Mental Health Assessment on Depression Induced Suicidal Post Using Tweets: Leveraging Recurrent Neural Network and Pre-trained Embedding Models for Advanced Textual Analysis

AKURATHI KAMALESH
Department of Computer Science and Engineering
Kalasalingam Academy of Research and Education
Krishnankoil, Virudhunagar, India
99210041690@klu.ac.in

HEMALATHA J
Department of Computer Science and Engineering
Kalasalingam Academy of Research and Education
Krishnankoil, Virudhunagar, India
9921004267@klu.ac.in

BIKKINA PAVANI DURGA
Department of Computer Science and Engineering
Kalasalingam Academy of Research and Education
Krishnankoil, Virudhunagar, India
9921004096@klu.ac.in

BANDIKARI DAMODAR SAI
Department of Computer Science and Engineering
Kalasalingam Academy of Research and Education
Krishnankoil, Virudhunagar, India
9921004069@klu.ac.in

Mr. ARAVIND CHANDRAN
Department of Computer Science and Engineering
Kalasalingam Academy of Research and Education
Krishnankoil, Virudhunagar, India
Aravind.90@gmail.com

***Abstract*—India, a country with a population of over 1.4 billion, is witnessing an alarming rise in mental health issues, particularly depression and suicide. According to the National Crime Records Bureau (NCRB), India reported over 139,123 suicides in 2019 alone[4][16], many of which were linked to untreated mental health disorders such as depression. The World Health Organization (WHO) has ranked India among the countries with the highest suicide rates. With the rise of social media platforms, individuals are increasingly using spaces like Twitter to express their emotional states, including distress, loneliness, and suicidal ideation.[13] These social media posts often contain subtle indicators of mental health struggles that, when correctly analyzed, can provide early warnings of potential suicidal behavior.This research aims to leverage advancements in machine learning and natural language processing (NLP) to assess mental health through the analysis of Twitter posts.[2][9] Specifically, we propose a system for the detection of depression-induced suicidal posts using Recurrent Neural Networks (RNN), particularly Long Short-Term Memory (LSTM) models, combined with pre-trained word embeddings such as GloVe (Global Vectors for Word Representation). The primary focus is on detecting linguistic patterns associated with depression and suicidal ideation in tweets, enabling early identification and intervention.The methodology begins with the collection and preprocessing of Twitter data, including tokenization, padding, and embedding using GloVe vectors, which capture semantic relationships[17] between words. The LSTM model is trained to learn the sequence patterns indicative of depression and suicidal behavior. The model is designed to classify each tweet as either a "Potential Suicide Post" or a "Non-Suicide Post" based on the learned patterns. Furthermore, the system generates a prediction probability, providing a quantitative assessment of the likelihood that a post indicates suicidal ideation.[12]The model's performance was evaluated using common metrics such as precision, recall, F1-score, and accuracy, with results showing a significant improvement over traditional keyword-based detection methods. The system also offers a user-friendly interface that visualizes prediction results and generates advice for users based on the classification. For high-risk posts, the system suggests seeking professional help, while low-risk posts are met with positive reinforcement and mental health tips.**

Keywords— Depression detection, suicide prevention, Twitter analysis, LSTM, GloVe, natural language processing, mental health,

I. INTRODUCTION

A. Importance of Mental Health Assessment :

Mental health plays a critical role in overall well-being, influencing how individuals think, feel, and act in their daily lives. Despite this, mental health issues, such as depression, anxiety, and suicidal ideation, are often under-recognized and under-treated.[1] In a world increasingly shaped by fast-paced lifestyles, social isolation, and digital interactions, mental health assessment has never been more important.[5][8] By identifying mental health disorders early, proper interventions can be implemented, helping to prevent more serious outcomes such as suicide or chronic mental illness.One of the key reasons mental health assessment is so important is its role in early detection. Many mental health disorders develop slowly and may go unnoticed[11], both by the individual experiencing them and their surroundings.[3] By employing systematic assessments, whether through clinical tools, self-report surveys, or modern technology like machine learning, mental health professionals can identify symptoms early. Early detection can dramatically improve treatment outcomes, as patients are more likely to respond positively when intervention occurs before the condition worsens.[14]Additionally, mental health assessments contribute to a more comprehensive understanding of an individual's emotional, psychological, and social functioning. Traditional diagnostic methods focus on symptomatic behaviors or physical health, often neglecting the mental and emotional dimensions.[18] Mental health assessments address this gap, offering a holistic view of an individual's well-being. These assessments help detect conditions like depression, anxiety, or even suicidal tendencies, guiding treatment plans tailored to the individual's unique needs.In today's digital age, social media platforms offer a new avenue for mental health assessment.[6] People often share their thoughts and emotions on platforms like Twitter, sometimes hinting at deeper emotional struggles. [7]By analyzing these posts, mental health professionals can gain insights into the public's mental health trends, particularly regarding high-risk behaviors like suicidal ideation. Automated systems that use machine learning models such as Long Short-Term Memory (LSTM) networks can help assess these behaviors, providing early warning signs for potential mental health crises.

