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FORECASTING WORK-FROM-HOME STRESS IN THE COVID ERA WITH MACHINE LEARNING

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ABSTRACT

Previous studies have highlighted that individuals with mental health disorders exhibit identifiable patterns on social media. They may participate in screening surveys, engage in community discussions on platforms like Twitter, or be active members of online forums. These patterns make them distinguishable from regular users based on their language use and online behavior. Several automated detection methods have been developed to aid in the identification of individuals experiencing depression through their social media activity. Furthermore, some authors have suggested a correlation between activities on Social Networking Sites and low self-esteem, particularly among young people and adolescents. In our project, stress analysis is conducted using algorithms, specifically GoogleNet as the established system and Inception V3 as the proposed system. The results demonstrate that the proposed GoogleNet algorithm outperforms the existing Inception V3 in terms of accuracy.

Keywords: Hysteretic, Stress Management, Psychological Stress, SNMDD.

I. INTRODUCTION

Psychological stress has emerged as a significant threat to public health in recent times. With the fast-paced nature of modern life, a growing number of individuals are experiencing heightened levels of stress. According to a global survey reported by New Business, more than half of the population has witnessed a notable increase in stress over the past two years. While stress itself is a common aspect of daily life, prolonged and excessive stress can have severe consequences on both physical and mental well-being. Research indicates that chronic stress is linked to various health conditions such as clinical depression, insomnia, and other mental health disorders.

The impact of stress is particularly concerning among young populations. In China, for instance, suicide has become the leading cause of death among youths, with excessive stress identified as a major contributing factor. This trend underscores the urgent need to address the escalating levels of stress to safeguard human health and improve overall quality of life.

Traditional methods of detecting psychological stress have primarily relied on face-to-face interviews, self-report questionnaires, or wearable sensors. However, these approaches are often reactive, resource-intensive, and subject to delays. The advent of social media platforms has revolutionized how people communicate and express their emotions, providing a wealth of real-time data that can be harnessed for stress detection and management.

Social media platforms like Twitter offer a unique opportunity to monitor and analyze users' moods, behaviors, and life events in real time. This data can be leveraged to develop innovative approaches for representing, measuring, and modeling stress patterns among individuals. By applying insights from psychology research, social media data can be instrumental in early detection and intervention strategies for addressing stress-related issues.

According to the World Health Organization (WHO), depression affects approximately 50 million people globally, with a significant portion concentrated in regions like South East Asia and the Western Pacific. The prevalence of depression has seen a substantial increase in recent years, highlighting the urgent need for effective detection and treatment measures.

Despite the effectiveness of face-to-face interviews in diagnosing depression, many individuals hesitate to seek professional help due to stigma or lack of awareness about their condition. Social media platforms have emerged as a valuable resource for understanding and addressing mental health concerns, as user-generated content provides valuable insights into users' emotional states and behaviors.

Researchers have explored various methodologies for analyzing social media data to identify signs of depression and related mental health issues. From sentiment analysis to behavioral patterns, these approaches offer promising avenues for proactive intervention and support for individuals experiencing stress and depression.

Machine learning, a subset of artificial intelligence, plays a pivotal role in processing and analyzing vast amounts of social media data to extract meaningful patterns and trends. By leveraging machine learning algorithms, researchers can develop predictive models and automated tools for early detection and intervention, thereby mitigating the adverse effects of stress on individuals' well-being. the integration of social media data analysis and machine learning techniques holds immense potential for revolutionizing stress detection and mental health management. By harnessing the power of digital platforms and advanced analytics, we can proactively address the growing challenges posed by psychological stress and improve health outcomes on a global scale.

