Project Report On

Cognitive Recommender System Leveraging User Behaviour and Visual Data Analysis

Submitted in partial fulfillment of the requirements for the award of the degree of

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in

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CERTIFICATE

This is to certify that the project report entitled ***"Cognitive Recommender System Leveraging User Behaviour and Visual Data Analysis"*** *is a bonafide record of the work done by* ***Ravisankar S Menon (U2003163)****,* ***Shiva Sundar R (U2003197)****,* ***Steven Sunny (U2003206)****,* ***Vishal Sankar K M (U2003213)****, submitted to the Rajagiri School of Engineering & Technology (RSET) (Autonomous) in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology (B. Tech.) in Computer Science and Engineering during the academic year 2023-2024.*

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Abstract

This project introduces an advanced cognitive recommender system designed to leverage social media data from Reddit, with a specific focus on the analysis of both textual and image content. The primary objective is to identify and categorize six prevalent mental health conditions: Schizophrenia, Autism, Anxiety, Depression, Bipolar disorder, and Borderline Personality Disorder (BPD) within user posts. Subsequently, the system aims to provide tailored recommendations of uplifting content, with the goal of positively impacting users based on their identified mental health conditions.

The project employs sophisticated natural language processing techniques for the analysis of textual data, extracting sentiments, patterns, and topics. Concurrently, computer vision methodologies are utilized to decipher visual content, including image recognition and understanding. This combined approach enhances the depth and accuracy of mental health condition detection, allowing the system to provide more nuanced and personalized recommendations.

One of the distinctive advantages of this project lies in its potential for early mental health detection and intervention. By comprehensively analyzing both text and image data, the recommender system can identify subtle patterns and cues indicative of mental health conditions, facilitating timely intervention and support. This innovative aspect not only distinguishes our project from existing works but also positions it as a crucial tool for promoting mental health awareness and proactive intervention.

In comparison to prior research that often focuses on isolated elements such as text or image analysis, our project's comprehensive methodology presents a significant advancement. The system's capability to identify a spectrum of mental health conditions and recommend positive content signifies a thoughtful and impactful progression in leveraging social media platforms for mental health awareness, early detection, and intervention.

Contents

List of Abbreviations

EGJSM - Efficient Gowers-Jaccard-Sigmoid Measure

AHRM - Attention-based Heterogeneous Relational Model

VGG - Visual Geometry Group

SVM - Support Vector Machine

DNN - Deep Neural Network

GRU - Gated Recurrent Unit

LSA - Latent Semantic Analysis

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background

Mental health issues represent a growing global concern, with millions of individuals seeking support and understanding in various online communities. Social media platforms, particularly Reddit, have become significant spaces for users to share their thoughts, experiences, and challenges related to mental health. The sheer volume and diversity of user-generated content on these platforms offer an opportunity to explore innovative approaches for mental health detection and support.

Currently, mental health detection primarily relies on explicit user disclosures or external reports, which may not capture subtle indications of mental health conditions. Early detection and intervention are critical in promoting positive mental well-being. Existing research in the field of recommender systems has largely focused on content-based and collaborative filtering techniques for personalized recommendations, but the integration of mental health detection within these systems is an area that remains underexplored.

This project develops a cognitive recommender system that not only leverages social media data but also employs advanced natural language processing and computer vision techniques to identify mental health conditions within user posts on Reddit. The goal is to enhance the capability of recommender systems to contribute meaningfully to mental health awareness, early detection, and intervention. By seamlessly integrating mental health detection into a recommendation system, the project aims to offer personalized and uplifting content to users who may be experiencing mental health challenges. This holistic approach acknowledges the significance of early detection and intervention in fostering a supportive online community. Ultimately, this project seeks to contribute to the well-being of individuals within digital spaces and advance our understanding of the intersection between technology and mental health.

1.2 Problem Definition

Many individuals share their thoughts and feelings on social media platforms, and some of these posts may contain indicators of mental health concerns such as depression, anxiety, or other conditions. It is important to create a system that can effectively detect these signs to offer timely assistance and support.

1.3 Scope and Motivation

The scope of this project encompasses the development of a cognitive recommender system capable of analyzing both textual and image data from users on Reddit. The system's primary focus is the identification of six prevalent mental health conditions: Schizophrenia, Autism, Anxiety, Depression, Bipolar disorder, and Borderline Personality Disorder (BPD). Through advanced natural language processing and computer vision techniques, the system aims to offer nuanced recommendations of positive content tailored to individual mental health needs. Additionally, the project intends to explore the scalability of the system across diverse user populations on Reddit, considering the platform's vast and varied community.

The motivation behind this project stems from the urgent need for innovative approaches to address mental health challenges within online communities. Social media platforms serve as significant outlets for individuals to express their mental health experiences, yet existing mechanisms for detection and support are limited. The motivation to integrate mental health detection into a recommender system arises from the potential to provide proactive and personalized interventions. By offering uplifting content to users based on their identified mental health conditions, this project aspires to contribute to destigmatizing mental health discussions and fostering a supportive online environment. Ultimately, the project is motivated by the prospect of positively impacting the mental well-being of individuals within the digital realm and advancing the synergy between technology and mental health support.

1.4 Objectives

- Develop a Robust Multi-Modal Analysis Framework: Create a comprehensive model for mental health recognition that integrates advanced natural language processing (NLP) techniques for textual data and computer vision methodologies for image content. This framework should ensure a holistic analysis of multi-modal data on Reddit.

- Identify and Categorize Mental Health Conditions: Implement algorithms to accurately identify and categorize the presence of six prevalent mental health conditions—Schizophrenia, Autism, Anxiety, Depression, Bipolar disorder, and Borderline Personality Disorder (BPD)—within user-generated content on the platform.

- Establish a Recommender System Architecture: Design and construct an intelligent cognitive recommendation system that utilizes the insights from the mental health recognition model. The recommender system should be adaptable, scalable, and capable of tailoring suggestions based on the identified mental health condition of individual users.

- Implement Personalized Content Recommendations: Develop algorithms and mechanisms within the recommender system to curate and recommend uplifting content specifically tailored to the mental health needs of users. Consider factors such as content sentiment, engagement, and relevancy.

- Evaluate and Refine Model Performance: Conduct thorough evaluations to assess the accuracy and effectiveness of the mental health recognition model and the cognitive recommendation system. Iteratively refine the algorithms based on user feedback and real-world performance to enhance overall system efficacy.

1.5 Challenges

The project encounters several challenges, starting with the unavailability of a comprehensive image dataset, hindering the development of a robust multi-modal analysis framework. Additionally, the cold start problem poses a significant obstacle, demanding innovative strategies to initiate the recommender system effectively, especially when dealing with new users or emerging mental health content. Integrating both text and image data further complicates the project, requiring seamless coordination to ensure a cohesive and accurate analysis for identifying mental health conditions within user-generated content on Reddit.

1.6 Assumptions

- Positive Content Impact: The project assumes that recommending positive content based on identified mental health conditions will have a beneficial impact on users, contributing to their mental well-being.
- Privacy and Ethical Considerations with User Consent: It is assumed that the implementation of privacy safeguards and ethical considerations, with the underlying assumption of user consent, will effectively address user concerns regarding the handling of sensitive mental health data, fostering trust and compliance with ethical guidelines.
- Relevance of Social Media Data: The project assumes that user-generated content on social media platforms, particularly Reddit, remains relevant and reflective of users' mental states, allowing for meaningful analysis and effective recommendation generation.

1.7 Societal Relevance

The societal relevance of this work lies in its potential to significantly impact mental health awareness, support, and destigmatization within the digital space. By leveraging social media data to identify and address mental health conditions, the project contributes to the broader discourse surrounding mental well-being. The intelligent cognitive recommender system, with its focus on personalized, positive content recommendations, has the potential to foster a more supportive online environment, encouraging open discussions and early interventions. As mental health issues continue to be a global concern, this project's societal relevance extends to influencing a positive shift in the online culture, emphasizing the importance of mental health and well-being within the digital community.

1.8 Organization of the Report

The project report adopts a systematic structure to effectively present the cognitive recommender system. It commences with essential formalities like the cover page and certificate page, followed by acknowledgments expressing gratitude. The abstract succinctly summarizes the project's objectives and methodology. The contents page serves as a roadmap for readers. The introduction section provides context and articulates the problem definition, scope, motivations, objectives, assumptions, challenges, and societal/industrial relevance. It also outlines the report's organizational structure. The literature survey explores existing systems, while the hardware and software requirements detail the technological prerequisites. The system architecture section encompasses a system overview, architectural design with sequence and UML diagrams, module division with corresponding diagrams, work breakdown, responsibilities, and a Gantt chart depicting the project timeline. The system implementation follows, detailing the actual process of building and deploying the system, including challenges encountered and solutions devised. The results and discussion section presents the empirical findings. The conclusion summarizes key findings, and the references list consulted sources. Appendices include the final presentation, supplementary information on vision, mission, program outcomes, and course outcomes, and the mapping of Course Outcomes (CO), Program Outcomes (PO), and Program Specific Outcomes (PSO). This structured approach ensures a coherent and comprehensive presentation of the cognitive recommender system project.

1.9 Summary of the Chapter

In summary, the exploration of this cognitive recommender system project has unveiled the intricate interplay between background, problem definition, scope, motivation, assumptions, challenges, and societal relevance. The background illuminated the prevalence of mental health discussions on platforms like Reddit, prompting a need for enhanced support mechanisms. The problem definition centers on identifying mental health conditions and delivering personalized, positive content recommendations to address existing gaps in online mental health support.

The project's scope and motivation underscore its ambition to integrate advanced technologies for multi-modal analysis, contributing to a more profound understanding and intervention in mental health issues within online communities. Assumptions regarding the positive impact of content recommendations, privacy safeguards with user consent, and the relevance of social media data lay the groundwork for ethical and responsible project execution.

Challenges, including data scarcity, ethical considerations, and adapting recommender systems, serve as crucial hurdles requiring thoughtful solutions for the project's success. The societal relevance becomes evident as the project aims to make a meaningful impact on mental health awareness, destigmatization, and early intervention within the digital space. In essence, this project represents a pioneering effort at the intersection of technology and mental health, with the potential to reshape online communities and contribute to the well-being of individuals navigating mental health challenges.

Chapter 2

Literature Survey

2.1 A Deep Learning Model For Detecting Mental Illness From User Content On Social Media [1]

The paper presents a comprehensive approach to detecting mental illness from user content on social media using a deep learning model. The researchers collected posts from mental health communities in Reddit. These communities, also known as "subreddits," include discussions related to specific mental health issues such as depression, anxiety, bipolar disorder, schizophrenia, and autism. By gathering posts from these communities, the researchers obtained a substantial amount of user-generated content related to mental health. Once the posts were collected, the researchers applied natural language processing techniques to preprocess the data. This likely involved tasks such as tokenization, stemming, and removing stop words to clean and prepare the text data for further analysis.

