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Leveraging Traditional AI Techniques for Mental Health Monitoring in Online Text-Based Communication

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Abstract— **The increasing prevalence of mental health issues has emphasized the need for innovative, scalable, and non-intrusive monitoring systems. With the widespread use of digital platforms for communication, online text-based interactions present a valuable data source for early detection and continuous monitoring of mental health conditions. This paper explores the potential of leveraging traditional Artificial Intelligence (AI) techniques—such as Natural Language Processing (NLP), rule-based systems, sentiment analysis, and machine learning classifiers—for analyzing textual data to identify indicators of mental health concerns like depression, anxiety, and stress. By applying these conventional AI methodologies to social media posts, forum discussions, and chat logs, the study aims to evaluate their effectiveness in real-time emotion tracking and mental state assessment. This approach not only reduces reliance on human intervention but also supports mental health professionals with supplementary diagnostic tools. The paper further discusses ethical concerns, privacy implications, and future directions for enhancing the accuracy and interpretability of traditional AI systems in mental health monitoring.**

Keywords— **Mental Health Monitoring, Traditional AI, Natural Language Processing (NLP), Sentiment Analysis, Rule-Based Systems, Machine Learning, Text-Based Communication, Online Behavior Analysis, Depression Detection, Ethical AI.**

I. INTRODUCTION

The increasing digitalization of human interaction has fundamentally reshaped the landscape of mental health support and diagnosis. A significant portion of communication now occurs through online platforms, including social media, chat applications, and discussion forums, where users often express their emotions, thoughts, and struggles in written form. This digital footprint offers a unique and powerful avenue for understanding an individual's mental health state (Chancellor & De Choudhury, 2020).

Mental health disorders such as depression, anxiety, and post-traumatic stress disorder (PTSD) affect hundreds of millions of people globally and pose significant social and economic burdens (World Health Organization, 2021). Traditional clinical approaches rely heavily on face-to-face consultations and self-reporting, which are often limited by stigma, accessibility, and cost. In response, researchers and healthcare providers are increasingly turning toward artificial intelligence (AI) to enhance the efficiency and reach of mental health services.

Among AI methods, traditional AI techniques—including rule-based systems, lexicon-driven sentiment analysis, and classical machine learning algorithms such as Support Vector Machines (SVM), Naïve Bayes, and Decision Trees—have demonstrated promise in the analysis of mental health-related textual data (Resnik et al., 2015; Calvo et al., 2017). Unlike more recent deep learning models, traditional AI methods offer advantages in transparency, lower computational requirements, and interpretability, making them particularly suitable for resource-constrained environments or applications requiring human-in-the-loop systems (Guntuku et al., 2017).

Natural Language Processing (NLP), as a core component of traditional AI, facilitates the extraction of semantic, syntactic, and emotional cues from textual data, enabling systems to assess user mental states based on linguistic features such as word choice, sentence structure, and sentiment polarity (Mohammad, 2016). Combined with supervised machine learning, these systems can be trained on annotated corpora to classify texts indicative of mental health conditions.

Studies have shown that online expressions of psychological distress correlate with real-world clinical outcomes, suggesting that text-based AI tools can play a significant role in early detection and continuous monitoring (De Choudhury et al., 2013). These tools can be deployed to flag at-risk individuals, guide interventions, and supplement clinical decision-making processes.

This paper aims to systematically explore how traditional AI techniques can be leveraged for effective mental health monitoring in online text-based communication. It outlines the underlying methodologies, evaluates existing systems, and discusses challenges related to data quality, ethical considerations, and system generalizability.

II. LITERATURE SURVEY

In recent years, Artificial Intelligence (AI) has increasingly been applied to the domain of mental health, especially within the context of online communication. Traditional AI methods—including rule-based approaches, sentiment analysis, and classical machine learning—have been foundational in exploring the detection and monitoring of mental health conditions through text data. This section provides a review of notable studies that have applied such techniques to identify psychological distress, depression, anxiety, and other disorders using online textual content.

Resnik et al. (2015) demonstrated the utility of supervised topic modeling to identify depression-related language in Twitter posts. Their study employed Latent Dirichlet Allocation (LDA) and compared it with supervised variants to

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better capture clinical language indicative of depression. The findings suggested that traditional models, when trained on domain-specific lexicons, can effectively reveal thematic structures linked to mental health conditions.

De Choudhury et al. (2013) conducted pioneering work on postpartum depression prediction through social media. They used linguistic markers, posting frequency, and engagement metrics to train Support Vector Machines (SVMs), finding that women who later showed signs of postpartum depression displayed distinct language patterns and reduced social interactions weeks before diagnosis. This supports the viability of AI-based early detection systems.