II. RELATED WORK

The surge in popularity of social networking platforms has brought forth concerns regarding problematic usage. This has led to the recognition of several social network mental disorders (SNMDs), including Cyber-Relationship Addiction, Information Overload, and Net Compulsion. These disorders often manifest subtly, making it challenging for timely clinical intervention. This paper argues for the proactive identification of SNMDs through the analysis of online social behavior. Unlike traditional approaches reliant on self-reported assessments, we propose a novel machine learning framework called Social Network Mental Disorder Detection (SNMDD). SNMDD leverages features extracted from social network data to detect potential cases of SNMDs. Additionally, we introduce multi-source learning and a new SNMD-based Tensor Model (STM) to enhance detection accuracy. To ensure scalability, we optimize STM's efficiency with performance guarantees. The framework's efficacy is evaluated through a user study involving 3,126 online social network users, including feature analysis and application on large-scale datasets. Our findings demonstrate the promise of SNMDD in identifying individuals at risk of SNMDs within online social networks.

The exponential rise in the popularity of social networking platforms has given rise to concerns surrounding problematic usage patterns. This surge has also brought attention to the emergence of various social network mental disorders (SNMDs), including Cyber-Relationship Addiction, Information Overload, and Net Compulsion. Unfortunately, symptoms of these disorders are often overlooked, leading to delayed clinical intervention. This paper contends that leveraging data from online social behavior presents an opportunity for proactive identification of SNMDs in their early stages. Detecting SNMDs poses a challenge as mental states cannot be directly observed from online social activity logs. To address this challenge, we propose a novel machine learning framework called Social Network Mental Disorder Detection (SNMDD). SNMDD utilizes features extracted from social network data to accurately identify potential cases of SNMDs. Moreover, we introduce multi-source learning within SNMDD and introduce a novel SNMD-based Tensor Model (STM) to enhance accuracy. To enhance the scalability of STM, we further optimize efficiency while ensuring performance guarantees. We evaluate our framework through a user study involving 3,126 online social network users, conducting comprehensive feature analyses and applying SNMDD on large-scale datasets. Our findings underscore the potential of SNMDD in effectively identifying online social network users exhibiting potential SNMDs.

Social media platforms have become integral for individuals seeking health information and providing social support. Nevertheless, research suggests that social media can also facilitate harm by disseminating content that encourages unhealthy behaviors. This study focuses on analyzing discussions surrounding pro-anorexia content on Tumblr, where individuals promote behaviors associated with the eating disorder, contending that extreme thinness equates to beauty. The objective is to examine how information promoting the pro-anorexia perspective circulates among social media users and to characterize these users. Specifically, the study will analyze content and identify common traits among users exposed to similar social media content who express a desire to share it.

Mental illnesses are recognized as some of the most disabling conditions worldwide, affecting millions of individuals across the globe. One of the significant challenges associated with mental disorders is their inherent difficulty to detect in individuals who are suffering. This challenge becomes even more pronounced in online environments, where gathering patient data and implementing effective algorithms for detection present additional complexities. In this paper, we introduce a novel approach to data collection and model development that focuses on leveraging language and behavioral patterns, particularly on Twitter, to ascertain whether a user is experiencing a mental disorder. Following the training of predictive models, we refine them to serve as the backbone for our demonstration tool, MIDAS. MIDAS offers an analytics web-service designed to explore various characteristics related to users' linguistic and behavioral patterns on social media in the context of mental illnesses.

III. PROPOSED SYSTEM

In 2012, the introduction of AlexNet marked a significant milestone in the evolution of convolutional neural network (CNN) architectures. AlexNet pioneered the concept of stacking convolutional layers sequentially, demonstrating the potential for improved performance in image classification tasks. The creators of AlexNet notably trained the network using graphical processing units (GPUs), unlocking faster processing speeds and enhanced training capabilities

The adoption of CNNs, coupled with the availability of larger datasets and more efficient computing resources, spurred rapid advancements in computer vision solutions. Researchers quickly realized that increasing the depth and breadth of neural networks led to substantial performance gains. However, the trade-off for creating larger networks came with challenges such as overfitting and the vanishing or exploding gradient problem.

To address these challenges, the GoogleNet architecture emerged as a groundbreaking solution, particularly with the introduction of the Inception module. The Inception module represents a neural network architecture that harnesses feature detection across different scales through the use of convolutions with varying filters. This approach not only enhanced the network's ability to detect features but also reduced the computational cost associated with training extensive networks through dimensional reduction techniques.

