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Unmasking Depression: Analyzing Disclosure Behavior on Social Media

J.D. Jadhav[1], Akanksha Ranpise[2], Divya Rane[3], Ridhima Bhat[4], Vaishnavi Shinde[5]
[1,2,3,4,5]Computer Engineering, Bharati Vidyapeeth's College of Engineering for Women, Pune, India
Email ID: *jayashree.jadhav@bharatividyapeeth.edu[1], akanksha20manu@gmail.com[2], ranedivya61@gmail.com[3], ridhimabhat40002@gmail.com[4], vaishnavi.shinde5122001@gmail.com[5]*

Abstract
Mental stress is a significant concern in today's fast-paced world, and detecting and addressing it in its early stages is challenging. However, the rise of web-based social networks presents a unique opportunity to tackle this issue. By analyzing the correlation between users' stress states and their social interactions, a system is developed to understand the dynamics at play. The system uses a dataset gathered from real-world social platforms to analyze sentiment analysis on social media posts. This analysis allows for deeper insights into users' emotions and mental states, enabling the system to classify whether users are currently experiencing stress or not. Once a user's stress state is identified, the system takes proactive steps to offer support. It provides recommendations for nearby hospitals on a map, ensuring users in distress can access immediate assistance if necessary. Additionally, administrators send users a precautionary list via email, offering guidance and tips to promote healthier and happier lives. In conclusion, this system represents a holistic approach to addressing stress detection and management in the digital age. By examining the relationship between users' stress states and their social interactions, the system can provide early intervention and support. This system contributes to enhancing the overall well-being of individuals in an increasingly interconnected digital world.

Keywords: *Mental stress, early detection; web-based social networking; stress detection; social media; stress state correlation; large-scale dataset; stress-related attributes; sentiment analysis; neural network; classification; user health.*

1. Introduction
The Mental stress is a growing concern in today's fast- paced lifestyle, with social media interactions providing valuable indicators for identifying stress. Social psychology research highlights the concept of mood contagion and the importance of understanding a user's emotional state through social interactions. With the widespread use of social networks like Facebook, Twitter, and Sina Weibo, individuals actively share their daily experiences and moods while engaging with friends on these platforms. To tackle this issue, a support vector method is employed to categorize whether users are undergoing stress. This approach utilizes both the content attributes of posts and social interactions to improve the precision of stress detection. Once the stress level is identified, the system can recommend suitable healthcare facilities for further treatment, offering a holistic strategy to address mental health concerns in the context of social media. Stress is a significant catalyst for altering a user's mood and potentially leading them into a state of depression. In today's digital age, social interactions on social networks can be a source of stress for users, presenting a critical challenge to human health and overall life quality. Recognizing the increasing prevalence of stress and its potential impact, there is a crucial need to detect stress early on, before it evolves into more severe problems. Social media platforms, due to the vast amount of data they host, present an opportunity for proactive intervention. This data encompasses valuable user behavioral attributes. Harnessing this wealth of information to predict the mental health status of

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social media users holds immense promise. Such predictive capabilities can empower psychiatrists, family members, and friends to provide timely medical advice and therapy to individuals experiencing depression, offering crucial support precisely when it is needed. The project aims to investigate and analyze the disclosure behavior related to depression on social media platforms using Convolutional Neural Networks (CNN). The project examines user interactions, posts, and engagement patterns on social media platforms to identify potential indicators of depression. Utilizes Convolutional Neural Networks (CNN) to analyze textual content shared by users on social media for patterns associated with depressive states. Develops predictive models to assess the mental health levels of social media users based on their disclosure behavior, providing an early warning system for potential depression. The project acknowledges the limitations of purely automated systems and recognizes the importance of human interpretation in understanding the nuances of depression disclosure behavior on social media. In conclusion, this multi-stage approach, leveraging advanced techniques like CNNs, can provide valuable insights and early warnings to predict depression from social media activity. This approach can facilitate timely interventions and improve mental health outcomes by facilitating timely interventions and incorporating user feedback, Refer Figure 1.