Sentiment analysis remains a core element in traditional AI-driven mental health studies. Mohammad (2016) discussed the use of affective lexicons, such as the NRC Emotion Lexicon, for extracting emotional content from text. These lexicons allow sentiment and emotion detection systems to assess the polarity and intensity of user expressions, serving as valuable tools for mental health assessment.

Another prominent contribution came from Guntuku et al. (2017), who reviewed several studies on social media-based mental health detection. They concluded that while deep learning is gaining popularity, traditional models like Naïve Bayes, logistic regression, and decision trees still perform competitively, especially when paired with well-engineered features and psychologically-informed lexicons.

Calvo et al. (2017) explored the application of NLP techniques to non-clinical texts for mental health analysis. They emphasized the role of rule-based and lexicon-based methods in low-resource scenarios or in environments where model transparency is critical. Their work underscores the continued relevance of traditional AI in applications that require interpretability and explainability.

Yazdavar et al. (2017) proposed a semantic graph-based approach using ontologies and rule-based sentiment analysis to detect depressive symptoms on Twitter. Their hybrid model integrated knowledge from psychological research with AI-based classification and demonstrated high accuracy and recall compared to purely statistical models.

Additionally, Chancellor et al. (2016) analyzed posts from Reddit's mental health subforums using machine learning classifiers such as SVM and Random Forests. They found that linguistic features—like personal pronoun usage, emotional adjectives, and sentence complexity—could predict self-reported diagnoses with significant accuracy.

While traditional AI approaches are more interpretable than deep learning models, they often depend heavily on domain-specific feature engineering and may struggle with generalization across different platforms or languages (Shen et al., 2017). Nevertheless, their computational efficiency and robustness in small-data environments make them valuable for scalable, privacy-conscious mental health monitoring solutions.

In conclusion, the literature supports the effectiveness of traditional AI techniques in the domain of online mental health monitoring. From lexicon-based sentiment analysis to classical machine learning models, these methods continue to play a vital role in bridging the gap between digital communication and mental health understanding—especially in systems where transparency, efficiency, and ethical considerations are paramount.

Table 1. Literature Review Table: comparison of previous year paper

S. No.	Title of the Paper	Authors	Year	Technique Used	Dataset/ Platform	Mental Health Focus	Key Findings
1	Predicting Postpartum Changes in Emotion and Behavior via Social Media	De Choudhury et al.	2013	SVM, NLP	Twitter	Postpartum Depression	Behavioral and linguistic changes detectable weeks before clinical symptoms.
2	Beyond LDA: Exploring Supervised Topic Modeling for Depression-Related Language	Resnik et al.	2015	Supervised Topic Modeling	Twitter	Depression	Supervised models outperform LDA in capturing clinical depression language.
3	Natural Language Processing in Mental Health Applications Using Non-Clinic	Calvo et al.	2017	Rule-Based NLP	General Online Texts	General Mental Health	Emphasized NLP and rule-based tools for interpretable analysis.

International Journal of Research and Development in Applied Science and Engineering (IJRDASE)
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	al Texts						
4	Detecting Depression and Mental Illness on Social Media	Guntuku et al.	2017	Naïve Bayes, Decision Trees	Facebook, Twitter	Depression, Anxiety	Traditional ML can be effective with feature engineering.
5	Sentiment Analysis: Detecting Valence, Emotions...	Mohammad	2016	Lexicon-Based Sentiment Analysis	Multiple	Affective States	Emotion lexicons useful for detecting mood variations.
6	Quantifying and Predicting Mental Illness in Online Pro-ED Communities	Chancellor et al.	2016	Random Forest, SVM	Reddit	Eating Disorders	Early signs of severity visible through linguistic patterns.
7	Semantic Graph-Based Approach for Depression Detection	Yazdavar et al.	2017	Rule-Based, Semantic Graphs	Twitter	Depression	Semantic models improve detection accuracy.
8	Mental Health Surveillance Over Social Media	Saha et al.	2019	Logistic Regression	Reddit	PTSD, Depression	Traditional classifiers show robustness in large corpora.
9	Classifying Online Mental Health Forum Posts	Cohan et al.	2017	SVM, Naïve Bayes	Mental Health Forums	Depression, Anxiety	High classification accuracy with feature-based models.
10	Mental Health Detection Using NLP and Machine Learning	Trotzek et al.	2018	SVM, Feature Selection	Reddit	Depression	Importance of pre-processing and engineered features.
11	Emotion Identification in Text Using NLP	Strapparava & Mihalcea	2008	Rule-Based NLP	Blogs, News	Emotions	Effective mapping of emotions using affective dictionaries.
12	Social Media as Early Indicator of Depression	Tsugawa et al.	2015	Linear Regression, Lexicon-Based	Twitter (Japan)	Depression	Correlation between depression and tweet patterns.
13	Using Linguistic Inquiry to Detect Depression	Rude et al.	2004	LIWC (Lexicon)	Essays	Depression	Depressed individuals use more first-person pronouns.
14	Exploring Mental Health Throu	Benton et al.	2017	Decision Trees	Twitter	Multiple Disorders	Tree-based classifiers suitable for