High Output Efficiency: GoogleNet, with its Inception module, delivers remarkable output efficiency by efficiently detecting features at various scales, leading to improved performance in image recognition tasks

User-Friendly Design: The architecture of GoogleNet is designed to be intuitive and easy to work with, allowing developers and researchers to implement complex neural networks with relative ease.

Time Efficiency: By optimizing the network's structure and utilizing the Inception module's capabilities, GoogleNet reduces training times, making it a more time- efficient solution for large-scale image analysis tasks.

Accuracy in Stress Level Prediction: The proposed system, based on GoogleNet architecture, demonstrates high accuracy in predicting stress levels or related psychological states. This is crucial for applications in mental health spurred rapid advancements in computer vision solutions. Researchers quickly realized that increasing the depth and breadth of neural networks led to substantial performance gains. However, the trade-off for creating larger networks came with challenges such as overfitting and the vanishing or exploding gradient problem.

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Accuracy in Stress Level Prediction: The proposed system, based on GoogleNet architecture, demonstrates high accuracy in predicting stress levels or related psychological states. This is crucial for applications in mental health

Applicability Across Datasets: One of the notable advantages of GoogleNet is its versatility. It can be effectively applied to a wide range of datasets, making it a valuable tool for various computer vision applications

Extract temporal patterns and trends from time-series data. This could involve creating features such as daily, weekly, or monthly averages of workload or stress levels.

Sentiment Analysis: Analyze text data from communication channels to extract sentiment features. Natural language processing techniques can be used to identify positive, negative, or neutral sentiments expressed in emails, chat messages, or social

In summary, the GoogleNet architecture, particularly with the innovative Inception module, represents a significant advancement in the field of convolutional neural networks. Its efficient feature detection, user-friendly design, time efficiency, high accuracy in stress prediction, and versatility make it a valuable asset for researchers and developers in the realm of computer vision..

IV. ARCHITECTURE

The term "SNMD classifier" typically denotes a classifier utilized within the realm of Social Network Mental Disorders (SNMDs). These disorders encompass mental health conditions that are either exacerbated or manifested through interactions and usage of social media platforms. The SNMD classifier operates as a machine learning model or algorithm intended to discern or predict the presence of SNMDs by analyzing various features extracted from social media data.

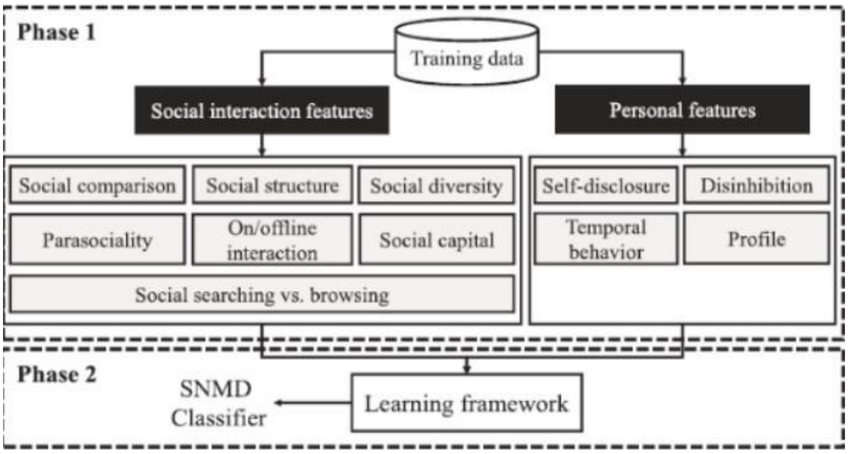

Fig 1: System Architecture

Here's a breakdown of the process involved in the SNMD classifier:

Data Collection: The classifier gathers data from social media platforms where users exhibit behaviors or express sentiments indicative of SNMDs. This data encompasses various forms such as textual posts, comments, images, user interactions, and other relevant information.