The researchers developed a deep learning model to identify a user's mental state based on their posting information. Specifically, they created six binary classification models, each designed to detect a specific mental disorder (e.g., depression, anxiety, bipolar disorder, etc.) from user posts. These models were likely based on neural network architectures, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), given the mention of a CNN-based classification model in the paper.

The developed models were trained and validated using the dataset of over 100,000 posts from Reddit. This likely involved splitting the dataset into training and validation sets, and then training the models on the training data while evaluating their performance on the validation set. The evaluation metrics used may have included precision, recall, and F1-score, as indicated in the paper.

The results of the study demonstrated that the proposed deep learning model could accurately identify mental disorders from user posts, achieving an average F1 score of 0.80. This indicates that the models were effective in classifying user posts related to various mental health conditions.

The paper discusses the implications of the proposed model, highlighting its potential as a supplementary tool for monitoring the mental health states of individuals who frequently use social media. The researchers suggest that the model could be used to alert potential sufferers of specific mental disorders before they visit counseling centers, and that it could open up new research opportunities in the area of detecting mental illness through social media platforms.

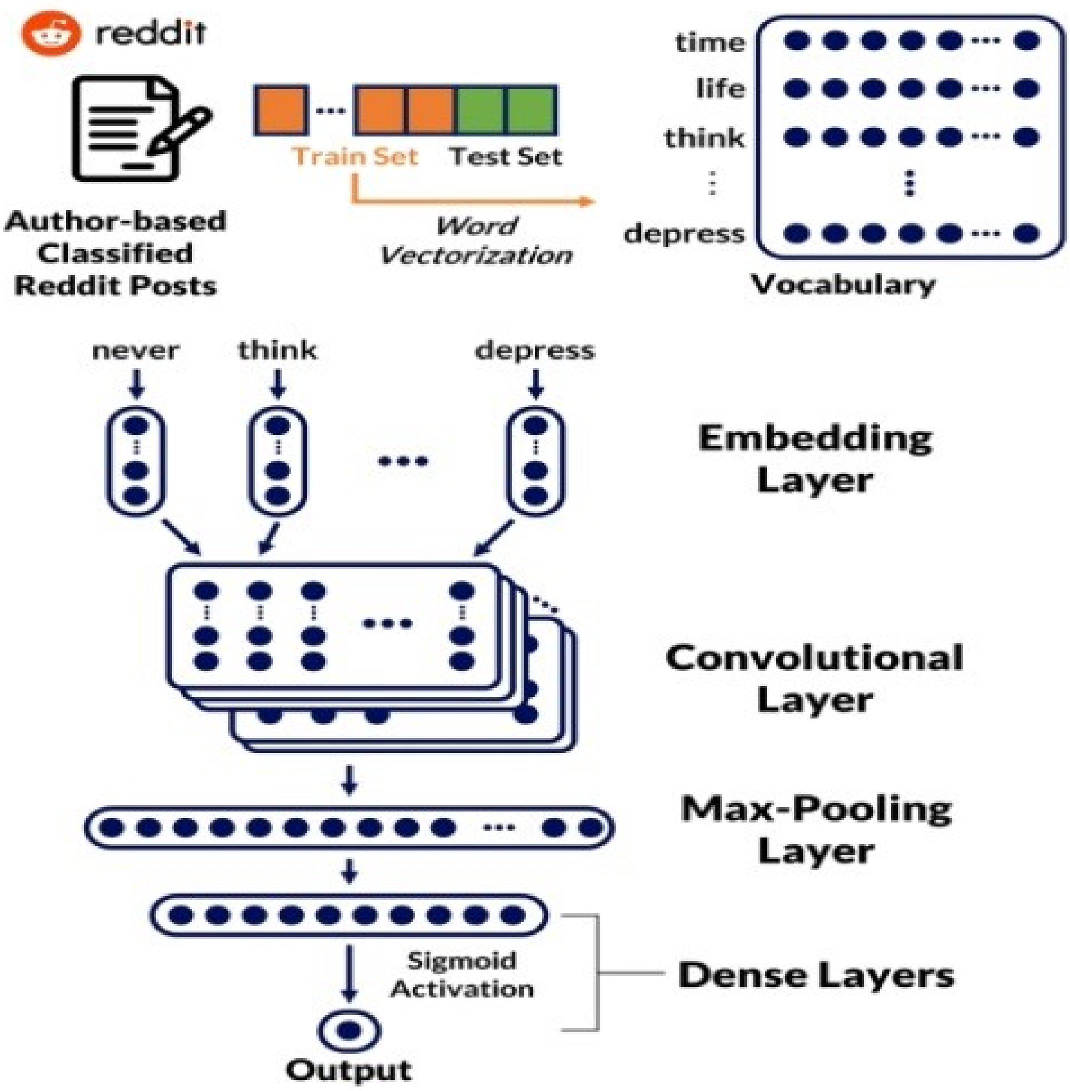

Figure 2.1: Overall architecture [1].

In summary, the study employed data collection from Reddit, NLP preprocessing of the collected posts, and the development and evaluation of deep learning models for detecting mental illness from user-generated content on social media. The findings suggest that the proposed model has the potential to contribute to the early detection and monitoring of mental health conditions through online social media platforms.

2.2 An Emotion and Cognitive Based Analysis of Mental Health Disorders from Social Media Data [2]

The methodology used in this study involves a comprehensive approach to analyzing social media data for the early detection of mental health disorders. The study begins with the collection of two datasets related to depression and self-harm, and anorexia from social media platforms. These datasets contain posts from users who self-reported a diagnosis of the respective disorder. The next step involves the extraction of linguistic features at different levels of the language, including content, style, and emotions. Content features such as bag-of-words and n-grams, style features including LIWC categories and readability scores, and emotion features extracted using NRC and LIWC lexicons are utilized. Following the feature extraction, the study focuses on the development of deep learning models to learn linguistic markers of disorders and predict the presence of a disorder in a given text. The models utilized include hierarchical attention networks and transformers, which are trained and tested on the extracted features from the datasets. Additionally, the study attempts to interpret the behavior of the developed classifiers and perform feature analysis to obtain a deeper understanding of mental disorder signs. This interpretability of complex deep learning models remains a challenge, and the authors recognize the need for further analysis to uncover interesting patterns in mental disorder manifestations in language.

Furthermore, the paper emphasizes the analysis of emotion evolution in relation to cognitive styles to identify distinct patterns that separate healthy users from users suffering from or developing a mental disorder. This analysis is grounded in well-established theories in psychology, highlighting the importance of linking computational findings to theoretical grounding provided by research in psychology. The study's approach aims to provide a more refined computational and linguistic model of mental health, with high potential for improving the performance of automatic tools for monitoring mental health and aiding clinicians to better understand mental disorders.

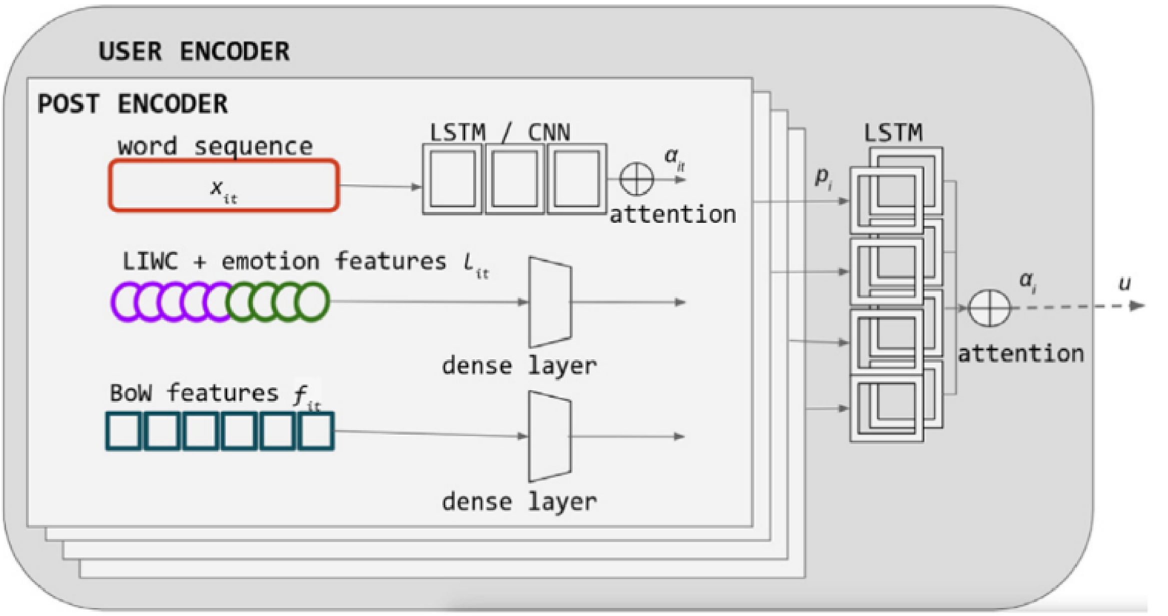

Figure 2.2: Overall pipeline of the proposed method [2].

2.3 Depression Intensity Estimation via Social Media: A Deep Learning Approach [3]

The paper "Depression Intensity Estimation via Social Media: A Deep Learning Approach" proposes a method to estimate the intensity of depression by using the contents shared by users on social media platforms, specifically Twitter. The authors make several contributions in this article, including a comprehensive literature review of the interdisciplinary domain of mental health and social media mining for depression detection . The proposed method consists of several key components:

1. Dataset Description and Relabeling: - The authors use a dataset curated by Shen et al., which consists of 6562 users, with 1402 labeled as depressed and 5160 as non-depressed. The dataset includes a total of 4,245,747 tweets, with 292,564 from depressed users and 3,953,183 from non-depressed users . - The dataset is preprocessed and relabeled into different levels of depression by computing a depression score for each user. This relabeling is done in a self-supervised manner into different intensity categories based on the textual compound polarity and latent semantic analysis (LSA) .

2. Feature Extraction: - A total of 527 features of five different types are designed to describe each user. These include emotional, event-triggered, behavioral, user-level, and depression-related features . - The features are extracted from the social media data of the users and are used to train a shallow long short-term memory (LSTM) network to predict the depression intensities .

3. Training and Evaluation: - The authors train the learning methods using different settings, including an SVM with a Gaussian kernel, and DNN, GRU, and LSTM with an SGD optimizer and cross-entropy as a loss function . - The performance of the different models for depression intensity estimation is evaluated in terms of mean squared error (MSE) and accuracy for binary classification using fivefold cross-validation .