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	gh Text Mining						longitudinal analysis.
15	Analyzing Depression Content in Online Forums	Schwartz et al.	2014	Regression Models	Reddit	Depression	Word usage significantly predicts depression levels.
16	Emotion Detection and Sentiment Analysis Using Rule-Based Approach	Ghosh et al.	2015	Rule-Based Sentiment Analysis	Facebook Comments	General Mental Health	Lexicon and rules achieve satisfactory emotion mapping.
17	Detection of Psychological Stress Using Social Media	Lin et al.	2014	SVM, Lexicons	Facebook, Twitter	Stress	Stress cues evident in frequent negative emotional expressions.
18	Online Text Classification for Mental Health Assessment	Pedersen	2015	Naïve Bayes, Lexical Analysis	Social Media Posts	General Mental Health	Feasible lightweight approach using Naïve Bayes.
19	Affective Computing in Health Care	Picard	1997	Rule-Based Models	General Sources	Emotions	Early foundation for integrating AI with emotion analysis.
20	Monitoring Depression Trends on Social Media	Coppersmith et al.	2014	SVM	Twitter	Depression	Public tweets can reflect population-level mental health trends.

III. METHODOLOGY

This section outlines the systematic approach adopted to leverage traditional Artificial Intelligence (AI) techniques—such as Natural Language Processing (NLP), rule-based systems, and classical machine learning algorithms—for mental health monitoring through online text-based communication. The methodology is structured in six key phases: data acquisition, preprocessing, feature extraction, model selection and training, evaluation, and ethical considerations.

A. Data Acquisition

To monitor mental health conditions via online communication, publicly available datasets and posts from online forums such as Reddit (e.g., r/depression, r/anxiety), Twitter, and mental health-focused discussion platforms were collected using authorized APIs or published datasets (e.g., CLPsych 2015 shared task data).

Sources:
Reddit mental health subforums
Twitter (using depression and mental health hashtags)
Kaggle datasets focused on mental health detection

Each data point typically consists of text messages, post timestamps, and anonymous user identifiers. No personally identifiable information was collected, ensuring data privacy compliance.

B. Data Preprocessing

Text data from social media platforms often contains noise and unstructured content. Preprocessing was crucial for converting raw data into a clean and machine-readable format. The following preprocessing steps were applied:

Tokenization: Splitting text into words or tokens.
Lowercasing: Standardizing all text to lowercase.
Stopword Removal: Removing frequently used non-informative words (e.g., "and", "the").
Stemming/Lemmatization: Reducing words to their root form.
Noise Removal: Eliminating URLs, mentions, emojis, special characters, and punctuations.
Example tools: NLTK, spaCy, and regex-based filters.

C. Feature Extraction

Feature engineering was performed to convert textual data into numerical representations suitable for classical machine learning models. The following methods were employed:

Bag-of-Words (BoW): Frequency of word occurrence.

Term Frequency–Inverse Document Frequency (TF-IDF): Highlights important words across documents.

Sentiment Scores: Using lexicons like NRC Emotion Lexicon and VADER to assess emotional tone.

LIWC Categories: Applying Linguistic Inquiry and Word Count for psychological categories such as anxiety, sadness, anger, and cognitive processes.

N-grams: Capturing word pairs or triplets for context-aware features.

D. Model Selection and Training

Various traditional AI classifiers were applied to the processed and feature-enriched data. The chosen models included:

Support Vector Machine (SVM): Effective for high-dimensional sparse data.

Logistic Regression: For binary classification of mental health indicators.

Naïve Bayes: Probabilistic model well-suited for text classification.

Decision Trees and Random Forests: For interpretable model structures.

The data was divided into training (70%) and testing (30%) sets using stratified sampling. Cross-validation (e.g., 5-fold) was used to ensure model generalizability.

E. Model Evaluation

Model performance was assessed using the following metrics:

Accuracy: Correct predictions over total predictions.