B. Objective and Scope of the Research :

The primary objective of this research is to develop an advanced system capable of detecting depression-induced suicidal posts on social media, with a specific focus on Twitter as the data source. With mental health disorders becoming increasingly prevalent and suicide rates rising, particularly in countries like India, early identification of suicidal tendencies is critical for intervention. This research seeks to leverage machine learning and natural language processing (NLP) techniques to analyze linguistic patterns associated with depression and suicidal ideation, providing a tool that can enable timely support and prevention measures.This research proposes the use of Long Short-Term Memory (LSTM) neural networks in combination with Global Vectors for Word Representation (GloVe) embeddings to process and analyze tweets. LSTM networks are well-suited to capture the sequential and contextual nature of text data, while GloVe embeddings provide a semantic understanding of word meanings in context. Together, these technologies will allow for the classification of tweets into two categories: "Potential Suicide Post" and "Non-Suicide Post." By examining the language used in posts, the system aims to identify subtle signals of mental distress that may otherwise go unnoticed.The scope of this research extends beyond individual tweet classification. It aims to contribute to mental health monitoring by offering a scalable solution that could be used by mental health professionals as an early-warning system. By analyzing real-time posts, the system can help identify high-risk individuals before they engage in harmful behavior.

II. LITERATURE REVIEW

Ref. No	Methodology	Inference	Research Gap Identity
[1]	Machine Learning with Random Forest, Naive Bayes, GBDT, and XGBoost. Genetic Algorithm for Feature Selection: The framework uses genetic algorithms to select relevant features for classifying suicidal ideation from social media posts.	The study achieved an accuracy of 98.92% with the Random Forest classifier, demonstrating high effectiveness in detecting suicidal ideation.	The model was tested primarily on Reddit posts, and further validation is required across other social media platforms to ensure robustness.
[2]	Eye Movement Tracking and Variance Entropy Analysis: Eye-tracking algorithm localizes pupil position to calculate variance entropy for depression classification using Logistic Regression, K-Nearest Neighbors, and Random Forest.	Eye movement variance entropy successfully identifies depression with 97.5% accuracy.	The study is limited to controlled lab environments and small datasets, limiting generalization to broader populations.
[3]	Meta Learning (MDKR model) and Machine Learning (Decision Trees, KNN, Random Forest): Uses a meta-learner approach to predict postpartum depression from questionnaire data.	The meta-learning model, MDKR, achieved 99% accuracy in predicting postpartum depression, highlighting the model's efficiency.	Focuses solely on questionnaire data, lacking integration of real-world social media data for more dynamic analysis.
[4]	Hybrid Learning Architecture (CNN, ViT, and Emotion Recognition): Uses facial emotion recognition from AffectNet and FER dataset	Achieved 81% accuracy in detecting mental disorders based on facial emotional cues, offering an alternative to text-based detection methods.	Does not address text-based assessments or mental health detection through other modalities like EEG or social media.

