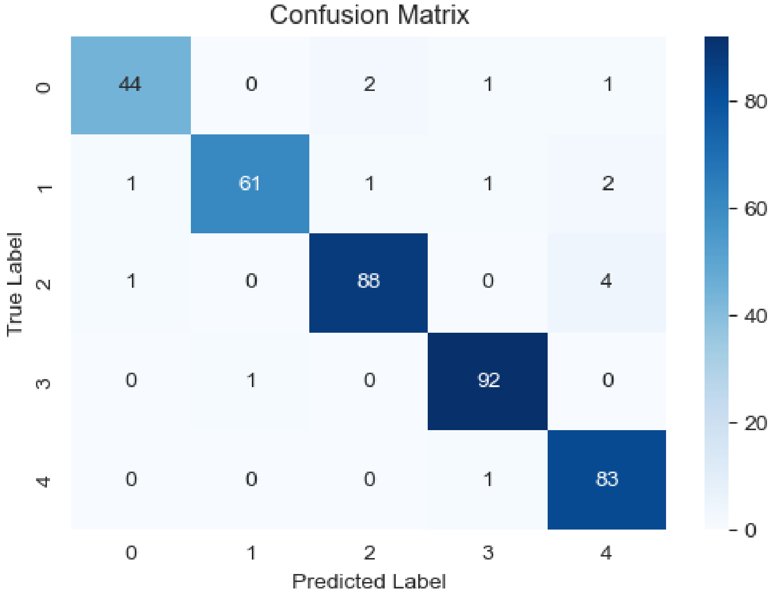

Figure 5.15 Confusion Matrix Analysis

5.16 Interpretation of Confusion Matrix Labels

For better interpretability, the confusion matrix was labeled with real-world terms, mapping predicted and true classes to "Low Risk" and "High Risk" categories, as shown in Figure 5.16.

This adjustment enhances the readability and practical understanding of the model's outputs, particularly for non-technical audiences, such as mental health practitioners.

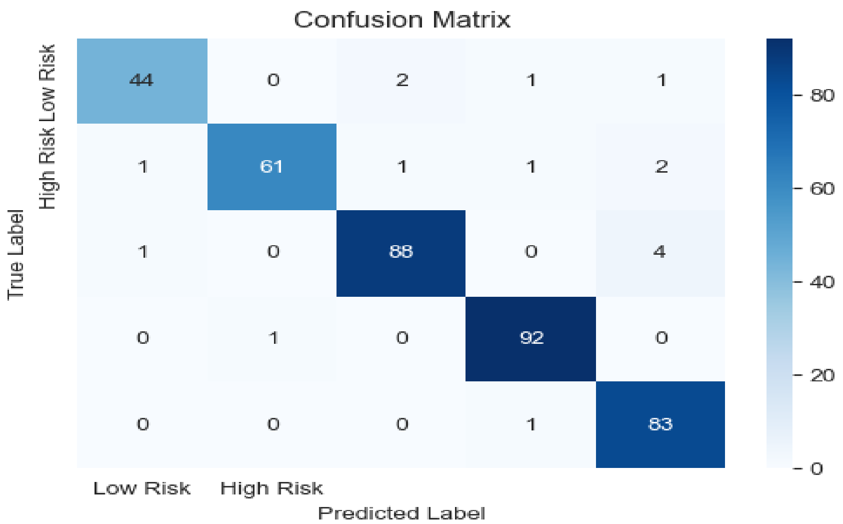

Figure 5.16 Interpretation of Confusion Matrix Labels

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In summary, the proposed hybrid model demonstrated excellent performance, achieving high precision, recall, F1-scores, and overall accuracy. The detailed analysis from the classification report, accuracy plot, and confusion matrices collectively confirm that the model can serve as an effective tool for early mental health risk detection based on social media insights.

