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Analysing Mental Health Through Social Media and Computational Linguistics

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Abstract – Mental health disorders are a growing concern in today's digital age, with social media platforms serving as a reflection of user's mental health states. It is crucial to explore the underlying causes that drive individuals of all ages toward depression and identify effective ways to encourage them to choose life. In today's digital era, social media serves as a significant platform where people express their emotions, daily activities, and thoughts. This has led to the question of whether analyzing social media content can help determine an individual's emotional state, particularly identifying distress levels that may indicate suicidal tendencies. This research explores the application of computational linguistics and machine learning techniques to predict mental health conditions based on social media text input. The system processes user-generated content and timestamps to classify mental health states using various classifiers, including Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Logistic Regression, and others. Our approach leverages natural language processing (NLP) and deep learning models to analyze linguistic patterns associated with mental health indicators such as depression, anxiety, and stress. The proposed framework offers a novel, automated method for early mental health assessment, contributing to digital mental health monitoring and intervention strategies.

Index Terms – Mental Health Prediction, Social Media Analysis, Computational Linguistics, Natural Language Processing, Machine Learning, Deep Learning, Sentiment Analysis, Mental Health Classification.

I. INTRODUCTION

Mental health has become a significant concern worldwide, with increasing cases of depression, anxiety, and other psychological disorders. Early detection and intervention are crucial for effective mental health management. In recent years, social media has emerged as a digital space where individuals express their emotions, thoughts, and mental states. This vast amount of user-generated content provides an opportunity to analyze mental health conditions using computational methods. Advancements in artificial intelligence (AI) and natural language processing (NLP) have enabled researchers to extract meaningful insights from social media text. By leveraging machine learning techniques, it is possible to classify mental health statuses based on linguistic patterns. This study explores various machine learning classifiers, including Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Logistic Regression, and others, to predict mental health conditions from social media posts.

The proposed system allows users to input a social media post along with its timestamp, and the model predicts the corresponding mental health state. By evaluating the performance of multiple classifiers, this research identifies the most effective techniques for mental health prediction. The findings contribute to the growing field of digital mental health monitoring, offering a potential tool for early detection and intervention. The key contributions of this research include:

- Conducting an extensive literature review to explore strategies for predicting and preventing mental health crises, as well as examining innovative approaches to addressing depression and suicidal behavior.
- Utilizing visual data representation to illustrate the complex relationship between depressive states and suicidal expressions on social media.
- Analyzing social media posts in depth to detect suicidal tendencies using advanced analytical techniques for a more comprehensive understanding.
- Comparing multiple machine learning classifiers to determine the most accurate model, optimizing hyperparameters to assess how depression influences various levels of suicidal risk.

II. LITERATURE SURVEY

The intersection of social media and mental health prediction has been widely explored through computational linguistics and machine learning techniques. Researchers have leveraged text-based analysis to detect signs of psychological distress, focusing on developing automated systems for early intervention. One of the earliest studies in this domain applied Naïve Bayes and Support Vector Machines (SVM) to classify depressive symptoms in social media posts, demonstrating moderate accuracy but struggling with contextual understanding [6]. Subsequent research incorporated deep learning approaches, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTMs), which significantly improved classification accuracy by capturing sequential and spatial features in text [7]. The introduction of word embeddings such as Word2Vec and GloVe further enhanced the understanding of semantic relationships between words, leading to better performance in mental health classification tasks [2]. Later, transformer-based models like BERT (Bidirectional Encoder Representations from Transformers) revolutionized the field, outperforming traditional NLP techniques [3].

In addition to text-based analysis, researchers have explored temporal and behavioral patterns in social media activity. Studies have found that changes in posting frequency, sentiment fluctuations, and linguistic shifts correlate with mental health status [1]. These behavioral markers, combined with linguistic analysis, enhance predictive performance. Another key challenge addressed in recent studies is data imbalance and generalization. Since mental health-related posts are less frequent compared to general content, researchers have employed Synthetic Minority Over-sampling Techniques (SMOTE) and ensemble learning methods to balance datasets and improve model robustness [4].