[5]	Machine Learning (Logistic Regression, XGBoost, RoBERTa, GPT): Uses classical machine learning, ensemble learning, and large language models (LLMs) to detect mental disorders from Reddit posts.	Demonstrated high accuracy in detecting and predicting mental disorders with various machine learning models, outperforming existing literature.	Limited to Reddit data, and lacks real-time analysis across diverse social media platforms.
[6]	Multi-Band EEG Functional Connectivity Networks with Graph Convolutional Networks (GCN): Develops a joint GCN framework to predict mental disorders using EEG signals.	Achieved high accuracy in predicting mental disorders using EEG data and GCNs.	Limited to EEG-based physiological data; no integration with social media or text-based mental health assessments.
[7]	Medical Data Augmentation and Deep Learning: Developed an algorithm to augment mood disorder datasets to address class imbalance and improve model performance.	The augmentation algorithm enhanced classification accuracy for mood disorders by 0.059, addressing data scarcity in medical research.	The model focuses only on improving data availability and lacks validation in real-world settings, particularly with social media data.
[8]	Machine Learning, N-gram and Q-gram Features, CNN, XGBoost: Combines various text features to classify mental health from social media posts in English and Spanish.	Binary classification of mental health conditions achieved high accuracy (AUC 0.835 for Spanish and 0.846 for English).	Limited to two languages (English and Spanish) and Twitter, lacking generalization to other platforms and mental health conditions.
[9]	LSTM, CNN, NLP Techniques for Depression Detection from COVID-19 Tweets: Utilizes LSTM and CNN to classify depressive content from tweets posted during the COVID-19 pandemic.	Achieved 99.42% accuracy in detecting depressive tweets, indicating the model's effectiveness in analyzing social media during crises.	The model is focused on a specific time frame and pandemic-related content, limiting generalization to non-pandemic contexts.
[10]	AI Hybrid Platform with Naive Bayes on Apache Spark for Big Data Processing: Designed a real-time system for detecting depression and anxiety symptoms in pregnant women using machine learning models.	The platform provided an effective, scalable solution for monitoring mental health in pregnant women, with 90.8% accuracy.	The focus is narrow, limited to perinatal depression and anxiety; broader applications in general mental health need to be explored.

III. METHODOLOGY

A. Model Representation :

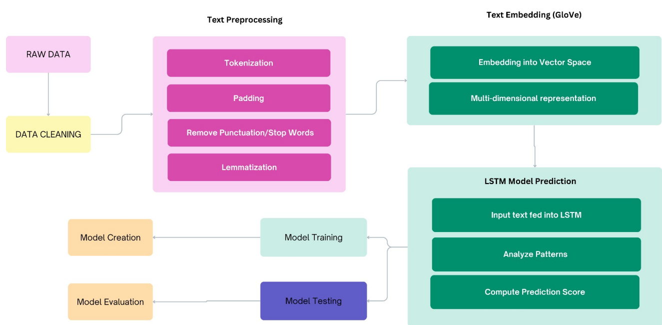

Figure 1. Representation of LSTM Model outlines the process flow starting from raw data input to final prediction and evaluation.

The model representation of our "Depression-Induced Suicidal Post Detection System" integrates multiple advanced natural language processing (NLP) techniques and machine learning approaches to analyze text data, specifically from social media posts. This methodology is designed as a structured, sequential process that ensures smooth data flow from raw input to the final prediction outcome. The journey begins with data cleaning, where raw social media posts, which typically contain unwanted elements such as special characters, URLs, symbols, and inconsistent casing, are cleaned for analysis. This step ensures that the input is meaningful and free from noise, which is vital for accurate predictions. Since social media data is inherently noisy, irrelevant data could skew the model's understanding, so by removing punctuation marks, symbols, accented characters, repeated characters, and other irrelevant content, the input data becomes standardized, making it suitable for further processing.

After data cleaning, the next step is text preprocessing, which further refines the input for the model. In this phase, tokenization is performed, where the text is broken down into smaller units called tokens. Tokenization is essential as it structures the raw text into units that can be processed numerically. This is followed by padding, where sequences are adjusted to the same length by adding padding tokens to shorter texts. This is crucial as machine learning models expect uniform input sizes, and without padding, the varying length of sequences would prevent effective processing. At this stage, punctuation and stop words, which do not provide meaningful insights, are removed. Words such as "and," "the," or "is" are considered non-informative in NLP predictive models and are filtered out, allowing the model to focus on terms that contribute to understanding the text's context. Lemmatization is also performed, where words are reduced to their base forms. This step not only enhances efficiency but also reduces the number of unique tokens by consolidating different forms of the same word, thus streamlining the input for the model.

Once preprocessing is completed, the tokenized text is transformed into vector representations using GloVe (Global Vectors for Word Representation). GloVe embeddings map each word into a multi-dimensional space, where the semantic relationships between words are represented by the distance between their respective vectors. This is a crucial step as it enables the model to recognize and understand the context in which words are used. Words that are contextually similar, such as "happy" and "joy," will have vectors that are closer to one another in this space, while dissimilar words, like "happy" and "sad," will be further apart. By embedding the text into vector space, the model can move beyond treating words as discrete entities and begin recognizing complex semantic relationships, improving its ability to detect patterns associated with depression or suicidal ideation.