Feature Extraction: Features specifically linked to SNMDs are isolated from the collected data. These features may encompass linguistic patterns, sentiment analysis, engagement levels, content themes, and behavioral signals associated with SNMDs.

Training: The classifier is trained utilizing a labeled dataset where instances are categorized as either positive (suggesting the presence of an SNMD) or negative (indicating the absence of an SNMD). Commonly employed supervised learning techniques such as logistic regression, support vector machines, or deep learning architectures are utilized for this purpose.

Model Evaluation: The trained classifier undergoes evaluation using various metrics like accuracy, precision, recall, F1-score, and area under the ROC curve (AUC) to gauge its proficiency in distinguishing between individuals with and without SNMDs.

Deployment: Once the classifier has been trained and assessed, it can be deployed to classify new instances of social media data. Users' posts or interactions are inputted into the classifier, which subsequently assigns a probability or label denoting the likelihood of the user displaying SNMD-related behaviors.

Monitoring and Iteration: The classifier may be subjected to ongoing monitoring in real-world settings to evaluate its performance and efficacy. Iterative enhancements, such as retraining with fresh data or adjusting

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model parameters, may be implemented to bolster the classifier's accuracy and generalizability over time.

Overall, the SNMD classifier serves as a vital tool in identifying individuals who may be at risk of or currently grappling with SNMDs based on their interactions and activities on social media platforms. Its utilization facilitates early detection, intervention, and support for individuals affected by these mental health conditions.

V. RESULT AND IMPLEMENTATION

Data Collection: To facilitate depression detection via social media, we curated two distinct datasets comprising depression and non-depression users on Twitter, leveraging its widespread usage and robust APIs. For each Twitter user, we retrieved their profile information along with an anchor tweet, which served as a basis for inferring their mental state. Recognizing the importance of observing users over a period, we collected all additional tweets published within one month from the anchor tweet.

Data Preprocessing: Before proceeding with feature extraction, we conducted extensive data preprocessing to address the inherent flexibility and variability of words in raw social media data. The following procedures were implemented: Emoji present compatibility issues with many text processing algorithms. To mitigate this, we utilized an emoji library sourced from Twitter to remove emojis from the text of tweets. Subsequently, we conducted separate counts of emojis.. To ensure uniformity in word representations irrespective of tense and voice, we employed stemming. This process involves reducing words to their root form. For instance, words like "married" and "marrying" were represented uniformly as "marri". We employed the Porter Stemmer algorithm [Porter, 2001] for this purpose. Social media content often contains irregular words due to typographical errors or common word abbreviations. To address this, we utilized a word2vec model trained on 400 million tweets to obtain regular representations of irregular words. When encountering a word not found in the model, we utilized the NLTK toolbox to identify the five most related words.

Feature Extraction: Our goal was to develop a methodology for identifying and analyzing individuals experiencing depression based on both their offline and online behaviors. While established criteria exist for defining offline behaviors associated with depression, such as those used in clinical diagnosis, online behaviors offer a unique opportunity to supplement this understanding. In our study, we collected data from social media platforms to identify common online behaviors indicative of depression. Drawing from insights in computer science and psychology, we carefully defined and extracted six feature groups specifically focused on depression-related behaviors. These feature groups were designed to provide a comprehensive overview of each user's digital footprint and emotional state. One key feature we extracted was the historical and recent number of tweets posted by each user. This metric helped us gauge the user's level of activity and engagement on social media, which can be indicative of their mental well-being. By combining offline and online behavioral data, we aimed to create a robust framework for identifying and understanding individuals experiencing depression in both digital and real-world contexts.