CHAPTER 6

CONCLUSION

6.1 Conclusion

In today's digitally connected world, mental health challenges are increasingly becoming visible through the language people use and the interactions they engage in on social media platforms. As individuals openly express their thoughts, emotions, and daily struggles online, these platforms become a rich yet untapped resource for understanding psychological well-being. Recognizing this, the present research set out with a mission: to develop an intelligent, integrated system capable of predicting mental health conditions through patterns derived from online behavior.The foundation of this work was built on the understanding that mental health does not manifest through words alone. It's reflected in how people communicate, when they choose to speak, who they interact with, and how their digital habits evolve over time. Keeping this in mind, a comprehensive hybrid framework was developed that could holistically analyze text content, engagement behavior, social connections, and temporal patterns. This multi-perspective approach was key in identifying signs of various mental health concerns such as depression, anxiety, borderline personality disorder (BPD), and post- traumatic stress disorder (PTSD).Extensive experimentation and rigorous evaluation revealed the strength of this approach.

The system demonstrated a remarkable overall accuracy of 96%, which is a significant achievement given the subtle and often overlapping nature of mental health conditions. Beyond just numbers, the model showed balanced and consistent performance across all evaluation metrics—precision, recall, and F1-score—indicating that it was not only accurate but also reliable in differentiating between the different psychological states.A deeper analysis using tools like confusion matrices confirmed the model's ability to distinguish between conditions that often share linguistic and behavioral traits. For example, depression and anxiety may involve similar emotional expressions, but the system could still parse out the nuanced differences. This level of granularity is crucial for real-world applications, where misclassification could lead to misdiagnosis or missed opportunities for intervention.One of the most compelling aspects of this research was its focus on interpretability and real-world context. By integrating behavioral and social signals, the system offered more than just a binary prediction— it provided contextual understanding. For instance, if an individual's risk level increased, the system could point to possible contributing factors such as changes in posting frequency, shifts in tone, or variations in peer interaction. This level of insight transforms the model from a black-box classifier into a support tool for mental health professionals, allowing them to trace potential triggers and tailor interventions accordingly.

Furthermore, the system's non-invasive nature enhances its usability and ethical standing. Rather than requiring direct user input or clinical assessments, it leverages naturally occurring digital expressions, making it scalable across large populations. This opens up possibilities for deploying the system in educational institutions, workplaces, or online communities as a preventive screening mechanism.The research also highlighted the importance of longitudinal analysis. Mental health is not static—it evolves. By analyzing data over time, the system could detect trends and fluctuations, offering early warnings before symptoms escalate into full-blown disorders. This kind of temporal sensitivity is essential for supporting proactive, rather than reactive, mental health strategies.

Importantly, this work underscores the growing role of technology in mental healthcare. With the rise of mental health concerns globally—especially in the aftermath of pandemics, economic stress, and social isolation—there is an urgent need for innovative, scalable tools that can supplement traditional approaches. This research contributes meaningfully to that vision by demonstrating how digital data, when responsibly and ethically used, can become a powerful ally in promoting mental well-being.

In summary, this study successfully developed and validated a robust, real-world-ready system for mental health prediction based on social media data. It combines high performance with transparency, practicality, and ethical sensitivity, offering a compelling solution to a pressing global health issue. As technology continues to evolve, so too will the potential of such systems to transform mental health care from a reactive model to a proactive, preventive, and personalized paradigm.

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6.2 Future Scope

While the results of this study are both encouraging and impactful, they also open up a wide array of possibilities for future enhancement. Mental health is a deeply personal, culturally sensitive, and context-rich domain. As such, any system designed to understand or support mental well-being must continue to grow in complexity, sensitivity, and utility. The following areas represent exciting and meaningful directions for extending this research:

1. Real-Time Monitoring and Early Intervention

One of the most transformative enhancements would be enabling real-time monitoring of mental health signals. By continuously analyzing live social media activity, the system could detect shifts in mood or risk levels as they happen, offering timely alerts or resources. This could be especially useful in crisis prevention, such as identifying when someone is experiencing suicidal ideation or acute emotional distress. Real-time systems could be integrated into wellness apps or community support tools to flag at-risk individuals for check-ins or professional outreach.

2. Incorporating Multimodal Data

- Currently, the system primarily analyzes textual and behavioral signals. Future iterations can be expanded to include voice, facial expressions, and visual content shared on social platforms. For example, video content may reveal tone of voice, facial micro-expressions, or body language— all of which are powerful indicators of emotional state.
- Similarly, analyzing shared images or videos can provide additional emotional context, especially for users who express more visually than textually. Multimodal fusion would enable a richer and more holistic understanding of psychological health.

