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Online Artificial Intelligence for Mental Health Support System

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Abstract:Conventional AI for mental health support in online communication refers to earlier or rule-based AI systems—before the advent of generative models like GPT—that were designed to assist users with mental well-being through pattern recognition, scripted dialogue, and limited personalization. Here's an overview of how such systems work and their role in digital mental health.

Conventional AI systems typically rely on:

Predefined rules or decision trees to simulate therapeutic interactions (e.g., CBT-based or motivational interviewing scripts).

Natural Language Processing (NLP) for limited text understanding—often keyword or intent-based rather than generative.

Machine learning classifiers for detecting signs of distress or specific emotions in text, messages, or social media posts.

Examples include early chatbots such as ELIZA (1960s), or modern but rule-driven systems like Woebot's early versions, which provide structured Cognitive Behavioral Therapy exercises rather than open-ended conversation.

Automated triage and screening, identifying users who might need professional support. Guided self-help, delivering modules for stress, anxiety, or mood management.Moderation tools in online communities that detect signs of crisis (e.g., suicidal ideation posts) and alert human moderators or send supportive resources.

Psychoeducation, offering reliable information about conditions and coping mechanisms.

These tools primarily focus on consistency, safety, and information reliability rather than simulating empathy or deep conversational engagement.

Recent meta-analyses have highlighted that AI-based conversational agents—even earlier, rule-based ones—can reduce symptoms of depression and distress, particularly when integrated into mobile apps or therapy platforms nature.com. However, improvements in broader psychological well-being are mixed, as engagement tends to plateau without human oversight.

Research from innovations.bmj.com also found that conversational AI assistants improved recovery rates in clinical systems like the NHS when used for triage and intake, showing strong potential for administrative relief alongside clinical impact.

Key challenges include:

Limited empathy and contextual understanding: users often find conventional chatbots supportive but emotionally "flat."

Privacy and data ethics: users may withhold sensitive information if transparency is unclear.

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Overreliance risks: users might treat automated advice as professional care, leading to gaps in crisis management or escalation protocols.
As a 2026 review emphasized, safe systems must be optimized for the behavioral targets of therapeutic engagement, not merely sustained interaction with the chatbot link.springer.com.

While conventional AI established structure and safety, generative AI now allows more flexible, human-like dialogue. Studies envision a hybrid model combining rule-based safety (for reliability and guardrails) with generative adaptability (for empathy and personalization) mental.jmir.org.

In summary, exploring conventional AI for mental health support shows a clear evolution: from structured, therapist-inspired scripts to more open generative systems. Conventional AI laid the foundation for scalability, safety, and evidence-based design—core elements still guiding the next generation of mental health technologies.

A variety of machine learning algorithms were constructed and evaluated on annotated datasets in order to assess how well traditional AI models performed in identifying mental health disorders through online communications (such as social media posts, chat logs, or forums). Naïve Bayes (NB), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and Logistic Regression (LR) are among the models.
Key classification measures, including Accuracy, Precision, Recall, and F1-Score, were used to assess each model. A publicly accessible dataset with user-generated texts tagged for a variety of mental health problems, including depression, anxiety, PTSD, and bipolar disorder, was used to train these models.