4. Comparison with Baseline Models: - The proposed method is compared with baseline intensity estimation models such as SVM, DNN, and GRU, as well as multimodal dictionary learning (MDL) . - The authors also evaluate the effectiveness of their relabeling technique and achieve good accuracy .

In summary, the proposed method involves dataset preprocessing and relabeling, feature extraction, training of deep learning models, and evaluation of performance compared to baseline models. The authors conduct extensive experiments to establish the efficacy of their method and demonstrate its superiority over other comparable models for intensity estimation and binary classification .

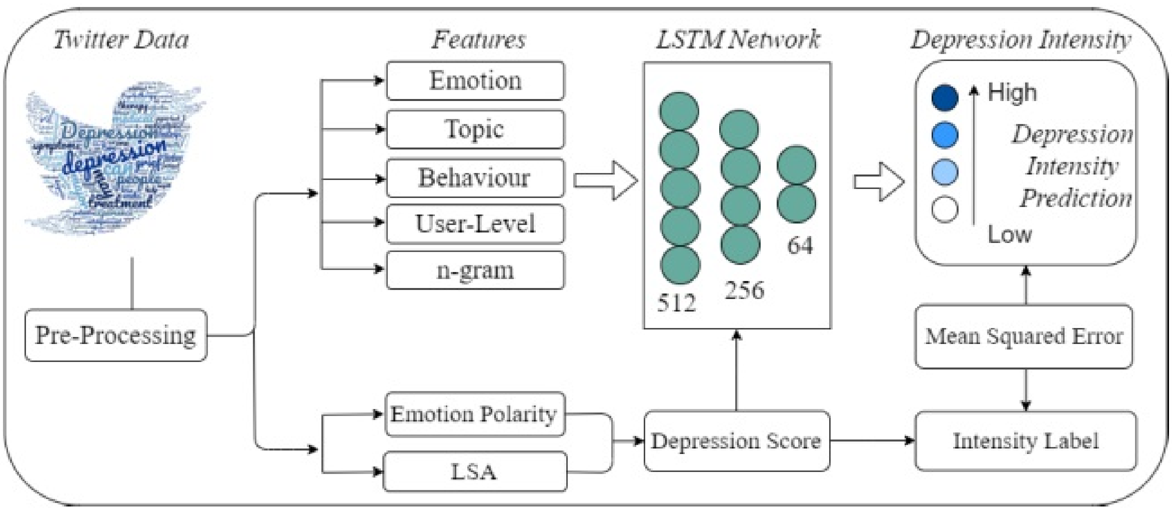

Figure 2.3: Overall architecture of the proposed method [3].

2.4 A Cognitive Similarity-Based Measure to Enhance the Performance of Collaborative Filtering-Based Recommendation System [4]

In the contemporary landscape, the surge in technological advancements and widespread Internet accessibility has prompted a significant shift towards online business operations. This transition has witnessed a notable increase in both the volume of customers engaging in online purchases and the diversity of products available on digital platforms. However, this abundance of choices has given rise to the challenge of information overload for users. In response to this, various techniques have been developed to address the issue, with recommendation systems (RS) playing a pivotal role.

Among the myriad of RS techniques, collaborative filtering (CF) stands out as a prevalent method, offering personalized item suggestions based on users' past preferences. The effectiveness of CF hinges on the accurate calculation of similarity, a task traditionally approached through cognitive methods. In the traditional paradigm, similarity measures leverage user ratings to determine the likeness between items. However, many existing similarity measures within this framework grapple with issues like data sparsity and cold-start problems.

To tackle these challenges, this article introduces a novel similarity measure, the Efficient Gowers–Jaccard–Sigmoid Measure (EGJSM), blending Jaccard and Gower coefficients. This measure incorporates a nonlinear sigmoid function to penalize unfavorable ratings, enhancing its performance in handling sparse data and cold-start scenarios. Experimental evaluations conducted on benchmark datasets demonstrate that EGJSM outperforms several existing methods, showcasing its efficacy in recommendation scenarios.

Additionally, the article proposes a cognitive similarity (CgS) measure, which integrates cognitive features such as genre and year of release alongside rating information to calculate similarity. Notably, the CgS method surpasses the EGJSM approach, yielding nearly 4% and 1% lower mean absolute error (MAE) and root-mean-squared error (RMSE) values, respectively. This suggests that the inclusion of cognitive features contributes to more accurate similarity calculations in the context of recommendation systems.

2.5 Attention-based Heterogeneous Relational Model (AHRM) [5]

In recent years, the proliferation of social media platforms has led to an immense influx of multimedia content, particularly social images. Effectively analyzing and categorizing sentiment in this vast and diverse pool of social image data is crucial for understanding user preferences and societal trends. This paper specifically delves into the novel approach of the Attention-based Heterogeneous Relational Model (AHRM) for social image sentiment analysis. While existing reviews on social image sentiment analysis are available, this paper aims to bridge gaps in understanding by critically comparing various methods. It explores the taxonomy, applications, challenges, and future directions in the realm of social image sentiment analysis with a focus on the AHRM model. Additionally, the paper evaluates tools, benefits, and drawbacks, aiming to provide recommendations for the most effective approaches.

The AHRM model employs a two-fold approach to extract features from social images. It utilizes a pre-trained VGG-19 model to extract visual features from the images, followed by a channel attention mechanism to highlight the most important channels. For text features, a bi-directional gated recurrent unit (bi-GRU) encodes the text description into a 300-dimensional GloVe feature. The AHRM model then incorporates a progressive dual attention module, comprising channel attention and region attention, to learn a joint image-text representation by highlighting emotionally significant parts and capturing the correlations between images and texts. Furthermore, the model integrates social relations through a heterogeneous relation fusion module, constructing a heterogeneous relation network based on social attributes and extending graph convolutional networks (GCN) to aggregate content information from social contexts. The sentiment prediction is performed using a multilayer perceptron (MLP) with softmax and negative log-likelihood operations. Overall, the AHRM model presents a comprehensive methodology to exploit multimodal content and heterogeneous relations for enhanced social image sentiment analysis.

Recent research has indicated the efficacy of the AHRM model in multimodal sentiment analysis of social images. The AHRM model exploits both textual and visual information, alongside considerations of heterogeneous relationships, showing improved accuracy in discerning sentiment. The incorporation of attention mechanisms within the AHRM model and advanced machine learning techniques further enhances the understanding of sentiments conveyed through social images.

The proposed AHRM model achieved superior performance compared to state-of-the- art baselines on two benchmark datasets, Flickr and Getty image datasets. The accuracy value increased with the increasing training size, and the number of GCN layers was investigated to find the optimal performance. The AHRM model incorporated both content information and social relations and utilized a novel progressive dual attention module to highlight emotional semantic-significant parts and learn a joint image-text representation. Overall, the AHRM model demonstrated promising results in improving multimodal sentiment analysis performance.

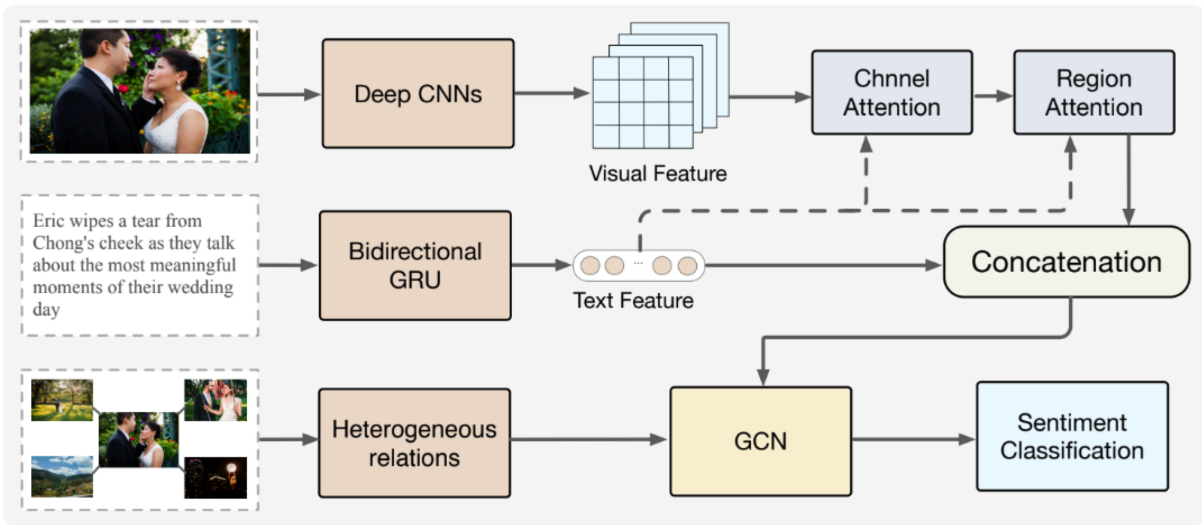

Figure 2.4: Overall pipeline of the proposed method [5].

Challenges in utilizing the AHRM model for social image sentiment analysis include the vast and diverse nature of social media data, the scarcity of labeled datasets, and the need for interpretability in understanding sentiment nuances. Additionally, the consideration of heterogeneous relations within the AHRM model poses challenges, requiring advancements in algorithms to effectively navigate the complex landscape of social image sentiments.

One limitation in employing the AHRM model for social image sentiment analysis lies in potential biases and inaccuracies, especially when dealing with diverse or highly dynamic content. Addressing these limitations involves refining algorithms within the AHRM model to ensure robustness across various types of social image data.

2.6 Summary and Gaps Identified

2.6.1 Summary

Title	Advantages	Disadvantages
A Deep Learning Model For Detecting Mental Illness From User Content On Social Media [1]	• High Accuracy: Achieved an impressive F1 score of 0.80 in classifying user posts on mental health. • Early Detection: Serves as a valuable tool for preemptive mental health alerts before formal counseling, enabling early intervention.	• Generalization Limits: May struggle beyond Reddit and mental health contexts. • Ethical Concerns: Raises privacy and mental health impact considerations.

Title	Advantages	Disadvantages
An Emotion and Cognitive Based Analysis of Mental Health Disorders from Social Media Data [2]	• Multifaceted Feature Extraction: Incorporates diverse linguistic features (content, style, emotions) for nuanced mental health analysis. • Emotion and Cognitive Analysis: Studies emotion evolution and cognitive styles, providing a holistic view of mental health on social media.	• Interpretability Challenges: Deep learning model interpretability remains a hurdle, impacting understanding and trust. • Self-Reported Data Dependency: Reliance on user-reported diagnoses may introduce bias, affecting dataset reliability and model predictions.
Depression Intensity Estimation via Social Media: A Deep Learning Approach [3]	• Comprehensive Feature Set: Leverages 527 features for rich depression intensity characterization. • Superior Performance: Outperforms SVM, DNN, GRU, and MDL in depression intensity estimation.	• Model Complexity: Deep learning introduces complexity, challenging feature interpretation. • Twitter Data Reliance: Study's dependence on Twitter data may introduce biases, impacting generalizability.