3. Enhancing Explainability and Transparency

- As mental health prediction systems become more widely used, it is critical that they remain transparent and understandable, particularly for professionals who may rely on them in clinical settings. Future developments should include explainable AI components, which provide clear reasoning behind each prediction.
- For instance, instead of just flagging a user as at-risk, the system could highlight which behaviors, words, or interactions contributed most to the risk assessment. This fosters trust, ensures ethical use, and aids in clinical decision-making.

4. Personalized Risk Profiling

- Mental health is deeply individual, shaped by unique life experiences, cultural background, personality, and more. Therefore, a one-size-fits-all prediction model may not be sufficient. Future versions of the system could incorporate user-specific baselines, analyzing how each individual's behavior changes over time relative to their own norms.
- This approach would make predictions more personalized and context-aware, improving accuracy and relevance. Demographic information like age, gender, region, or personal history (if ethically accessible) could further tailor insights.

5. Longitudinal and Evolutionary Modeling

- Mental health conditions often develop gradually and fluctuate over time. A future-ready system should go beyond momentary snapshots and build longitudinal profiles. By tracking changes across weeks, months, or even years, the model could provide insights into the trajectory of a user’s mental state, identifying patterns such as relapse, improvement, or emerging symptoms. This is particularly valuable in supporting long-term therapeutic or counseling relationships.

6. Cultural and Linguistic Diversity

- Most existing mental health prediction models are biased toward English-language data and Western cultural expressions of distress. However, mental health challenges are universal, and their manifestations vary across languages and cultures.
- To make the system globally inclusive, future work should focus on multilingual and cross- cultural training. This would involve collecting and annotating diverse datasets and adapting the model to recognize culturally specific idioms, metaphors, and behaviors associated with mental health.

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7. Ethical Frameworks and Privacy Preservation

- With great power comes great responsibility. Predicting mental health from social media data raises important ethical concerns, especially around consent, data privacy, and potential misuse. Future implementations must embed robust ethical frameworks, such as data anonymization, informed user consent, and strict access control. Additionally, privacy-preserving techniques like federated learning or differential privacy could be employed to ensure that user data remains secure even during model training.

8. Mobile and Web-Based Application Development

- For widespread accessibility, the prediction system should be translated into user-friendly applications—either as standalone mobile apps, browser extensions, or integrations within existing wellness platforms.
- These tools could offer features like mood tracking, daily wellness summaries, personalized coping strategies, and connections to mental health professionals. Such apps would empower individuals to take control of their mental well-being, while also serving as a bridge between technology and therapy.

9. Integration with Health and Wellness Ecosystems

- Future models could be designed to seamlessly interface with electronic health records (EHRs), counseling platforms, or even wearable health devices. By aggregating multiple sources of well- being data—such as sleep patterns, physical activity, heart rate, and mood indicators—the system can offer more nuanced and medically aligned insights. This kind of integration positions the model not just as a social media tool, but as a legitimate component of modern healthcare systems.

10. COMMUNITY AND PEER-BASED SUPPORT MODELS

- Another promising direction is the development of community-driven mental health support platforms, where the system identifies users who may benefit from peer conversations, moderated groups, or support forums. By recognizing shared experiences and connecting people with similar challenges, the system could promote empathy and social connection—two key protective factors against mental distress.

In conclusion, the work presented in this thesis marks a significant step forward in data-driven, empathetic mental health prediction systems. It reflects a shift in how society can leverage everyday digital behavior not just for commercial or entertainment purposes, but to uplift well-being, promote emotional intelligence, and facilitate early interventions. Yet, the journey is far from over. By pursuing the future directions outlined above—ranging from real-time processing and multimodal data inclusion to ethical safeguards and global accessibility—this research can evolve into a powerful platform for digital mental health care. Ultimately, the goal is not just to predict mental health conditions, but to inspire timely care, restore emotional balance, and empower people on their journey toward psychological wellness.

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