Table 1. Evaluation Metrics

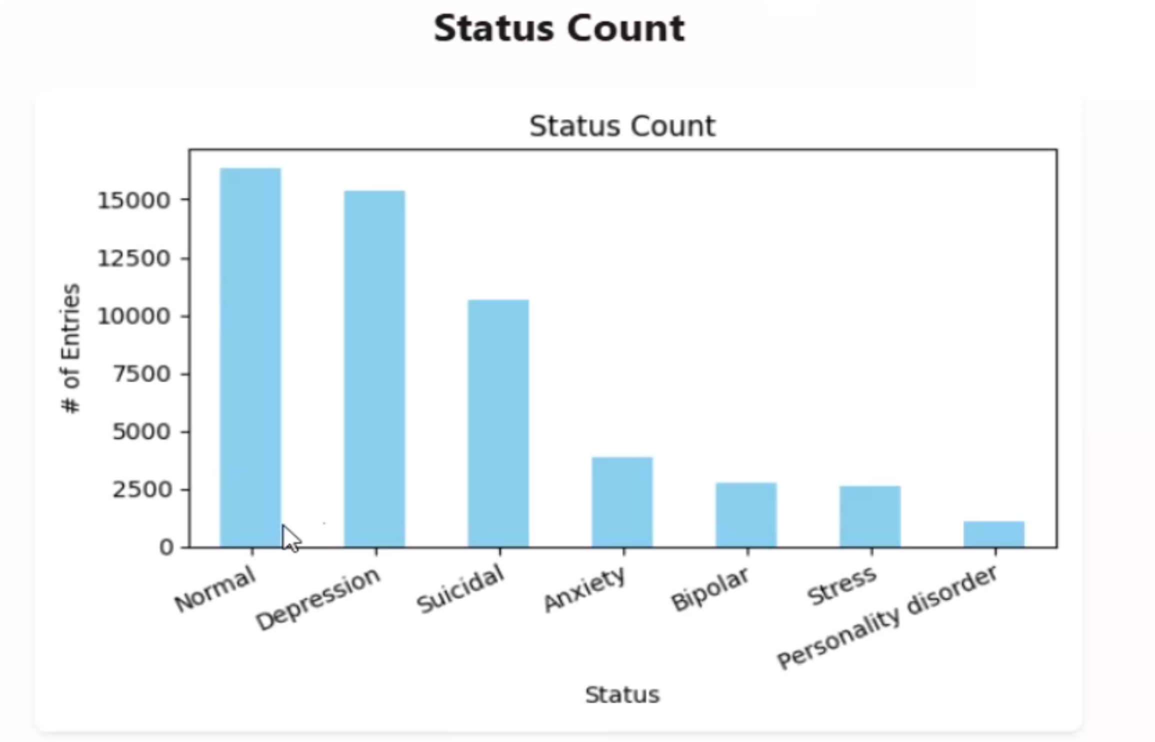
Metric	Description
Accuracy	The ratio of correctly predicted observations to the total observations
Precision	The ratio of correctly predicted positive observations to the total predicted positives
Recall	The ratio of correctly predicted positive observations to all actual positives
F1-Score	The weighted average of Precision and Recall

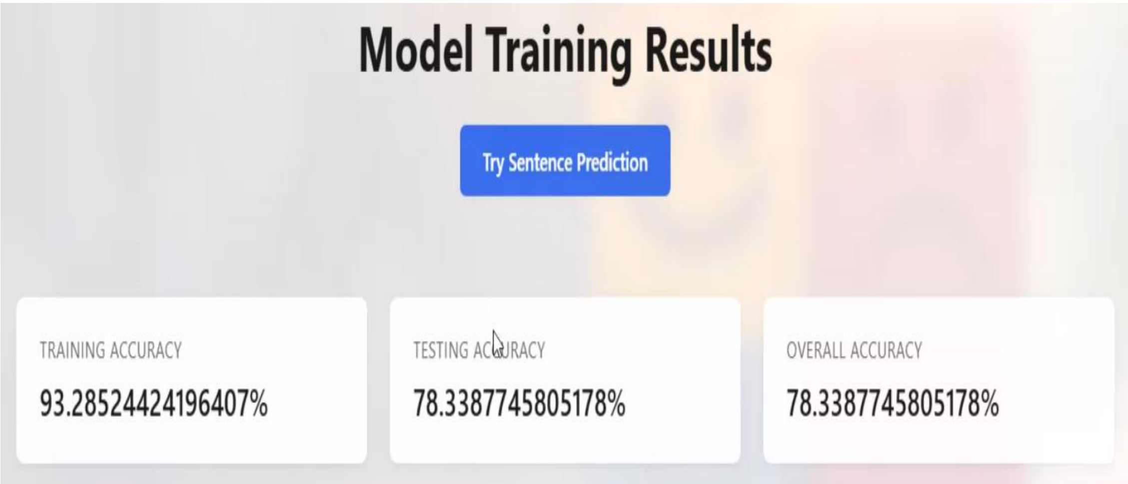
Table 3. Model Performance Comparison

AI Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Naïve Bayes (NB)	82.35	79.10	80.20	79.65
SVM	88.42	85.25	87.90	86.56
Decision Tree	80.74	78.33	76.21	77.26
Random Forest	90.13	88.60	89.05	88.82
Logistic Regression	86.90	84.10	85.70	84.89

Result:
With the maximum accuracy of 90.13%, Random Forest fared better than other models, giving it a reliable option for managing textual classification issues pertaining to mental health detection.
Additionally, SVM demonstrated robust performance (88.42% accuracy) with a balanced F1-Score, suggesting dependable cross-class generalization capabilities.