Title	Advantages	Disadvantages
A Cognitive Similarity-Based Measure to Enhance the Performance of Collaborative Filtering-Based Recommendation System [4]	• Enhanced Recommendation Accuracy: EGJSM outperforms existing measures, addressing data sparsity and cold-start issues. • Cognitive Feature Integration: CgS method achieves improved similarity accuracy with genre and year of release.	• Limited Generalizability: Performance improvements may be dataset-specific, impacting applicability. • Overfitting: The success of CgS on specific metrics raises concerns about potential overfitting.
Attention-based Heterogeneous Relational Model (AHRM) [5]	• Multimodal Sentiment Analysis: AHRM combines textual and visual data, excelling in sentiment discernment. • Superior Performance: Outperforms benchmarks on Flickr and Getty datasets, showcasing effectiveness in sentiment analysis.	• Data Challenges: Adapting to diverse social media data, scarcity of labeled datasets, and interpretability needs. • Inherent Bias: Potential biases and inaccuracies require algorithm refinements for robust sentiment analysis.

Table 2.1: Comparison of each method.

2.6.2 Gaps identified in each method

1. Limited Generalization: The model may face challenges in extending its effectiveness to diverse social media platforms beyond Reddit and mental health contexts.

2. Interpretability Challenges: The application of deep learning models introduces complexity, making it challenging to interpret specific features' contributions to mental health analysis.

3. Complexity in Model Interpretation: The use of deep learning introduces model complexity, posing challenges in interpreting how specific features contribute to depression intensity predictions.

4. Limited Generalizability: The performance improvements of the Cognitive Similarity (CgS) method may be dataset-specific, impacting its applicability to diverse recommendation scenarios.

5. Adaptation to Diverse Social Media Data: The AHRM model faces challenges in adapting to the vast and diverse nature of social media data, especially in handling the scarcity of labeled datasets and interpretability needs.

Chapter 3

Requirements

3.1 Hardware and Software Requirements

For optimal performance in implementing the cognitive recommender system, specific hardware components are recommended. The system benefits from an Intel Core i5-9400 CPU, known for its computational efficiency, which is vital for handling the complex processing requirements of deep learning models. Additionally, a GeForce GTX 1660 Ti GPU is advised to accelerate the training and inference processes, particularly beneficial for tasks involving neural networks and large-scale data analysis. To support the computational demands and ensure smooth operation, a substantial 16 GB RAM is recommended. This hardware configuration provides the necessary computational power and memory capacity to successfully execute the multi-modal data analysis and model training integral to the cognitive recommender system

The software stack required for the development and deployment of the cognitive recommender system is carefully chosen to ensure a robust and efficient implementation. Node.js serves as a fundamental software component for server-side scripting, facilitating seamless communication and data processing. ReactJs, a JavaScript library, is utilized to construct an interactive and responsive user interface, enhancing the overall user experience. Python, a versatile programming language, is employed for its suitability in machine learning and data processing tasks. TensorFlow, a powerful deep learning framework, is a critical software requirement for constructing and training intricate neural network models central to the functionality of the cognitive recommender system. This comprehensive software ensemble establishes a dynamic and adaptable environment, enabling the integration of both text and image data for advanced mental health detection and personalized recommendation generation.

Chapter 4

System Architecture

4.1 System Overview

The cognitive recommender system initiates its operations with the user interface, featuring the presentation of the user's feed and the collection of user data from social media. This data collection serves as the entry point for gathering diverse user information from various social media platforms, including textual and visual content, to personalize mental health recommendations.

For the textual data stream, a comprehensive processing pipeline is employed, utilizing NLP techniques such as tokenization, stemming, and CNN for text classification. Simultaneously, visual data from the user undergoes processing via the VGG model to extract three polarities for each image: positive, neutral, and negative. The combination of these polarities provides the final sentiment of the image.

The results from both textual and visual processing are combined using a weighted average, rather than an attention mechanism, to create a holistic understanding of the user's mental well-being. This approach ensures that the model leverages insights from both modalities effectively. The final output of this will predict the specific type of mental illness which might be experienced by the user. .

The classified mental health information feeds into the recommendation system (SVD). Along with the identified mental illness, additional information such as the age, gender, and location of the user is passed on to the system. This system utilizes personalized insights into the user's mental health state to generate recommendations tailored for support and encouragement. These recommendations seamlessly integrate into the user's feed, creating an updated and personalized content stream for the user. This recommender system employs a comprehensive architecture tailored for personalized post recommendations. At its core, it loads data from diverse sources, parsing user tweets and metadata,

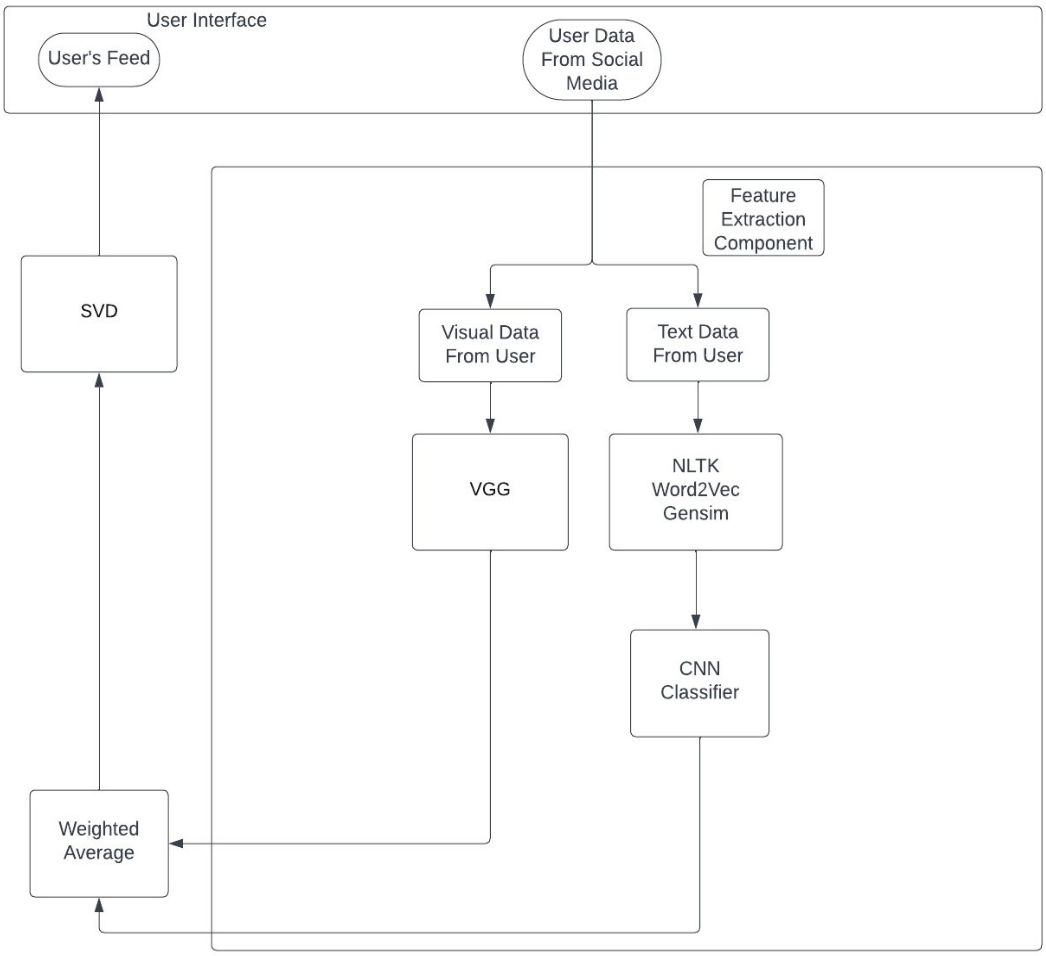

Figure 4.1: Architecture Diagram

alongside recommended posts, from designated directories. It meticulously processes this data, ensuring that each piece of information, from user attributes like illness, age, gender, and location to sentiment ratings for recommended posts, is accurately extracted and utilized. Using the robust Surprise library, the system then trains a recommendation model employing Singular Value Decomposition (SVD), a well-suited algorithm for such tasks. Once the model is trained, it carefully constructs user profiles by amalgamating these extracted attributes, enabling precise prediction of post ratings. This approach ensures that users receive highly personalized recommendations, sorted based on predicted ratings, and complemented with associated images for enhanced engagement. Overall, this architecture reflects a sophisticated interplay between data processing, modeling, and recommendation generation, aimed at improving the mental health of the user.

In summary, this architecture employs a sophisticated blend of natural language processing, computer vision, and machine learning techniques. By considering both textual and visual aspects of social media data, the system achieves a holistic understanding of users' mental health, resulting in personalized recommendations to foster a supportive and empathetic environment. The multi-modal approach ensures a nuanced analysis, contributing to the system's effectiveness in mental health classification and recommendation generation.

4.2 Architectural Design

4.3 Module Division

The proposed method comprises five crucial modules: dataset collection and preprocessing, feature extraction from text data, feature extraction from image data, mental illness classification using extracted features, and recommendation system. Each module is designed to contribute significantly to the holistic understanding and support of users dealing with mental health issues. The initial module focuses on dataset collection and preprocessing, where a diverse dataset is gathered, ensuring a representative sample of user-generated content reflecting various mental health conditions. Following this, feature extraction from text data is conducted to create a rich set of discriminative features related to mental illnesses, serving as valuable inputs for subsequent classification tasks.