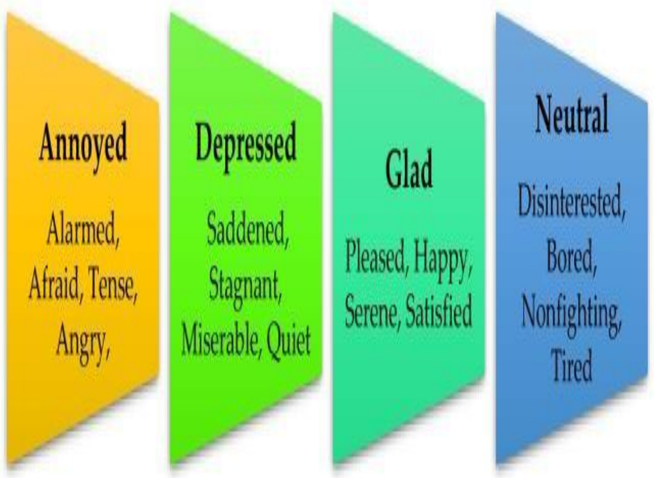

Figure 1 Different Emotional States Adapted from Circumflex Model

2. Literature Review

The paper "Mood cast: Emotion prediction via dynamic continuous factor graph model" presents a novel approach to predicting emotions by leveraging a dynamic continuous factor graph model. This model accounts for temporal dependencies and continuous nature of emotions, aiming to improve the accuracy of emotion prediction. The authors integrate contextual information and user interactions within social networks, creating a more comprehensive understanding of emotional states over time. Their method is validated using real- world data, demonstrating its potential for applications in social media analytics and personalized emotional support systems. [1] Liqiang Nie and colleagues address the challenge of the vocabulary gap between health information seekers and the specialized terminology used in healthcare knowledge bases. Their work proposes a solution involving the construction of a mapping framework that translates layman's terms into professional medical vocabulary, thereby enhancing the accessibility and relevance of health information retrieval. By employing techniques from natural language processing and information retrieval, the authors bridge the communication gap, facilitating better understanding and usage of healthcare resources by the general public. [2] This paper by Frank R. Kschischang and Brendan J. Frey explores the theoretical foundations and applications of factor graphs and the sum-product algorithm. Factor graphs provide a powerful representation for expressing the factorization of functions, particularly in the context of probabilistic graphical models. The sum-product algorithm operates on these graphs to perform efficient inference, which is crucial for various applications in coding theory, artificial intelligence, and machine learning. The authors present a comprehensive overview of the algorithm's derivation, properties, and practical implementations. [3] The work by Xiao jun Chang et al. delves into zero- shot event detection, a challenging problem where the system must recognize events without having seen any examples during training. They propose a method for semantic concept discovery that leverages auxiliary information and knowledge transfer techniques to detect novel events at a large scale. By utilizing semantic attributes and relationships between known and unknown events, their approach enables the system to generalize and identify new events effectively. This research contributes to advancements in multimedia analysis and event detection in large-scale datasets. [4] Jennifer Golbeck and her team investigate the possibility of predicting personality traits based on Twitter activity. Utilizing the Five Factor Model (FFM) of personality, they analyze various features from users' tweets, such as linguistic cues, tweet frequency, and interaction patterns. Their findings suggest that certain personality traits can be reliably inferred from social media behavior, with potential applications in personalized content delivery, targeted advertising, and social media analytics. This study highlights the intersection of psychology and computational social science, demonstrating the predictive power of online behaviors. [5] Sepandar D. Kamvar's paper "We feel fine and searching the emotional web" introduces a system designed to capture and analyze the emotional expressions found in blog posts. By collecting sentences that contain phrases like "I feel" or "I am feeling," the system aggregates and visualizes the emotional states of bloggers over time and across different demographics. This work showcases an innovative approach to emotional analysis on the web, providing insights into the collective emotional well-being and trends within the digital landscape. [6] Dan C. Ciresan and colleagues present a study on convolutional neural networks (CNNs) optimized for image classification tasks. Their research focuses on developing flexible and high-performance CNN architectures capable of achieving state-of-the-art results on benchmark datasets. They emphasize the importance of architectural innovations, efficient training procedures, and the utilization of large-scale data for enhancing the performance of CNNs. This work contributes significantly to the field of computer vision, influencing subsequent advancements in deep learning techniques for image recognition. [7] Chi Wang and his co-authors explore the dynamics of social influence using time-dependent factor graphs. Their approach models the temporal evolution of social influence, capturing how individuals' behaviors and decisions are affected by their peers over time. By incorporating temporal information and interaction patterns into the factor graph framework, the authors provide a more accurate and dynamic analysis of social influence phenomena. This research has implications for understanding and predicting trends in social networks, marketing, and information dissemination. [8] The paper by Andrey Bogomolov et al. focuses on recognizing daily stress levels using data collected from mobile phones, combined with weather conditions and personal traits. By employing machine learning algorithms, the authors develop models that can predict stress based on contextual and behavioral data. Their study demonstrates the feasibility of using ubiquitous mobile technology for continuous stress monitoring, with potential applications in mental health and well-being interventions. This interdisciplinary research integrates insights from psychology, data science, and mobile computing. [9] H. Lin and colleagues address the challenge of detecting psychological stress from cross-media microblog data using deep sparse neural networks. Their approach leverages the diverse data sources available on microblogging platforms, such as text, images, and user interactions, to create a comprehensive model for stress detection. By applying deep learning techniques, they enhance the accuracy and robustness of stress recognition. This research contributes to the development of advanced tools for mental health monitoring and the broader application of deep learning in multimedia data analysis. [10]