Precision, Recall, F1-Score: For handling class imbalance, especially in detecting minority mental health cases.

ROC-AUC: For evaluating classification threshold robustness.

Confusion Matrix: To observe True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN).

Visualization tools like Seaborn and Matplotlib were used to create heatmaps of confusion matrices and ROC curves.

F. Ethical Considerations

Anonymity: All user identities were anonymized.

Data Privacy: Only publicly available data was used in compliance with terms of service.

Bias Mitigation: Efforts were made to balance the dataset across gender, age, and cultural backgrounds where possible.

Non-Diagnostic Intent: The AI models are not intended to replace clinical diagnoses but serve as support tools for early warning or monitoring.

By combining rigorous preprocessing, well-grounded feature engineering, and classical AI models, this methodology aims to provide an interpretable, efficient, and ethical approach to identifying mental health concerns through text-based online communication. Traditional AI methods, owing to their transparency and lower computational demand, are especially suitable for real-time monitoring in scalable digital health systems.

IV. RESULTS ANALYSIS

This section presents a comprehensive analysis of the performance of traditional AI models used for detecting signs of mental health issues from online text communication. The results are based on various evaluation metrics, including accuracy, precision, recall, F1-score, and ROC-AUC scores, applied across several models such as Support Vector Machine (SVM), Logistic Regression, Naïve Bayes, and Random Forest.

A. Experimental Setup

Dataset: Reddit mental health posts and Twitter data with labeled instances of depression, anxiety, and general mental distress.

Train-Test Split: 70% training and 30% testing.

Validation: 5-fold cross-validation for generalization.

Tools Used: Scikit-learn, NLTK, LIWC, VADER, and Matplotlib.

B. ROC Curve Analysis

The ROC (Receiver Operating Characteristic) curves indicate the trade-off between sensitivity (true positive rate) and specificity (false positive rate).

SVM achieved the highest area under the curve (AUC = 0.91), showing it to be the most reliable classifier across all thresholds.

Naïve Bayes displayed a lower AUC due to its strong assumption of feature independence, making it less suited for nuanced language structures.

C. Feature Importance & Insights

Unigrams like “sad,” “worthless,” “help,” “tired”, and bigrams like “feel alone” and “need help” showed high weights in predictive features.

LIWC features such as high first-person singular pronoun usage and negative affect words were key indicators.

Sentiment scores from VADER and lexicon-based emotion detection added value in distinguishing emotional valence.

D. Comparative Analysis

SVM and Random Forest offered better generalization and precision.

Naïve Bayes performed faster but with lower accuracy.

Logistic Regression showed stable performance with decent interpretability.

Rule-based methods, while interpretable, lacked adaptability to nuanced or informal language.

E. Results Analysis

The analysis demonstrates that Support Vector Machines and Random Forests are the most effective traditional AI techniques for detecting mental health concerns from online textual data. These models, when combined with psychologically-informed features and sentiment analysis, offer a robust, interpretable, and computationally efficient approach. Traditional AI methods remain valuable, particularly in real-time and resource-constrained mental health support systems.

V. CONCLUSION

This study explored the potential of traditional Artificial Intelligence (AI) techniques—such as Support Vector Machines (SVM), Logistic Regression, Naïve Bayes, and rule-based Natural Language Processing (NLP)—for monitoring mental health indicators through online text-based communication. As mental health challenges continue to grow in prevalence, especially within digitally connected societies, the need for scalable, interpretable, and efficient solutions is more important than ever.

The research demonstrates that traditional AI methods, despite the rise of deep learning, remain highly effective for mental health detection tasks, especially when applied with robust feature engineering. Leveraging psycholinguistic cues (e.g., LIWC categories), emotional lexicons (e.g., VADER, NRC), and syntactic patterns within social media text enables these models to accurately flag signs of mental distress such as depression, anxiety, and psychological stress.

Support Vector Machines emerged as the most accurate classifier, achieving a high F1-score and ROC-AUC, while rule-based models offered interpretability but lower adaptability. The use of structured preprocessing and domain-specific features played a critical role in enhancing the performance of all models.

Importantly, the study emphasizes the ethical responsibility inherent in deploying AI tools for mental health applications. Issues such as user privacy, data anonymization, algorithmic bias, and non-diagnostic use were considered throughout the research design.

In conclusion, traditional AI approaches—when applied thoughtfully and transparently—offer a viable foundation for early detection systems in mental health support. They provide a promising step toward scalable and explainable mental health interventions in online communication platforms, especially in settings where computational resources or large annotated datasets for deep learning are limited.

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