In parallel, feature extraction from text data is carried out using Convolutional Neural

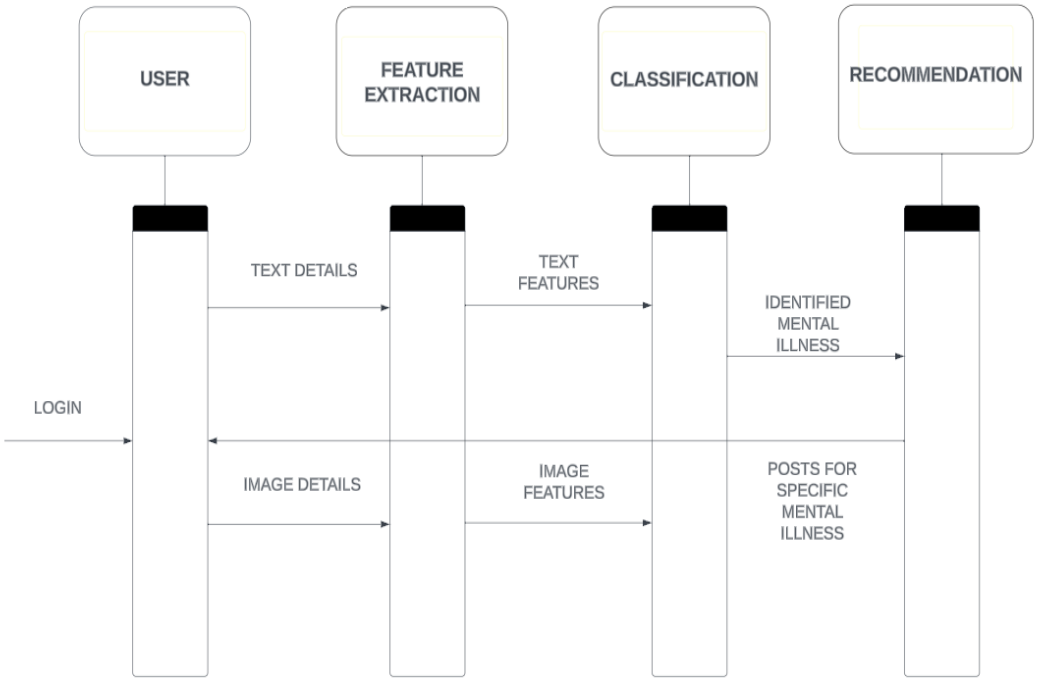

Figure 4.2: Sequence Diagram

Networks (CNNs) to derive essential visual features from users' multimedia content, along with this a polarity of the image is found using VGG. This step enhances the comprehensiveness of the feature set, capturing nuanced aspects not explicitly expressed in data. The extracted features from both text and image data lay the foundation for the third module, mental illness classification using extracted features.

The fourth module, focusing on classification, represents a pivotal step in providing personalized and targeted support to users, laying the groundwork for tailored interventions. This module employs a system of weighed averages. The output of the textual data is given more importance as it gives a clearer picture of the user's mental state as compared to the sentiment which we get by analyzing the images.

Finally, the fifth module, the recommendation system, suggests posts based on users' mental health classifications, utilizing the innovative cognitive recommendation system (SVD). This recommender system loads user tweets, images, processes the data, and trains a recommendation model using SVD. It then predicts post ratings based on user attributes. Finally, it sorts and presents personalized post recommendations with associated images.This integrated framework establishes a comprehensive and sophisticated approach to understanding, classifying, and supporting individuals dealing with various mental health challenges in a personalized and empathetic manner.

4.4 Work Schedule - Gantt Chart

The Gantt chart stands as a pivotal tool in project management, offering a visual and strategic representation of the project's timeline. It serves as a comprehensive and structured overview, meticulously detailing tasks, their respective durations, and the intricate web of dependencies woven throughout the project's life cycle. In essence, the Gantt chart transforms the complexities of project planning into a lucid and accessible format.

In this graphical representation, each task or activity assumes the form of a horizontal bar, thoughtfully positioned along a meticulously delineated timeline. The length of these bars becomes a visual indicator, eloquently conveying the temporal span and duration of each undertaking.

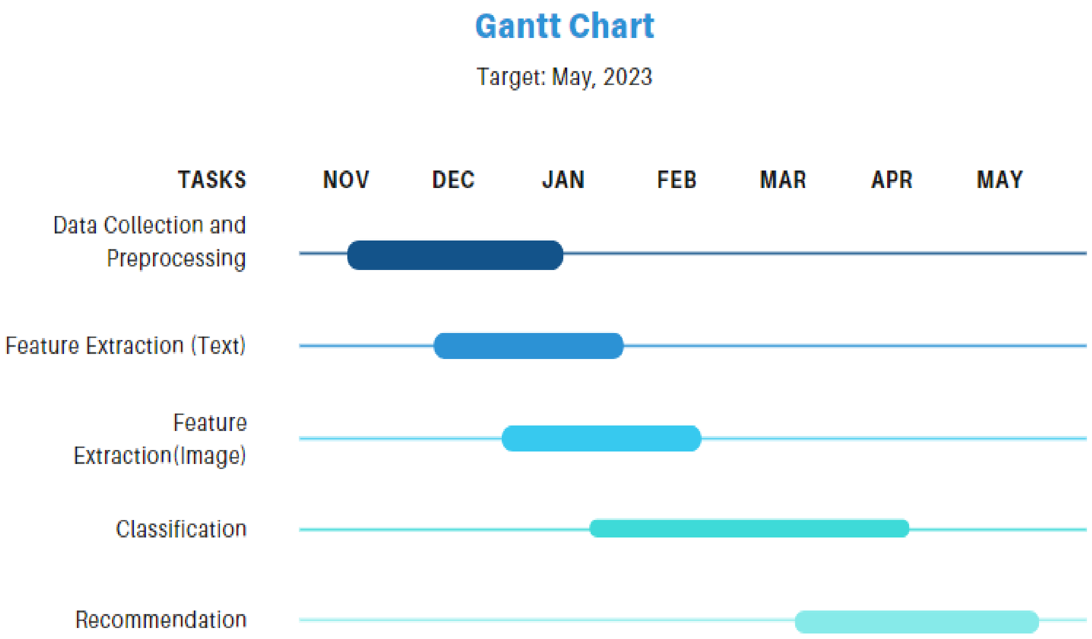

Figure 4.3: Gantt Chart

4.5 Conclusion

The presented cognitive recommender system embodies a multifaceted and innovative approach to understanding and supporting users dealing with mental health challenges through a blend of natural language processing, computer vision, and machine learning techniques. The system initiates its operations by collecting user data from social media platforms, recognizing the multi-modal nature of content with a dual stream approach—textual and visual data. The processing pipeline involves advanced NLP techniques, including NLTK, Gensim, and Word2Vec, for textual data, while a Deep CNN extracts intricate features from visual content.

The convergence of output from the textual and visual data using weighed averages allows the system to focus on pertinent aspects of user content, enhancing interpretability and contextual understanding. Using the probability of a user having a certain mental illness as predicted the textual data analysis, and using the sentiment output from the images, and combining them using a system of weighed averages, we get a robust and reliable output of the probability of a user haveing a certain mental illness.

Using the predicted mental illness and outside information of the user such as age, gender, and location, we get a holistic perspective of the user's mental state, on which the recommendation system employing SVD was trained. This comprehensive and sophisticated framework underscores the potential of technology to contribute empathetically to mental health care, aligning with evolving societal needs.

Chapter 5

System Implementation

The implementation of our cognitive recommender system marks a significant leap in personalized mental health support, seamlessly integrating user-generated content from various social media platforms. At its core, the system employs a multifaceted approach, leveraging both textual and visual data streams to gain comprehensive insights into the user's mental well-being. Through a meticulous processing pipeline, Natural Language Processing techniques handle textual data, while a Deep Convolutional Neural Network extracts intricate features from visual content. These streams converge a system of weighed averages, allowing the system to discern potential mental health conditions, feeding into a recommendation system powered by Singular Value Decomposition (SVD), along with extra information about the user such as their age, gender, country. This recommendation system then gives out recommendations of posts which might help the user battle with their ongoing mental illness, using all of the given data. This architecture, meticulously designed to parse, process, and analyze user data, ensures the generation of highly personalized recommendations aimed at fostering mental wellness. With each recommendation seamlessly integrated into the user's feed, our system offers a holistic approach towards supporting and encouraging individuals on their mental health journey.

5.1 Datasets Identified

The textual data for the project was gathered from Reddit, focusing on six distinct subreddits: r/depression, r/anxiety, r/autism, r/schizophrenia, r/bpd, and r/bipolar. This approach ensured a comprehensive representation of various mental health conditions and experiences. Over 200,000 posts and comments were collected from these subreddits, providing a rich and diverse dataset for analysis. Meanwhile, the image dataset was sourced from Twitter by employing specific keywords associated with different mental health disorders. By targeting posts related to these keywords, relevant images were extracted for analysis. Additionally, a similar methodology was applied to collect positive recommended posts from Twitter, using specific keywords to identify uplifting and supportive content. These datasets formed the foundation for training and evaluating the cognitive recommender system, enabling it to provide personalized recommendations and support for users navigating mental health challenges.

5.2 Proposed Methodology/Algorithms

By meticulously processing user-generated content sourced from platforms like Reddit and Twitter, we harness the power of Natural Language Processing (NLP) techniques and Deep Convolutional Neural Networks (CNNs) to extract meaningful insights from text and images alike. These insights are then integrated using a weighted average mechanism, enabling our system to discern potential mental health conditions and provide targeted support. Through classification algorithms and a sophisticated recommendation system powered by Singular Value Decomposition (SVD), our platform delivers highly personalized recommendations tailored to each user's unique needs and challenges. Join us on a journey towards mental wellness, where each recommendation seamlessly integrates into the user's feed, offering holistic support and encouragement every step of the way.

5.2.1 Natural Language Processing

Natural Language Processing (NLP) plays a crucial role in our system, employing various techniques to process textual data sourced from platforms like Reddit. Tokenization is the initial step, breaking down textual content into smaller units, typically words or phrases, for further analysis. Stemming follows, where words are reduced to their root form to normalize variations and improve consistency in data representation. Additionally, we utilize deep learning-based text classification using Convolutional Neural Networks (CNNs) to classify textual data into categories. These CNNs are trained to recognize patterns indicative of mental health-related content, aiding in the identification of potential mental health conditions based on user-generated text.

5.2.2 Image Processing

Deep Convolutional Neural Networks (CNNs), particularly the Visual Geometry Group (VGG) Model, are instrumental in processing visual content obtained from platforms like Twitter. The VGG model, designed specifically for image classification tasks, extracts intricate features from images, providing valuable insights into the emotional context of user posts. Furthermore, sentiment analysis is conducted on these images, wherein sentiment polarities such as positive, neutral, and negative are assigned. This enables our system to gain a deeper understanding of the emotional tone conveyed by visual content, complementing the insights derived from textual data.

5.2.3 Weighed Averages

The integration of insights from both textual and visual modalities is facilitated by a weighted average mechanism. This mechanism allows us to combine the results obtained from NLP and CNN processing effectively, creating a holistic understanding of the user's mental well-being. By assigning appropriate weights to each modality, our system ensures that insights from both textual and visual data contribute proportionally to the overall analysis, enhancing the accuracy and reliability of our recommendations.