3. Proposed System

The proposed system architecture as shown in Figure 2, aims to detect user stress levels based on their social network interaction, specifically on Facebook. Users interact with others through various posts, and three types of information can be used as inputs: Facebook-level attributes, user-level posting behavior attributes, and user-level social interaction attributes. Facebook-level attributes describe linguistic and visual content, while user-level posting behavior attributes include monthly postings, post time, and post type. Social interaction attributes are

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extracted from users' interactions with friends. This system can help users manage stress and improve their social interactions. The methodology for "Depression analysis using social media posts" involves a series of steps, including data collection, data cleaning, data normalization, feature extraction, model training for depression classification, and analyzing the detection outcome. The dataset should consist of user-generated content from social media platforms. Data cleaning involves preprocessing the collected data to ensure quality and consistency, such as text cleaning, tokenization, lowercasing, removing stop words, spell checking, and handling missing data.

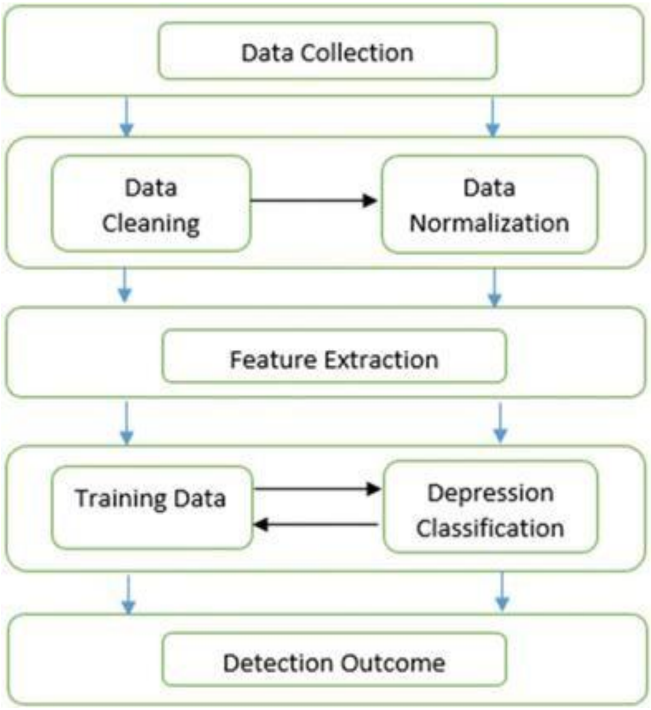

Figure 2 Architecture of Proposed System

Data normalization involves normalizing the data as needed, such as scaling numerical features, standardizing text, and encoding categorical variables. Feature extraction is performed using Convolutional Neural Networks (CNN) to capture hierarchical features and patterns in the text data. A CNN-based machine learning model is trained on the training data to classify text data into two classes: depressed and non-depressed. Model evaluation is performed using appropriate evaluation metrics, fine-tuning the model by adjusting hyper parameters based on validation results. The trained CNN model is applied to classify social media posts into depressed or non-depressed categories, predicting the likelihood of a post being associated with depression. Detection outcome analysis is conducted to assess the model's performance in real-world scenarios and identify key features or patterns associated with depressive posts. This comprehensive methodology aims to unmask depression-related disclosure behavior on social media using CNN-based techniques.

4. Algorithm-CNN

The CNN algorithm is utilized for detecting breast cancer by taking an image of breast tissue as input and providing the corresponding output. Neural networks encompass a collection of algorithms that interpret sensory data through machine perception. They categorize or group raw input data into clusters or categories. These patterns are represented numerically, typically in vectors, allowing neural networks to process various types of real-world data, including images, sound, text, or time series data. Through clustering and classification, neural networks aid in grouping unlabeled data, enabling the identification of patterns and meaningful information within datasets.