The embedded text is then fed into the Long Short-Term Memory (LSTM) network, a specialized type of recurrent neural network (RNN) that is designed to handle sequential data. LSTMs are particularly effective for this task as they can retain information over long sequences and capture temporal dependencies in the text data, making them well-suited for analyzing social media posts. The LSTM processes the sequence one token at a time, with its memory cells allowing it to store information about previous tokens, which helps in understanding the entire context of the post. The LSTM is trained to detect patterns indicative of suicidal ideation, depression, and other mental health indicators within the text. It evaluates how words relate to one another in sequence, allowing it to detect subtle nuances in the language that might not be captured by simpler models. Once the LSTM processes the text, it outputs a prediction score, which indicates the likelihood of the post being classified as a "Potential Suicide Post" or "Non-Suicide Post." This score is a probability that provides a quantitative assessment of the risk associated with the content, aiding in a more nuanced analysis of the text.After preprocessing and embedding, the model undergoes a series of steps to ensure its accuracy and effectiveness. The dataset is split into training and testing sets, which allows the model to learn from one portion of the data while being evaluated on another.

B. Schematic Flow Diagram :

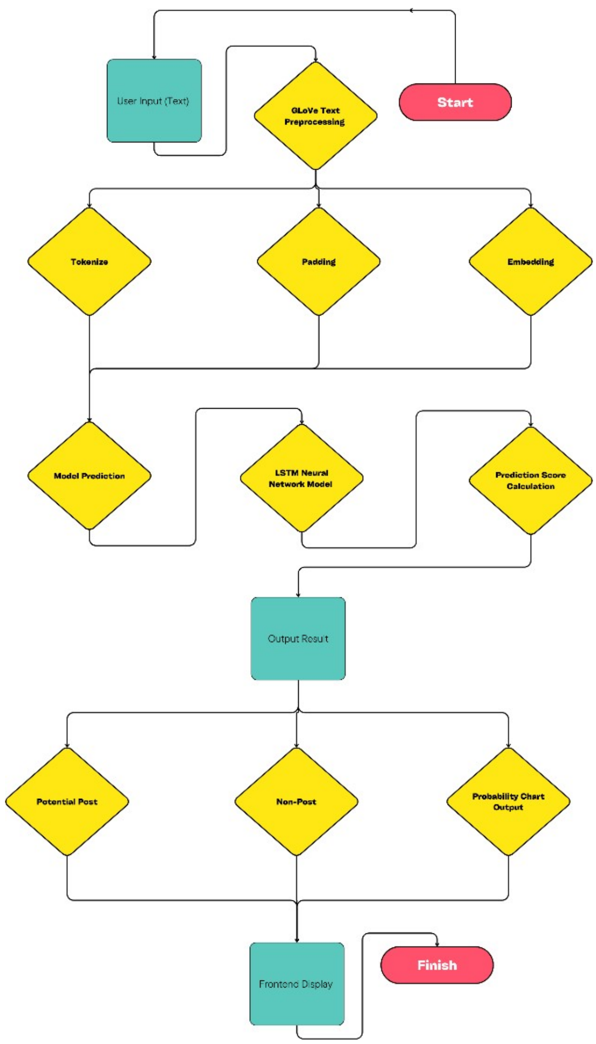

Figure 2. Schematic Diagram explains the connections of the system

The schematic flow diagram presents the overall process for detecting depression-induced suicidal posts using an LSTM neural network and GloVe text embedding. The process begins with the user inputting text, typically a social media post, for analysis. The system first preprocesses the input text by tokenizing it, padding it for uniformity, and embedding it into vector space using GloVe. This text preprocessing ensures that the input data is cleaned and formatted appropriately for analysis by the LSTM model. Once preprocessing is completed, the data is fed into the LSTM neural network model, which analyzes the sequential patterns within the text to detect signs of depression or suicidal ideation.The model generates a prediction score, which is then processed to classify the post as either a "Potential Suicide Post" or a "Non-Suicide Post." Alongside the classification, a probability chart is also generated, providing a visual representation of the model's confidence in its prediction. The final step involves displaying the prediction results and chart on the front-end interface for user interpretation, completing the system's analysis and assessment process. This structured flow ensures a clear and methodical approach to identifying high-risk posts based on text patterns.