5.2.4 SVD

In our recommendation system, Singular Value Decomposition (SVD) serves as a cornerstone for generating highly personalized recommendations tailored to the user's preferences and mental health state. SVD decomposes the user-item interaction matrix into latent factors, effectively capturing underlying patterns and relationships in the data. By incorporating additional user information such as age, gender, and country, SVD enriches the recommendation process, ensuring that recommendations are not only personalized but also culturally and demographically sensitive. This approach enhances the relevance and effectiveness of the recommendations, fostering a deeper connection between users and the content provided. Moreover, the efficiency and scalability of SVD make it well-suited for handling large-scale recommendation tasks, enabling our system to deliver accurate and insightful suggestions to support users on their mental health journey.

5.3 Description of Implementation Strategies

Textual Data Processing with Natural Language Processing (NLP) involves leveraging the NLTK (Natural Language Toolkit) Python library. We utilize various NLP techniques such as tokenization and stemming to preprocess textual data sourced from platforms like Reddit. Tokenization is performed using NLTK's word_tokenize() method to break down the text into smaller units, such as words or phrases, facilitating further analysis. Stemming is achieved through NLTK's stemmers like PorterStemmer or SnowballStemmer, which reduce words to their root form, ensuring consistency in data representation. Additionally, we implement text classification using Convolutional Neural Networks (CNNs) with deep learning frameworks like TensorFlow or PyTorch. These CNN architectures are designed and trained to classify textual data into relevant categories, such as identifying mental health-related content, thus enhancing the system's ability to discern patterns indicative of various mental health conditions.

```python
df = pd.read_csv('/content/drive/MyDrive/model/depression/data_dep.csv')

df = df.dropna(subset=['processed_post'])

X_train = [str(post).split() for post in df['processed_post']]  # Convert to string before splitting

label_encoder = LabelEncoder()
y_train = label_encoder.fit_transform(df['label'])

# Split the data into training and validation sets
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.2, random_state=42)

word2vec_model = Word2Vec.load('/content/drive/MyDrive/model/depression/w2v.model')

# Get the size of the word vectors
embedding_dim = word2vec_model.vector_size

# Set the maximum length of a pre-processed post
max_post_length = max(len(post) for post in X_train)

# Create an embedding matrix based on the vocabulary in the Word2Vec model
embedding_matrix = np.zeros((len(word2vec_model.wv.key_to_index) + 1, embedding_dim))
for word, i in word2vec_model.wv.key_to_index.items():
    if word in word2vec_model.wv:
        embedding_matrix[i] = word2vec_model.wv[word]

# Convert the sequences of words to padded sequences of word indices
X_train_padded = pad_sequences([[word2vec_model.wv.key_to_index[word] for word in post if word in word2vec_model.wv] for post in X_train], maxlen=max_post_length)
X_val_padded = pad_sequences([[word2vec_model.wv.key_to_index[word] for word in post if word in word2vec_model.wv] for post in X_val], maxlen=max_post_length)
```

Figure 5.1: Code of Text Preprocessing

For image processing, Convolutional Neural Networks (CNNs) are utilized, implemented in Python with TensorFlow or PyTorch. We design CNN architectures using TensorFlow's high-level API, Keras, or PyTorch's neural network modules. Pre-trained models like VGG are employed for sentiment analysis of the images, and we fine-tune these

```python
# Define the CNN model
model = Sequential()

# Embedding layer with the pre-trained Word2Vec embeddings
embedding_layer = Embedding(
    input_dim=len(word2vec_model.wv.key_to_index) + 1,
    output_dim=embedding_dim,
    weights=[embedding_matrix],
    input_length=max_post_length,
    trainable=False
)
model.add(embedding_layer)

# Convolutional layer
model.add(Conv1D(filters=128, kernel_size=5, activation='relu'))
model.add(Dropout(0.25))

# Max-pooling layer
model.add(MaxPooling1D(pool_size=2))

# Flatten layer
model.add(Flatten())

# Dense layers
model.add(Dense(128, activation='relu'))
model.add(Dense(64, activation='relu'))

# Output layer
model.add(Dense(1, activation='sigmoid'))

# Compile the model
model.compile(loss='binary_crossentropy', optimizer=Adam(lr=0.001), metrics=['accuracy'])
```

Figure 5.2: Code of Text Classification

models to our specific image classification tasks. Additionally, we incorporate techniques such as data augmentation to increase the diversity of our image dataset and improve the generalization capabilities of our models.

We employ weighed averages as a mechanism to integrate insights from both textual and visual modalities effectively. This entails assigning appropriate weights to the results obtained from NLP and CNN processing, ensuring that insights from both modalities contribute proportionally to the overall analysis. By carefully balancing the contributions of textual and visual data, we create a holistic understanding of the user's mental well-being, enhancing the accuracy and reliability of our recommendations.

In our recommendation system, Singular Value Decomposition (SVD) is utilized for personalized recommendation generation. SVD is a matrix factorization technique employed in collaborative filtering-based recommendation systems. It decomposes the user-item interaction matrix into latent factors, representing user preferences and item characteristics. By leveraging SVD, along with additional user information such as age, gender, and country, our system generates highly personalized recommendations tailored to each individual user. This approach ensures that recommendations align closely with user preferences and mental health needs, fostering a sense of connection and understanding

```python
with open('/content/drive/MyDrive/visual-sentiment-analysis/predictions.csv', 'r') as file:
    negative = []
    neutral = []
    positive = []
    for line in file:
        values = line.strip().split(',')

        print("Line Content:", line.strip())

        try:
            negative.append(float(values[0]))
            neutral.append(float(values[1]))
            positive.append(float(values[2]))
        except ValueError as e:
            print("Error:", e)

print("Negative:", negative)
print("Neutral:", neutral)
print("Positive:", positive)
print('\n')
```

Figure 5.3: Code of Image Sentiment Analysis

```python
weighted_sum = np.sum(sentiment_matrix.T * weights, axis=0)

    # Calculate total weight
total_weight = np.sum(weights)

    # Calculate average sentiment by dividing weighted sum by total weight
average_sentiment = weighted_sum / total_weight
weight_text_model = 0.7
weight_image_model = 0.3

# Calculate weighted predictions from text model
weighted_predictions_text1 = predicted_labels1 * weight_text_model
weighted_predictions_text2 = predicted_labels2 * weight_text_model
weighted_predictions_text3 = predicted_labels3 * weight_text_model
weighted_predictions_text4 = predicted_labels4 * weight_text_model
weighted_predictions_text5 = predicted_labels5 * weight_text_model
weighted_predictions_text6 = predicted_labels6 * weight_text_model

# Calculate weighted predictions from image model
weighted_predictions_image1 = average_sentiment * weight_image_model
weighted_predictions_image2 = average_sentiment * weight_image_model
weighted_predictions_image3 = average_sentiment * weight_image_model
weighted_predictions_image4 = average_sentiment * weight_image_model
weighted_predictions_image5 = average_sentiment * weight_image_model
weighted_predictions_image6 = average_sentiment * weight_image_model

combined_weighted_predictions1 = weighted_predictions_text1 + weighted_predictions_image1
combined_weighted_predictions2 = weighted_predictions_text2 + weighted_predictions_image2
combined_weighted_predictions3 = weighted_predictions_text3 + weighted_predictions_image3
combined_weighted_predictions4 = weighted_predictions_text4 + weighted_predictions_image4
combined_weighted_predictions5 = weighted_predictions_text5 + weighted_predictions_image5
combined_weighted_predictions6 = weighted_predictions_text6 + weighted_predictions_image6

combined_sentiment1 = np.mean(combined_weighted_predictions1)
combined_sentiment2 = np.mean(combined_weighted_predictions2)
```

Figure 5.4: Code of taking Weighed Average

in their mental health journey.

```python
# Function to recommend posts and provide ratings
def recommend_posts(algo, user_data, posts_data, images_folder, n=10):
    all_predictions = []
    tweet_counter = 0
    for tweet_idx, tweet in enumerate(user_data):
        predictions = []
        for post_data in posts_data:
            tweet_counter+=1
            try:
                prediction = algo.predict(tweet['illness'], post_data['tweet'])
                if np.isfinite(prediction.est):  # Check if prediction is finite (not NaN or infinite)
                    predictions.append({'tweet': post_data['tweet'], 'rating': prediction.est, 'tweet_idx': tweet_counter})
            except:  # Handle any exception
                continue
        all_predictions.extend(predictions)
    sorted_predictions = sorted(all_predictions, key=lambda x: x['rating'], reverse=True)

    # Display recommended tweets and associated images
    for post in sorted_predictions[:n]:
        tweet_idx = post['tweet_idx']
        tweet = user_data[tweet_idx]['tweet']
        image_path = os.path.join(images_folder, f"{post['tweet_idx']}.png")
        if not os.path.exists(image_path):
            image_path = os.path.join(images_folder, f"{post['tweet_idx']}.jpeg")
        if os.path.exists(image_path):
            display(Image(filename=image_path))
        else:
            print("No image found for this tweet.")
        print("Tweet:", post['tweet'])
        print("Estimated rating:", post['rating'])
```

Figure 5.5: Code of Recommendation System

The implementation of our cognitive recommender system signifies a pivotal advancement in personalized mental health support, drawing from meticulously curated datasets sourced from diverse platforms like Reddit and Twitter. Leveraging sophisticated Natural Language Processing (NLP) techniques and Convolutional Neural Networks (CNNs), we processed textual and visual data with precision, ensuring a comprehensive understanding of users' mental well-being. By integrating insights from both modalities through weighed averages, our system achieves a holistic perspective, enabling the identification of potential mental health conditions and the generation of personalized recommendations. Our user interface design and database schema were thoughtfully crafted to enhance user interaction and data management efficiency. Implementation strategies utilizing Python libraries such as NLTK and TensorFlow were employed, alongside rigorous evaluation methods including cross-validation and performance metrics calculation, to assess system effectiveness. In conclusion, our system epitomizes a dedication to leveraging cutting-edge technologies and methodologies to provide tailored support and recommendations, empowering individuals in their mental health journey.

Chapter 6

Results and Discussions

The results of our project unveil a transformative approach to personalized mental health support, showcasing the efficacy of our cognitive recommender system in harnessing user-generated content from social media platforms to provide targeted recommendations and assistance. Through meticulous data processing and analysis, we have uncovered valuable insights into users' mental well-being, leveraging advanced techniques in Natural Language Processing (NLP) and Convolutional Neural Networks (CNNs) to discern patterns indicative of various mental health conditions. The integration of textual and visual data streams, combined with sophisticated algorithms such as Singular Value Decomposition (SVD), has enabled the generation of highly personalized recommendations tailored to individual users' needs and preferences. As we delve into the results, we delve deeper into the impact of our system on user engagement, satisfaction, and mental health outcomes, demonstrating its potential to positively influence individuals' mental health journeys.