4.1. The CNN Architecture Consists of Several Layers

1. Convolutional Layer: This layer applies 14 filters of size 5x5 to extract features from the input image.
2. Pooling Layer: Performs max pooling with a 2x2 filter and stride of 2, reducing the spatial dimensions of the feature maps.
3. Convolutional Layer: Applies 36 filters of size 5x5 with a ReLU activation function to further extract higher-level features.
4. Pooling Layer: Performs max pooling with a 2x2 filter and stride of 2, further reducing the spatial dimensions of the feature maps.
5. Dense Layer (Logits Layer): Consists of 1,764 neurons with a dropout regularization rate of 0.4. This layer is responsible for making predictions, with one neuron for each digit target class (0-9).

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4.2. In Creating a CNN, The Following Important Modules Are Used

- **Conv2d():** Constructs a two-dimensional convolutional layer with parameters such as the number of filters, filter kernel size, padding, and activation function.
- **Max_pooling2d():** Constructs a two-dimensional pooling layer using the max-pooling algorithm, specifying the size of the pooling window and the stride.
- **Dense():** Constructs a dense layer with parameters for specifying the number of hidden layers and units. This layer is typically used for the final classification step.

4.3. Mathematical Equations for A Convolutional Neural Network (CNN) Used in Depression Detection Typically Involve Several Components

4.3.1. Convolutional Layer

The output of a convolutional layer **O** can be computed as:

$$\boldsymbol{O_{i,j}} = \boldsymbol{f}\left(\sum_{m-0}^{M-1}\sum_{n-1}^{N-1} i_{i+m+j+n} \times k_{m,n} + b\right)$$

I is the input image,
K is the convolutional filter,
b is the bias term,
f is the activation function, and
M and N are the dimensions of the filter.

4.3.2. Pooling Layer

The output of a pooling layer P can be computed as:

$$\boldsymbol{P}_{i,j} = \textit{Polling Function}\left(\boldsymbol{O}_{i\times s, j\times s}\right)$$

Where: s is the stride of the pooling operation.

4.3.3. Fully Connected Layer

The output of a fully connected layer F can be computed as:

$$F = f\,(WT \,.\, X + b\,)$$

Where:
W is the weight matrix,
X is the input vector, and
b is the bias vector.

4.3.4. Output Layer

The output of the output layer can be computed using the softmax function:

$$Softmax(zi) = \frac{e^{zi}}{\sum_{j=1}^{N} e^{zj}}$$

Where: z_i is the input to the output layer, N is the number of classes.