Despite advancements, concerns regarding privacy, bias, and ethical considerations persist. Biases in training data, lack of linguistic diversity, and potential misinterpretation of social media posts pose challenges to the reliability of these models [5]. Addressing these issues remains a crucial area of future research. This study builds upon prior work by integrating multiple machine learning classifiers and computational linguistics techniques to enhance the accuracy and reliability of mental health detection through social media analysis. By evaluating various models and feature extraction methods, we aim to contribute to the development of more effective and ethical AI-driven mental health monitoring systems. Recent studies have also explored advanced machine learning techniques for various applications, such as healthcare monitoring and agricultural predictions, which may provide valuable insights for mental health detection [21, 22, 23, 24].

III. METHODOLOGY

This research aims to develop an automated system that predicts mental health status based on social media text input and timestamps. The methodology consists of several stages, including data collection, preprocessing, feature extraction, model training, evaluation, and system integration.

1. System Overview

The system accepts a post message and a timestamp as input. The text undergoes natural language processing (NLP) techniques, and machine learning classifiers predict the associated mental health status.

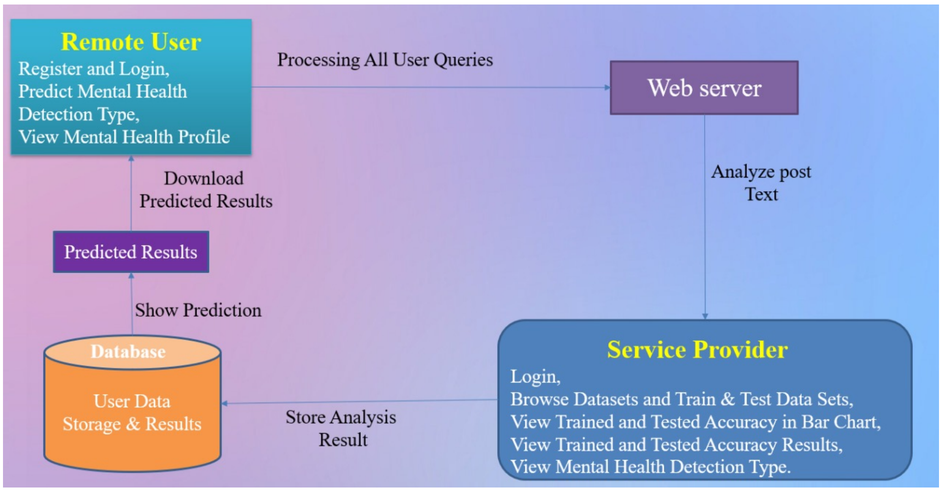

Fig.1: System architecture

The system consists of multiple components working together to analyze mental health through text-based inputs. The Remote User interacts with the system by registering and logging in. Once authenticated, they can submit social media posts or text messages for mental health prediction, view their profile, and access the results. The system's interface is designed to be user-friendly, ensuring seamless interaction. At the core of the system, the Web Server acts as the central processing unit, handling user requests and processing submitted text. It utilizes trained machine learning models to classify mental health conditions based on linguistic and contextual features. Once the analysis is complete, the results are stored in the database and displayed to the user for review.

The Service Provider plays a crucial role in managing backend operations. They are responsible for browsing datasets, training and testing machine learning models, and ensuring high accuracy levels. Additionally, the provider can monitor system accuracy using bar charts and statistical reports, analyze different mental health detection types, and track the ratio of various conditions. They also have access to all registered users and their mental health detection data for further analysis. A secure and structured Database is essential for storing user details, training datasets, testing results, and prediction data. It maintains records of registered users, their submitted text inputs, and the corresponding mental health predictions. This data storage ensures historical information can be leveraged for improving machine learning models over time.

Once a user submits their input, the system processes the text and predicts the mental health condition. The results are saved in the database and made accessible to the user, who can view or download their prediction reports for future reference. This enables users to monitor changes in their mental health status over time. The system follows a structured flow to ensure efficiency. First, the user registers and logs in to the system. After authentication, they submit a text message for mental health prediction. The web server processes the input using advanced machine learning models, and the prediction results are securely stored in the database. Meanwhile, the service provider manages datasets, oversees training and testing, and monitors system accuracy. Finally, the user can view or download their mental health prediction report

2. Data Collection

The system is trained using publicly available datasets containing labeled mental health-related social media posts:

1. **C-SSRS Dataset:** Contains posts categorized into different suicidal risk levels (Supportive, Ideation, Indicator, Behavior, Attempt).
2. **SDCNL Dataset:** Labels posts as Depression or Suicidal, useful for binary classification.