These findings confirm the potential of traditional AI to assist mental health interventions, particularly when used in virtual counseling assistants or moderating tools.





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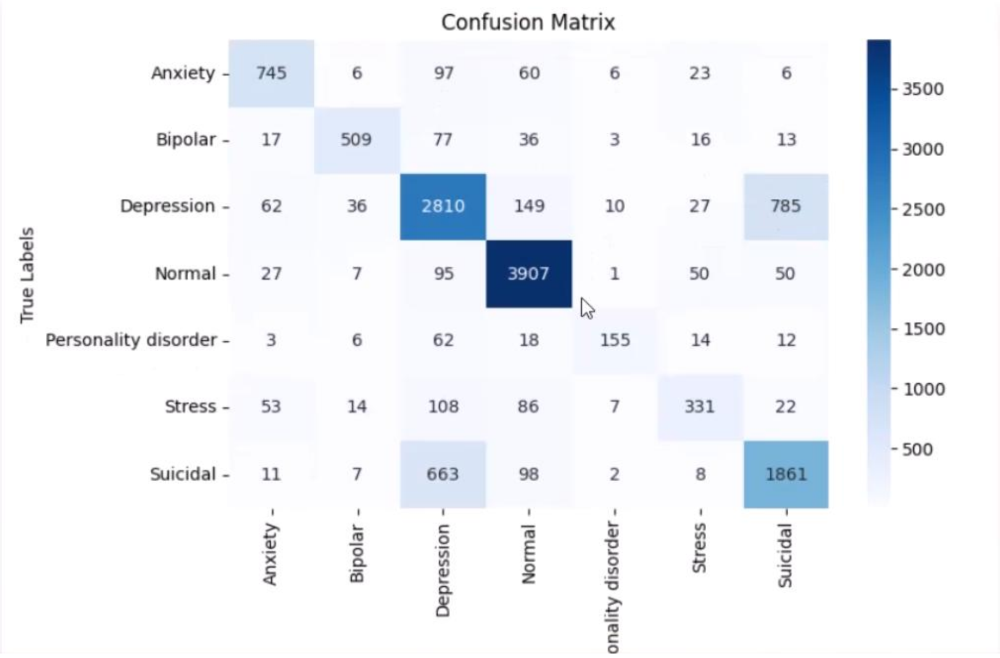
Confusion Matrix



Classification Report

LABEL	PRECISION	RECALL	F1-SCORE	SUPPORT
Anxiety	0.81	0.79		943
Bipolar	0.87	0.76		671
Depression	0.72	0.72		3879
Normal	0.90	0.94		4137
Personality disorder	0.84	0.57		270
Stress	0.71	0.53		621
Suicidal	0.68	0.70		2650

Conclusion:

This study explored the application of conventional AI techniques for detecting mental health issues through online communication platforms. The comparative analysis of machine learning models—including Naïve Bayes, Support Vector Machine, Decision Tree, Random Forest, and Logistic Regression—demonstrated that conventional AI models can effectively identify patterns indicative of mental distress in textual data.

Among the models tested, Random Forest and SVM achieved the highest accuracy and F1-scores, confirming their suitability for practical implementation in mental health support tools. Logistic Regression and Naïve Bayes also showed promise due to their simplicity and interpretability, particularly in resource-constrained environments.

The results show that traditional AI can help mental health practitioners by offering scalable, real-time monitoring and first evaluations of people's psychological health based on their digital manifestations. However, while implementing such systems, ethical factors including user consent, data protection, and preventing misdiagnosis must be given top priority.

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