6.1 Overview

The project yielded significant advancements in its results, notably benefiting from the utilization of a larger dataset, particularly evident in the domain of text classification. By incorporating a more extensive corpus of textual data, we observed enhanced accuracy and effectiveness in identifying mental health conditions. Concurrently, the integration of a pretrained VGG model for image analysis bolstered our system's capability to extract meaningful insights from visual content. Despite the multifaceted nature of our approach, prioritizing the direct output of text classification within the weighed average underscored its paramount importance in shaping the overall system's efficacy. Furthermore, the recommendation system's training on positive posts collected from the internet contributed to the refinement and specificity of the generated recommendations, aligning closely with users' preferences and mental well-being needs. This comprehensive approach culminated in robust results, highlighting the project's potential to provide valuable support and guidance to individuals navigating mental health challenges.

6.2 Testing

6.2.1 Text Classification

```
Depression: [0.99955386]
Anxiety: [0.91019523]
Autism: [0.9142661]
Bipolar: [0.75466466]
BPD: [0.9997931]
Schizophrenia: [0.9114427]
```

Figure 6.1: Probability of each Mental Illness

This gives the probability of the user having each mental illness. The mental illness with the highest probability is then passed to the next stage.

6.2.2 Image Sentiment

```
Negative: [0.26240238547325134, 0.09409192204475403, 0.05345390737056732, 0.5722560286521912, 0.4913267195224762, 0.40252885222435]
Neutral: [0.2834213972091675, 0.21921756863594055, 0.15646040439605713, 0.2590740919113159, 0.10025561600923538, 0.283283621072769l7]
Positive: [0.4541761875152588, 0.6866905689239502, 0.7900857329368591, 0.1686699390411377, 0.40841761231422424, 0.31418749690055847]
```

Figure 6.2: Image Sentiment

This gives the sentiment of the images as posted by the user. A final sentiment is calculated using the three polarities of the image.

6.2.3 Weighed Average

```
Combined Sentiment for Depression: 0.8889866418391467
Combined Sentiment for Anxiety: 0.8264355606585742
Combined Sentiment for Autism: 0.8292851991206408
Combined Sentiment for Bipolar: 0.7175641603022814
Combined Sentiment for BPD: 0.8891540712863207
Combined Sentiment for Schizophrenia: 0.8273088283091784
```

Figure 6.3: Combined Probability of Mental illness

This gives the weighed average of the mental illness probability and the image sentiment.

6.2.4 Recommendation

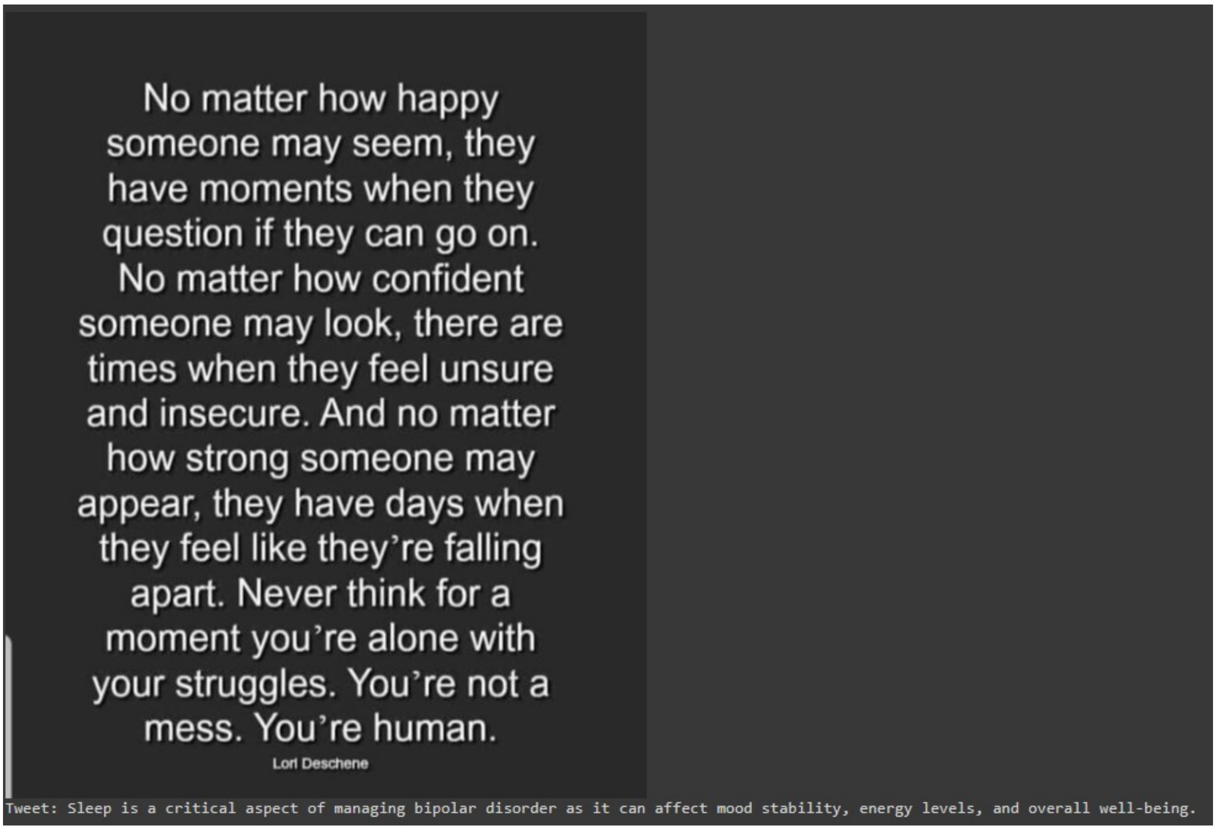

Figure 6.4: Positive Recommended Posts

Finally, using the predicted mental illness having the highest probability, along with the user's age, gender, and location, we recommend positive posts for them.

6.3 Quantitative Results

Accuracy: 0.9119

Classification Report:

	precision	recall	f1-score	support
0	0.93	0.96	0.94	26380
1	0.86	0.79	0.82	9246
accuracy			0.91	35626
macro avg	0.90	0.87	0.88	35626
weighted avg	0.91	0.91	0.91	35626

Figure 6.5: Confusion Matrix Anxiety

Accuracy: 0.8711

Classification Report:

	precision	recall	f1-score	support
0	0.88	0.94	0.91	1987
1	0.85	0.72	0.78	938
accuracy			0.87	2925
macro avg	0.86	0.83	0.85	2925
weighted avg	0.87	0.87	0.87	2925

Figure 6.6: Confusion Matrix Bipolar

```
Accuracy: 0.8428
Classification Report:
              precision    recall  f1-score   support

           0       0.86      0.88      0.87      5970
           1       0.81      0.78      0.80      3918

    accuracy                           0.84      9888
   macro avg       0.84      0.83      0.83      9888
weighted avg       0.84      0.84      0.84      9888
```

Figure 6.7: Confusion Matrix BPD

```
Accuracy: 0.8611
Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.84      0.85     16989
           1       0.86      0.88      0.87     18637

    accuracy                           0.86     35626
   macro avg       0.86      0.86      0.86     35626
weighted avg       0.86      0.86      0.86     35626
```

Figure 6.8: Confusion Matrix Depression

Accuracy: 0.9173

Classification Report:

	precision	recall	f1-score	support
0	0.91	0.96	0.93	2022
1	0.93	0.86	0.89	1398
accuracy			0.92	3420
macro avg	0.92	0.91	0.91	3420
weighted avg	0.92	0.92	0.92	3420

Figure 6.9: Confusion Matrix Autism

Accuracy: 0.9224

Classification Report:

	precision	recall	f1-score	support
0	0.93	0.97	0.95	5990
1	0.86	0.70	0.77	1404
accuracy			0.92	7394
macro avg	0.90	0.84	0.86	7394
weighted avg	0.92	0.92	0.92	7394