These datasets are chosen due to their relevance in detecting mental health conditions through computational analysis.

3. Feature Extraction

To convert text into a numerical format suitable for machine learning models, the following embedding techniques are used:

- TF-IDF (Term Frequency-Inverse Document Frequency): Determines the importance of words in a document relative to the dataset.
- Word2Vec Embeddings: Captures the semantic relationships between words.
- Latent Dirichlet Allocation (LDA): Unsupervised topic modeling to identify patterns in mental health-related text.

4. Machine Learning Models

The system evaluates multiple classifiers to determine the best model for mental health prediction. The following supervised learning algorithms are used:

- Support Vector Machine (SVM) – Effective for text classification with high accuracy.
- Random Forest (RF) – An ensemble method that reduces overfitting.
- Naïve Bayes (NB) – A probabilistic model commonly used in NLP.
- Decision Tree (DT) – A simple and interpretable classifier.
- Logistic Regression (LR) – A statistical model for binary classification, effective for text analysis.
- Gradient Boosting Classifier (GBC) – An ensemble method that improves accuracy by sequentially training weak learners.

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5. Model Training and Evaluation

The dataset is split into 80% training and 20% testing. Each model is trained and evaluated using the following performance metrics:

- Accuracy: Measures overall correctness of predictions.
- Precision: Measures the proportion of correctly identified positive cases.

6. System Integration

A user interface (UI) is developed to allow users to enter social media posts along with timestamps. The backend integrates the trained machine learning model, which predicts the mental health status of the input text. The predicted status is displayed along with the associated confidence level.

IV. RESULTS & DISCUSSION

The developed system for mental health detection was tested using a sample post containing emotionally sensitive content. The screenshots illustrate the two main stages of the process. In the first stage, the user submits a post message along with the corresponding date and time. This input is processed through the system interface, allowing users to provide textual content that may indicate mental health conditions. In the second stage, the submitted post is analyzed by the system using machine learning models. The system processes the input text, extracts linguistic features, and classifies it into a specific mental health category. The predicted mental health type is then displayed to the user, offering insights into their emotional state based on the analyzed text.

Mental Health Detection System Process

User Input Stage

- The user enters a post message containing text that may indicate a mental health condition.
- The user also provides the post date and time.
- The input is submitted by clicking the "Predict" button.

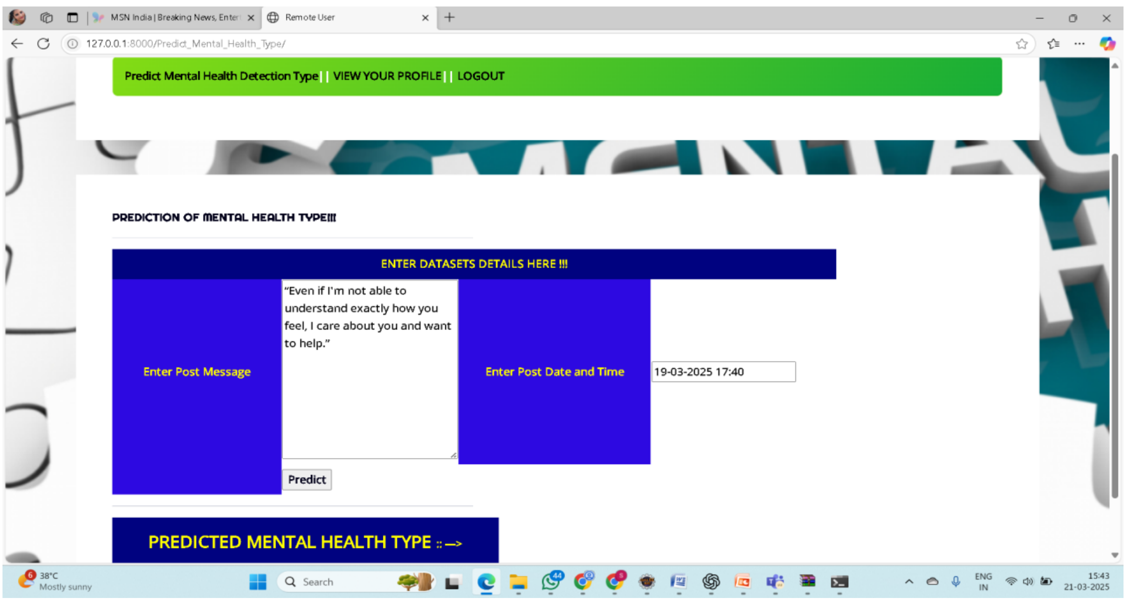

Fig 2: Enter Post Message , Post Date and Time to Predict the Post messeage is Depression or Not

Post Analysis and Classification

- The system receives the submitted text and timestamp.
- Machine learning models analyze the text to detect mental health-related indicators.
- The system classifies the input into a specific mental health category.