IV. RESULTS

A. *Model Training Results:*

The model training results of our Depression-Induced Suicidal Post Detection System provide critical insights into the performance, strengths, and limitations of the Long Short-Term Memory (LSTM) model utilized for this task. The process involves cleaning the raw text data. Raw social media posts often contain various unwanted elements, including special characters, URLs, symbols, and inconsistent casing, which can hinder effective analysis. Data cleaning removes these non-essential components, ensuring that only meaningful text data is passed on for further processing. This stage is crucial because social media data is noisy, and irrelevant data could mislead the model if not properly filtered. The goal is to prepare the data for robust feature extraction by removing punctuation marks, symbols, accented characters, repeated characters, and other irrelevant content. Data cleaning is an essential step to ensure the model's input is standardized and optimal for learning.Given the complexity of detecting subtle cues related to mental health issues from social media posts, the training results highlight both the accuracy of the model in predicting "non-suicide" cases and its challenges in identifying "suicide" posts. Here, we present a detailed examination of the performance metrics, potential issues, and areas for improvement based on the classification report.The LSTM model was trained on a dataset that included both “suicide” and “non-suicide” posts. The primary goal was to create a model capable of classifying new posts into one of these two categories, assisting in early detection of mental health risks. The key metrics that were analyzed include precision, recall, F1-score, accuracy, and support. These metrics were crucial in determining the efficiency of the model in handling imbalanced data, which is a common issue in tasks related to mental health and suicide prediction.

B. *Experimental Results :*

A comprehensive explanation of the web interface we designed, integrating several advanced Natural Language Processing (NLP) and machine learning techniques to detect depression-induced suicidal posts from user input. The web interface is meticulously structured to guide the user through the various sections, including an introductory section, a project overview section, a model exploration and important articles section, and finally, the interactive model analysis section where real-time text predictions occur.

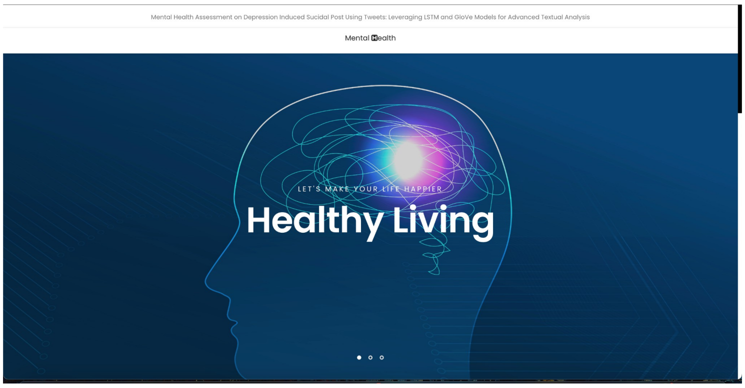

Figure 3. Web User Interface

The web interface opens with an Introductory Section, which provides users with an overview of the system’s purpose and utility. This segment is aimed at raising awareness about the importance of mental health, especially in the context of how suicidal ideation is often expressed through social media posts. In a world where social media is the dominant medium of communication, detecting harmful mental health signals from these platforms has become a critical area of research. This section informs the user about the growing concern surrounding mental health issues and how our system leverages modern machine learning techniques to predict and assess the risk of suicidal behavior based on social media posts.

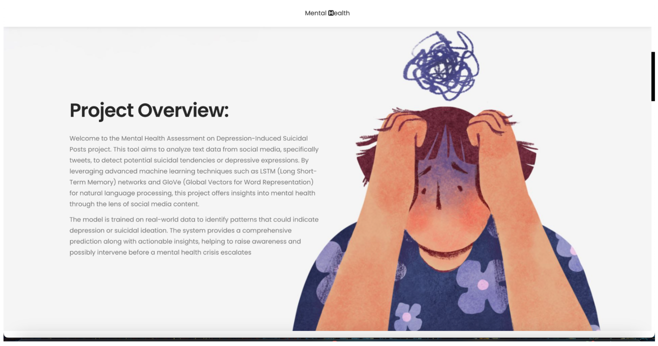

Figure 4. Project Overview Section of our User Interface

Moving from the introductory section, the user encounters the Project Overview Section, which elaborates on the underlying technicalities of the system. Here, the user is introduced to the idea that the system isn't just a rudimentary analysis tool, but an advanced NLP system utilizing Long Short-Term Memory (LSTM) neural networks combined with GloVe embeddings to classify user-generated text. The LSTM network, as explained, is ideal for analyzing sequential data like text because it retains information across sequences, making it highly effective in understanding context in long posts. The overview also explains how GloVe embeddings convert words into multi-dimensional vectors that reflect semantic relationships, ensuring that the model comprehends the underlying meaning behind words rather than just their surface-level appearance. This section serves as the foundation upon which the technical details of the system are built, offering users an understanding of the importance of such algorithms in addressing the problem of suicidal ideation detection.