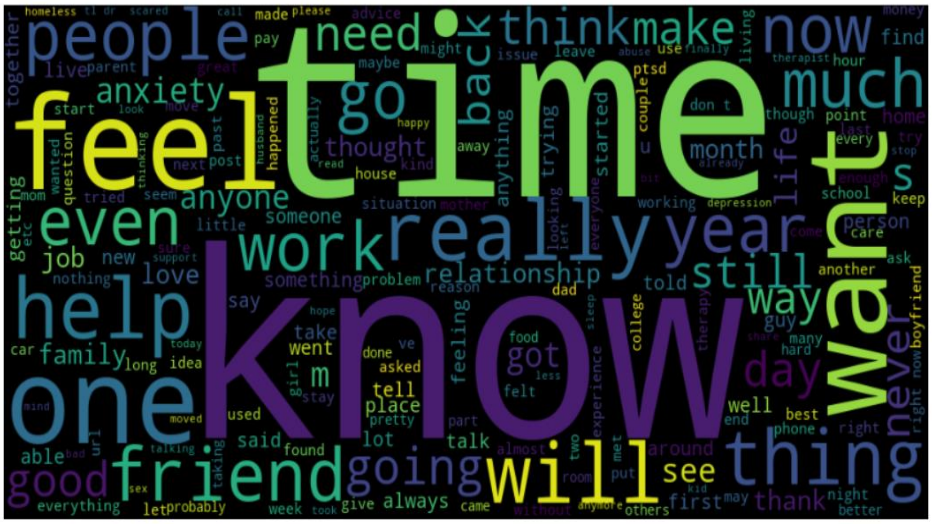

Fig 2: This figures illustrates about depressed words that is More frequently used by the users

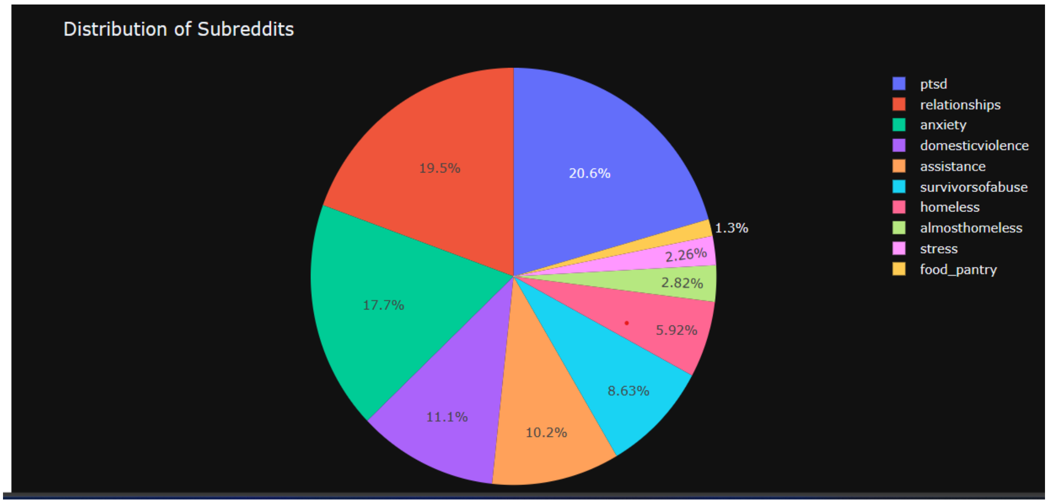

Fig 3: This figures illustrates about distribution of the depressed words which belongs to some category