5. Results and Discussion

Figure 3-7 shows the results of the Proposed System.

Figure 3 GUI of Sign-Up Page

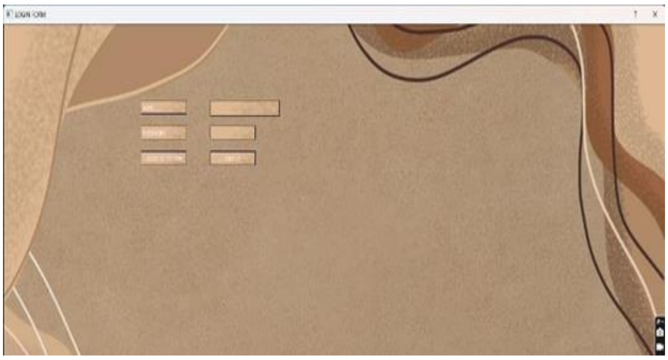

Figure 4 GUI of Login Page

Figure 5 Model Interface

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Figure 6 Training of The Model

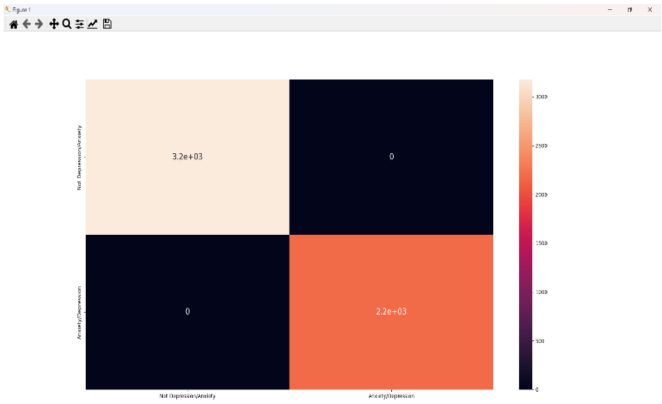

Figure 7 Accuracy of The Model

Conclusion

The prevalence of mental stress poses a significant threat to individuals' health, necessitating proactive detection for timely care. In this context, we propose a framework designed to identify users' psychological stress states using their monthly social media data, with a focus on leveraging the content of Facebook posts and users' social interactions. Utilizing authentic social media data, our study delves into the correlation between users' psychological stress states and their behaviors in social interactions. Upon detecting signs of stress, the system recommends health consultants or doctors for further assistance. To enhance user accessibility, we employ graph-based techniques to showcase hospitals, indicating the shortest path from the user's current location. Additionally, the system sends health precautions via email to facilitate user interaction. Furthermore, the system provides insights into stress prevalence among different age categories, offering a comprehensive understanding of the demographic aspects of mental stress.

Future Scope

The future of the depression prediction system from social media data includes enhancing data sources, advancing machine learning models, personalizing user experiences, improving user interfaces, expanding mental health insights, ensuring ethical practices, collaborating with health professionals, and extending global reach. This includes incorporating physiological data from wearable devices like Fitbit and Apple Watch, enhancing predictive accuracy with physiological indicators like heart rate and sleep patterns. Advanced machine learning models, such as transformers and attention mechanisms, will improve text and image analysis. Real-time processing will provide instant feedback and interventions. Personalization and customization will include creating personalized prediction models tailored to individual users' behavior and history, offering customized mental health recommendations and alerts based on user-specific data. The system will also be improved through mobile application development, enhanced visualization tools, and expanded mental health metrics. Longitudinal studies will validate and refine predictive models based on longitudinal data. Ethical practices will be ensured, including transparency, fairness, and accountability in predictive analytics. The system will also be adapted for different languages and cultural contexts and formed partnerships with international health organizations to promote widespread adoption and impact. These advancements aim to make the system more accurate, user-friendly, and widely applicable, ultimately contributing to better mental health outcomes worldwide.

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