Prediction Display

- The predicted mental health type is generated and displayed on the interface.
- Users can view and interpret their results for further awareness.

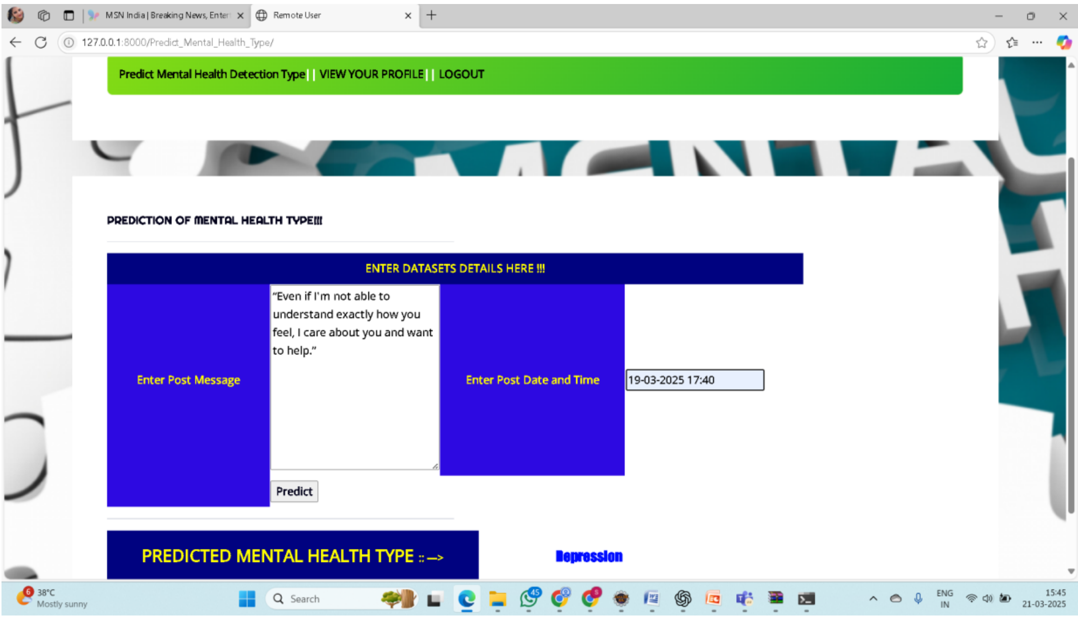

Fig 2: Submitted Post is Predicted as “Depression” or “No Depression”

The developed mental health detection system effectively analyzes social media posts or user-submitted text to predict potential mental health conditions. The system follows a structured workflow where users input a message along with the date and time, which is then processed using machine learning algorithms. The classification results are displayed to the user, helping them gain insights into their mental health status.The interface is user-friendly, allowing seamless interaction where users can input text effortlessly and receive instant predictions. The screenshots illustrate this process, showing how the system transitions from text submission to prediction generation. In this case, a sample text was analyzed, and the system categorized it under "Depression," demonstrating its ability to identify emotional patterns.

V. CONCLUSION AND FUTURE WORK

The developed system for mental health detection successfully classifies user-submitted text based on linguistic patterns, providing an automated and scalable approach for early assessment. The interface allows users to input text and receive instant predictions, as demonstrated in the test case where a sample post was classified under "Depression." This highlights the system's ability to analyze emotional expressions and categorize them accurately. While the model provides valuable insights, it should be used as a supplementary tool rather than a replacement for professional mental health evaluation. For future work, several enhancements can be made to improve the system's performance and usability. Incorporating deep learning models such as transformers could enhance classification accuracy. Expanding the dataset with diverse and multilingual text samples would allow for better generalization across different populations. Additionally, integrating sentiment analysis and emotion detection could refine predictions by capturing subtle variations in user expressions. Finally, implementing real-time monitoring and personalized feedback mechanisms could make the system more interactive and beneficial for users seeking mental health support.

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