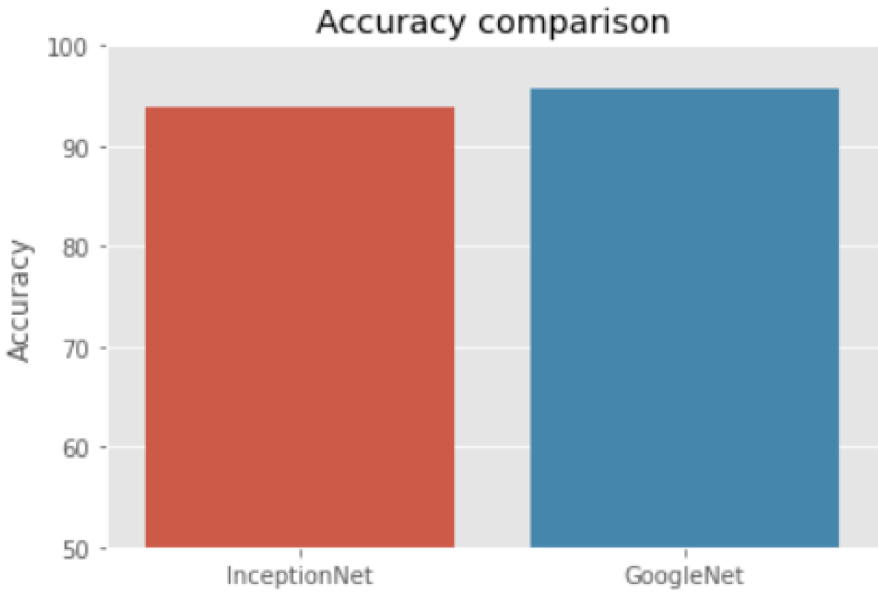

Fig 4: Accuracy comparison of GoogleNet and InceptionNet

The Multimodal Depressive Dictionary Learning (MDL) model is designed to detect depressed users by learning the latent and sparse representation of users through dictionary learning. The model operates on the premise that the original multimodal feature representation of users exhibits common patterns, while representations of depression are sparse according to depression criteria.

The key components of the MDL model encompass:

Learning the latent and sparse representation of users through dictionary learning.

Jointly modeling cross-modality relatedness to capture common patterns and learn joint sparse representations. Training a classifier to detect depressed users using the learned features.

By leveraging these components, the MDL model aims to effectively identify depressed users by extracting meaningful patterns and representations from multimodal data while considering the sparsity associated with depression criteria.

We adopted a strategy to learn the latent and sparse representation of users through dictionary learning, addressing challenges associated with noisy and diverse social media content. Dictionary learning aims to uncover a set of latent concepts or feature patterns (D) and a corresponding latent sparse representation (A) from the original feature representation (X). The process minimizes an empirical cost function, subject to constraints on the norm of the learned patterns.

The unsupervised loss function (l) minimizes the reconstruction error between the original data and its

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approximation using the learned dictionary and sparse representation. Additionally, regularization terms ($\lambda 1$ and $\lambda 2$) are incorporated to encourage sparsity and limit the complexity of the learned representation. Specifically, the l1-norm is utilized to enforce sparsity in the learned representation (αn).

By employing dictionary learning, we aimed to extract meaningful and compact representations from the noisy and high-dimensional feature space, ultimately enhancing the accuracy and interpretability of our depression detection model.

VI. CONCLUSION

We aimed to detect and analyze depressed users through their offline and online behaviors. We defined six depression-oriented feature groups, encompassing Social Network Features, User

This project focuses on timely depression detection through the analysis of social media data. By utilizing benchmark depression and non-depression datasets along with carefully defined depression-oriented feature groups, we introduced a multimodal depressive dictionary learning approach to identify depressed users on Twitter. Our analysis included an examination of the contributions of different feature modalities and the detection of depressed users on a large-scale depression-candidate dataset. Through this analysis, we aimed to uncover underlying discrepancies in online behaviors between depressed and non-depressed users on social media platforms. Given the significance of online behaviors in modern life, we anticipate that our findings will offer valuable perspectives and insights for research in both computer science and psychology domains related to depression.

We present an innovative approach to automatically identify potential online users with Social Network Mental Disorders (SNMDs). Our proposed SNMD Detection (SNMDD) framework leverages various features extracted from data logs of Online Social Networks (OSNs), along with a novel tensor technique for deriving latent features from multiple OSNs for SNMD detection. This collaborative effort between computer scientists and mental healthcare researchers addresses emerging issues in SNMDs.

Moving forward, our next steps involve studying features extracted from multimedia contents using techniques in Natural Language Processing (NLP) and computer vision. Additionally, we plan to explore new issues from the perspective of social network service providers, such as Facebook or Instagram, with the aim of enhancing the well-being of OSN users while maintaining user engagement. This ongoing research seeks to advance our understanding of SNMDs and improve support mechanisms for affected individuals in the online environment.

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