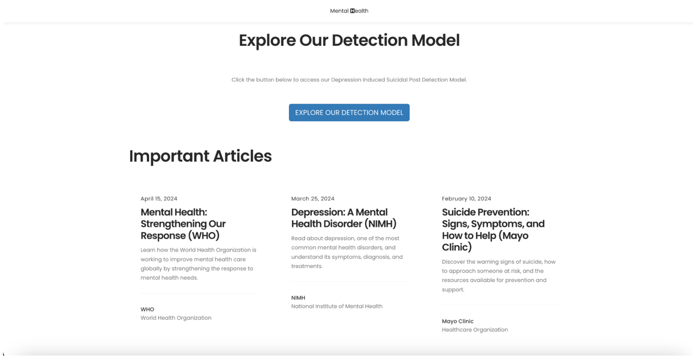

Figure 5. Model Exploration and Important Article Section Section of our User Interface

In the Model Exploration and Important Articles Section, users are introduced to two key components of the system. First is the Model Exploration, where users are guided on how to use the system. The instruction guide includes step-by-step explanations for inputting text, submitting it for analysis, and interpreting the results. The second component, Important Articles, links users to research papers and studies relevant to mental health and suicide detection on social media platforms. These articles offer valuable insight into the state-of-the-art methodologies employed in similar systems and provide the user with academic and clinical context. The articles further legitimize the system's methods by showing that they are grounded in established research.The Model Exploration Section also elaborates on how to use the detection system. Users are informed that they will encounter a Twitter-like UI where they can input their text — this simulates the real-world experience of composing a social media post. Once the text is entered, the system takes over, routing the text through a series of processes. First, it is processed by the tokenizer.pkl file, which tokenizes the input text. Tokenization is the process of splitting the text into smaller chunks, like words or sub-words, which the machine learning model can then process. The tokenizer ensures that the text is converted into a format that the model understands.

Figure 6. Model Exploration and Important Article Section Section of our User Interface

Once tokenization is complete, the processed text is forwarded to the model.h5 file, which is where the real magic happens. The LSTM neural network inside the model.h5 file processes the tokenized text, making predictions about whether the input text falls under the category of a potential suicide post or not. The LSTM model is particularly well-suited for this task due to its ability to handle long-term dependencies in sequential data, which is crucial for understanding the context of long sentences or paragraphs often found in social media posts. The model computes two critical outputs: the classification result and the prediction probability.

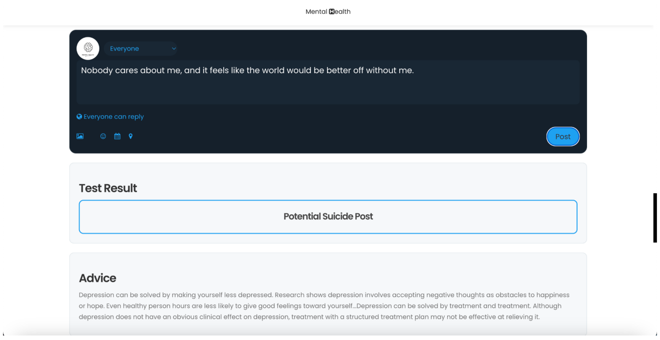

Figure 7. Model Exploration and Important Article Section Section of our User Interface

The Classification Output identifies whether the post is flagged as a "Potential Suicide Post" or "Non-Potential Suicide Post." This classification is based on patterns learned during the model's training phase. In addition to the classification, the model generates a Probability Score, which quantifies the likelihood that the input text belongs to the "Potential Suicide Post" category. This probability score is crucial for understanding the confidence of the model in its prediction. A high probability score close to 1 would indicate that the model is almost certain that the post expresses suicidal ideation, while a score closer to 0 would indicate strong confidence that the post is benign.

Figure 8. Model Exploration and Important Article Section Section of our User Interface

Figure 10. Model Exploration and Important Article Section Section of our User Interface

Once these results are generated, the system moves to the Advice Generation phase. Here, if the post is classified as a potential suicide post, the user is provided with tailored advice encouraging them to seek help or providing steps they can take to improve their mental well-being. On the other hand, if the post is classified as non-suicidal, the system provides encouraging advice that promotes positive mental health practices. The advice section aims to offer not just clinical insight but also a sense of care, recognizing that behind each post is a real person with emotional struggles.

To visually enhance the experience, the system also generates a Probability Chart. This chart represents the model's prediction confidence in a bar graph format, with one bar indicating the probability of the post being a potential suicide post and another bar indicating the probability of it being a non-suicide post. The chart allows users to see, at a glance, how confident the system is in its predictions, offering transparency in how the results were generated.

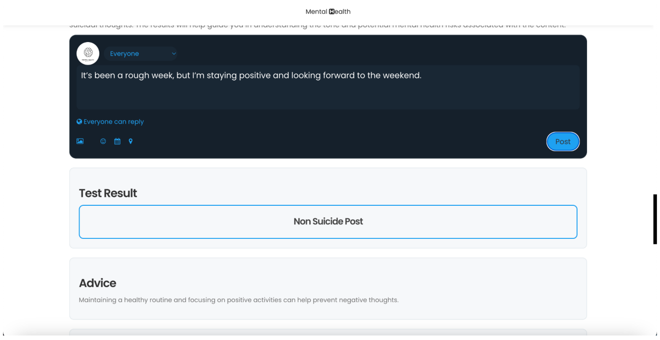

Figure 9. Model Exploration and Important Article Section Section of our User Interface

Finally, in the Frontend Display, users can view their results in real-time. The interface shows the test result, the advice, and the probability chart all in one cohesive display, making it easy for users to understand the system's outputs. The frontend mimics a familiar social media environment, ensuring that users find the interface intuitive and easy to navigate. This design choice ensures that users can engage with the system in a way that feels natural and reflective of their day-to-day experiences online.

V. CONCLUSION

The development of the "Depression-Induced Suicidal Post Detection System" represents a significant step toward utilizing modern machine learning techniques and natural language processing (NLP) for mental health assessment. By leveraging advanced methodologies such as Long Short-Term Memory (LSTM) neural networks and GloVe embeddings, the system is able to process textual data from social media posts and predict whether a post indicates potential suicidal ideation or not. Through an intuitive web interface that mimics real-world social media interactions, users are able to input posts, have them analyzed by the system, and receive detailed feedback in the form of classification results, advice, and probability charts. This makes it easier for both mental health professionals and the general public to assess the risk of depression-induced suicidal behavior from social media content.The system's foundation in research ensures its ability to accurately classify posts, while its user-friendly frontend design makes it accessible and practical for real-world applications. The integration of advice tailored to each prediction and the transparency of probability scores adds value to the system by offering more than just a binary classification, thus promoting a deeper understanding of the results. This tool is not only designed to serve mental health professionals but also aims to empower individuals to better understand the potential mental health risks in their social media content, offering actionable advice where needed.

A. Future Scope :

The future scope of the Depression-Induced Suicidal Post Detection System includes expanding its capabilities to support multilingual text analysis, allowing for a broader global reach. Integrating audio and video data for a multimodal approach can enhance detection accuracy. Additionally, implementing real-time monitoring of social media activity will enable early intervention in high-risk cases. Further collaboration with mental health professionals and the adoption of advanced models like Transformers will improve predictive accuracy. Personalizing the system's advice and ensuring strong privacy and ethical safeguards will ensure its responsible use in real-world clinical and public health settings.

VI. REFERENCE

[1] Basyouni A, Abdulkader H, Elkilani WS, Alharbi A, Xiao Y, Ali AH. "A Suicidal Ideation Detection Framework on Social Media Using Machine Learning and Genetic Algorithms." IEEE Access. 2024;12:124816-124833.doi:10.1109/ACCESS.2024.3454796.

[2] Jiang Z, et al. "Classification of Depression Using Machine Learning Methods Based on Eye Movement Variance Entropy." IEEE Access. 2024. doi: 10.1109/ACCESS.2024.3451728.

[3] Nasim S, et al. "Novel Meta Learning Approach for Detecting Postpartum Depression Disorder Using Questionnaire Data." IEEE Access. 2024;12:101247-101259. doi: 10.1109/ACCESS.2024.3427685.

[4] Aina J, Akinniyi O, Rahman MM, Odero-Marah V, Khalifa F. "A Hybrid Learning-Architecture for Mental Disorder Detection Using Emotion Recognition." IEEE Access. 2024;12:91410-91425. doi: 10.1109/ACCESS.2024.3421376.

[5] Abdullah M, Negied N. "Detection and Prediction of Future Mental Disorder From Social Media Data Using Machine Learning, Ensemble Learning, and Large Language Models." IEEE Access. 2024;12:120553-120569. doi: 10.1109/ACCESS.2024.3406469.

[6] Li C, Gao S, Zhang J. "Multi-Bands Joint Graph Convolution EEG Functional Connectivity Network for Predicting Mental Disorders." International Journal of Crowd Science. 2024;8(2):65-70. doi: 10.26599/IJCS.2024.9100003.

[7] Yoo JH, An JH, Chung TM. "Feature Distribution-Based Medical Data Augmentation: Enhancing Mood Disorder Classification." IEEE Access. 2024;12:127782-127791. doi: 10.1109/ACCESS.2024.3396138.

[8] Villa-Pérez ME, Trejo LA, Moin MB, Stroulia E. "Extracting Mental Health Indicators From English and Spanish Social Media: A Machine Learning Approach." IEEE Access. 2023;11:128135-128152. doi: 10.1109/ACCESS.2023.3332289.

[9] Banna MHA, et al. "A Hybrid Deep Learning Model to Predict the Impact of COVID-19 on Mental Health From Social Media Big Data." IEEE Access. 2023;11:77009-77022. doi: 10.1109/ACCESS.2023.3293857.

[10] Ogur NB, et al. "Development of an Artificial Intelligence-Supported Hybrid Data Management Platform for Monitoring Depression and Anxiety Symptoms in the Perinatal Period: Pilot-Scale Study." IEEE Access. 2023;11:31456-31466. doi: 10.1109/ACCESS.2023.3262467.

[11] Skaik RS, Inkpen D. "Predicting Depression in Canada by Automatic Filling of Beck's Depression Inventory Questionnaire." IEEE Access. 2022;10:102033-102047. doi: 10.1109/ACCESS.2022.3208470.

[12] Guo T, Zhao W, Alrashoud M, Tolba A, Firmin S, Xia F. "Multimodal Educational Data Fusion for Students' Mental Health Detection." IEEE Access. 2022;10:70370-70382. doi: 10.1109/ACCESS.2022.3187502.

[13] Danowitz A, Beddoes K. "Mental Health in Engineering Education: Identifying Population and Intersectional Variation." IEEE Transactions on Education. 2022;65(3):257-266. doi: 10.1109/TE.2022.3182626.

[14] Hacohen-Kerner Y, Manor N, Goldmeier M, Bachar E. "Detection of Anorexic Girls in Blog Posts Written in Hebrew Using a Combined Heuristic AI and NLP Method." IEEE Access. 2022;10:34800-34814. doi: 10.1109/ACCESS.2022.3162685.

[15] Crawford JR, Goh YM, Hubbard EM. "Generalised Anxiety Disorder and Depression on Implicit and Explicit Trust Tendencies Toward Automated Systems." IEEE Access. 2021;9:68081-68092. doi: 10.1109/ACCESS.2021.3076681.

[16] Meng X, Zhang J. "Anxiety Recognition of College Students Using a Takagi-Sugeno-Kang Fuzzy System Modeling Method and Deep Features." IEEE Access. 2020;8:159897-159905. doi: 10.1109/ACCESS.2020.3021092.

[17] Ding Y, Chen X, Fu Q, Zhong S. "A Depression Recognition Method for College Students Using Deep Integrated Support Vector Algorithm." IEEE Access. 2020;8:75616-75629. doi: 10.1109/ACCESS.2020.2987523.

[18] Ahmed S, Yousuf MA, Monowar MM, Hamid A, Alassafi MO. "Taking All the Factors We Need: A Multimodal Depression Classification With Uncertainty Approximation." IEEE Access. 2023;11:99847-99861. doi: 10.1109/ACCESS.2023.3315243.

[19] Mortensen JA, Mollov ME, Chatterjee A, Ghose D, Li FY. "Multi-Class Stress Detection Through Heart Rate Variability: A Deep Neural Network Based Study." IEEE Access. 2023;11:57470-57480. doi: 10.1109/ACCESS.2023.3274478.

[20] PVilla-Pérez ME, Trejo LA, Moin MB, Stroulia E. "Extracting Mental Health Indicators From English and Spanish Social Media: A Machine Learning Approach." IEEE Access. 2023;11:128135-128152. doi: 10.1109/ACCESS.2023.3332289.