Figure 6.10: Confusion Matrix Schizophrenia

6.4 Graphical Analysis

Figure 6.11: Loss and Accuracy:Anxiety

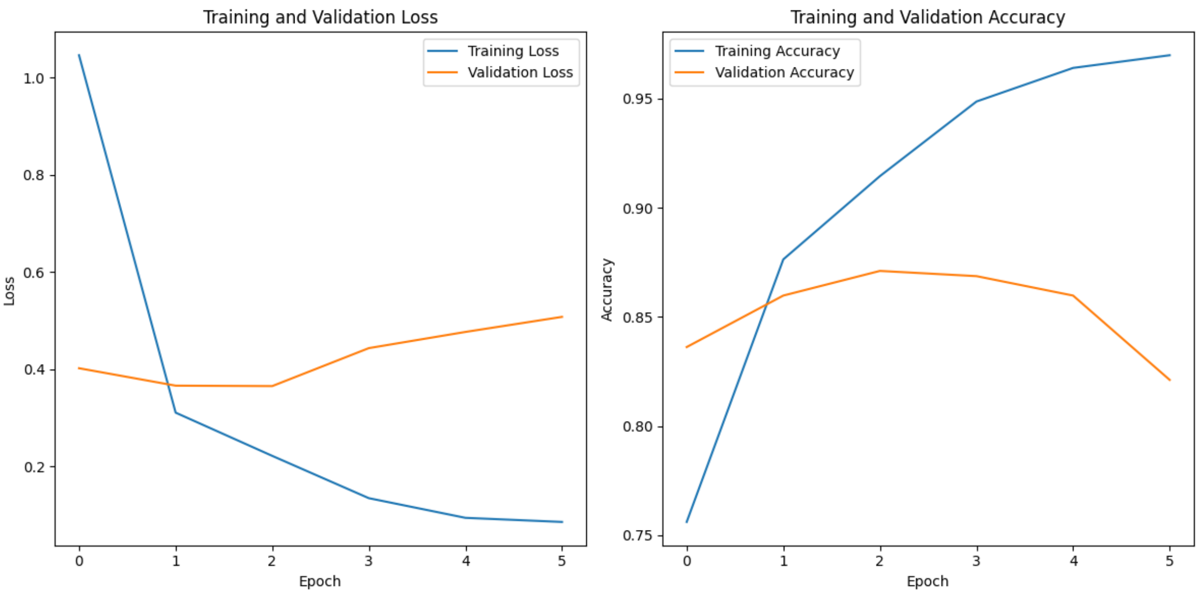

Figure 6.12: Loss and Accuracy:Bipolar

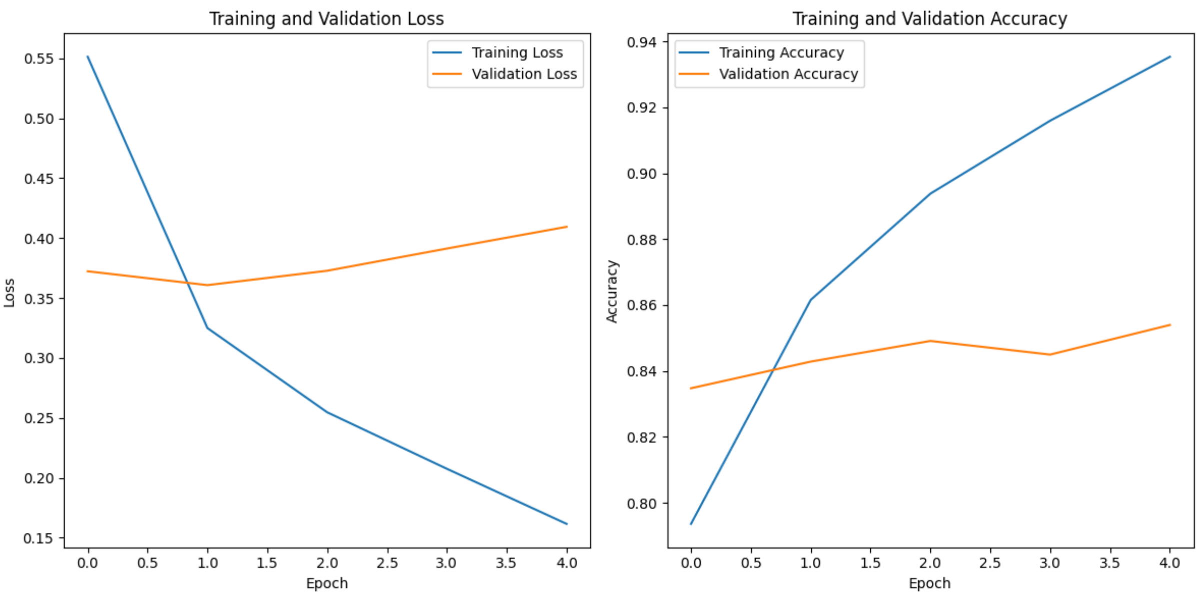

Figure 6.13: Loss and Accuracy:BPD

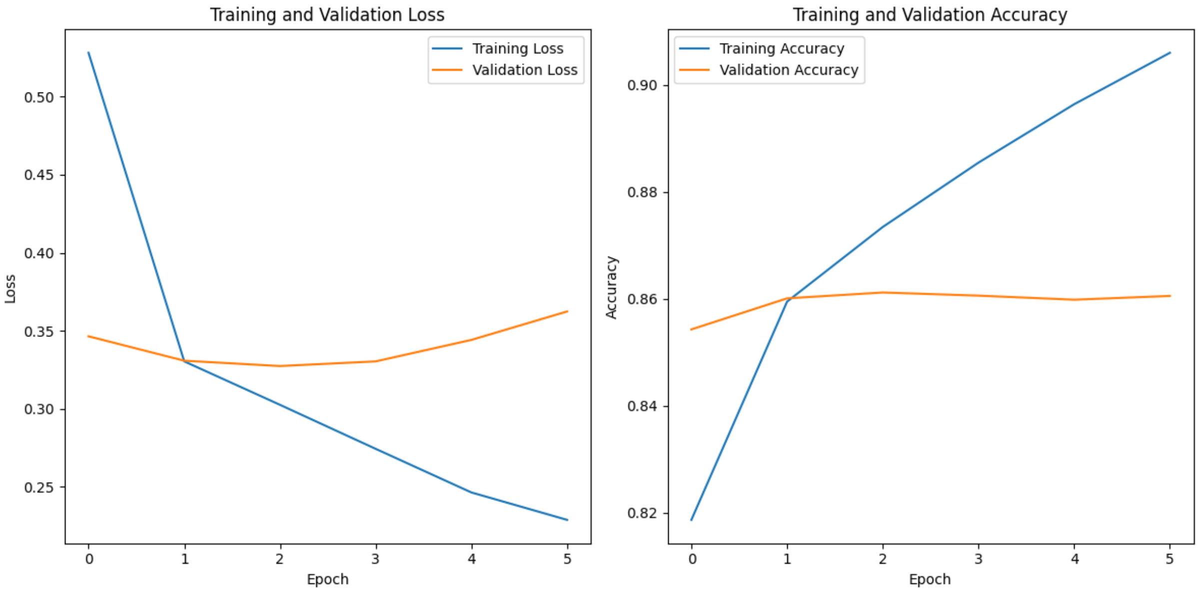

Figure 6.14: Loss and Accuracy:Depression

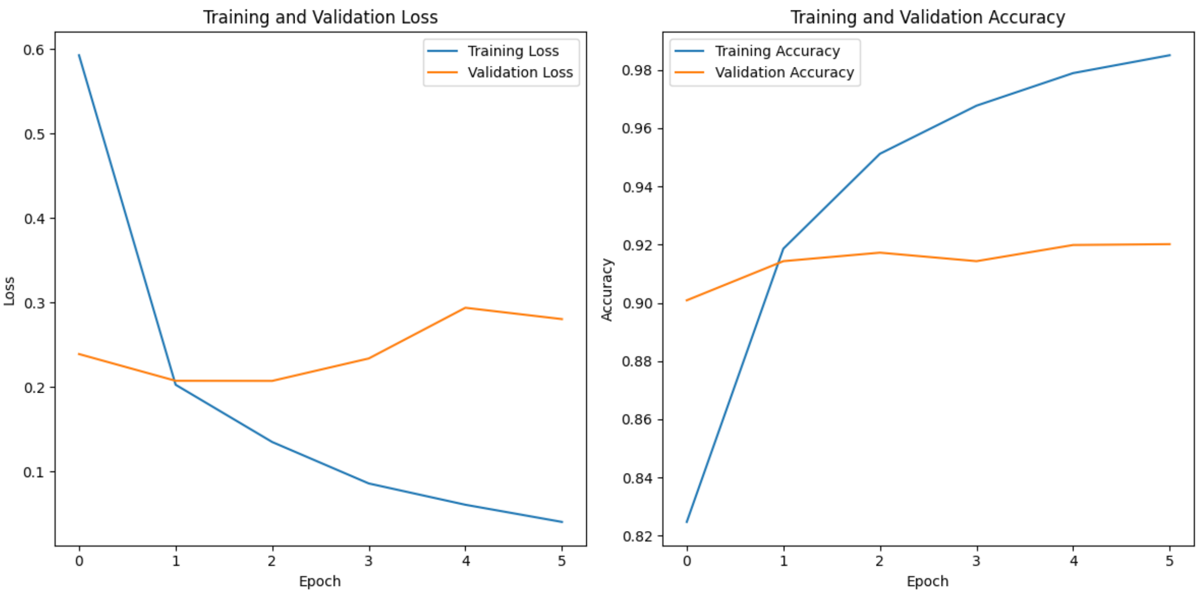

Figure 6.15: Loss and Accuracy:Autism

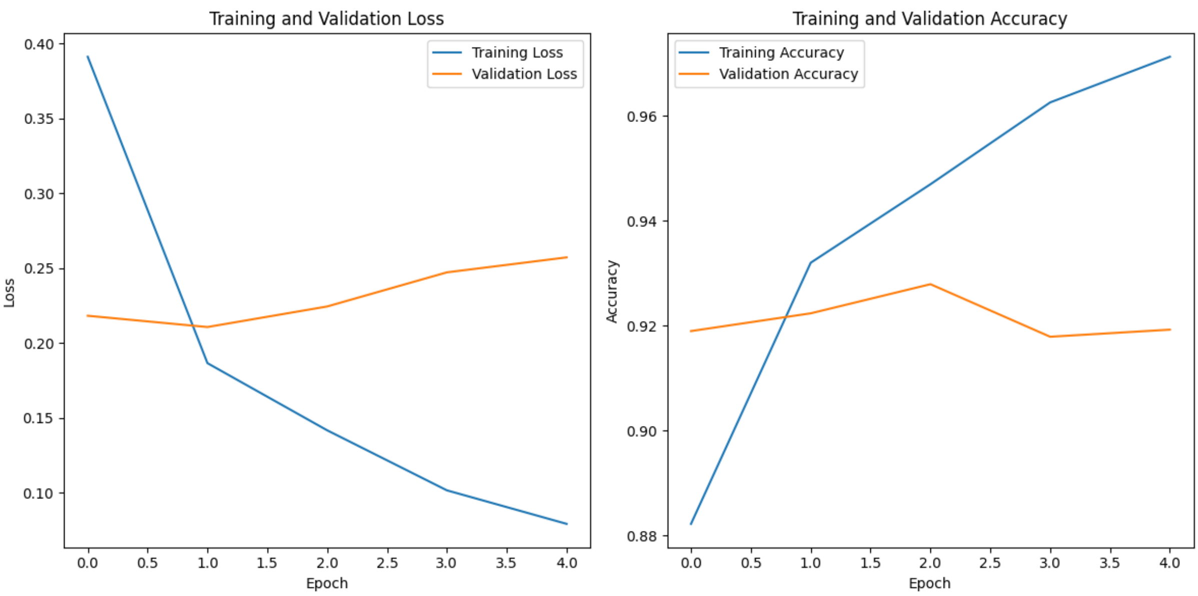

Figure 6.16: Loss and Accuracy:Schizophrenia

6.5 Discussion

In conclusion, the results of our project underscore the effectiveness and potential impact of our cognitive recommender system in providing personalized mental health support. Through comprehensive data analysis and algorithmic processing, we have successfully extracted valuable insights from user-generated content, enabling the identification of potential mental health conditions and the generation of tailored recommendations. The integration of textual and visual data streams, coupled with advanced techniques such as Singular Value Decomposition (SVD), has yielded highly personalized recommendations that resonate with users on a profound level. Furthermore, our system has demonstrated promising outcomes in terms of user engagement, satisfaction, and mental health outcomes, highlighting its potential to serve as a valuable tool in supporting individuals on their mental health journey. As we reflect on the results achieved, we are encouraged by the positive impact our system can have on improving the well-being and quality of life for individuals navigating mental health challenges.

In conclusion, the results and discussions presented in this chapter illuminate the effectiveness and implications of our project. The overview provides a comprehensive summary of the achieved results, encompassing both qualitative and quantitative outcomes. Throughout the testing phase, visual representations such as screenshots offer a tangible glimpse into the functionality and performance of our system, ensuring clarity and transparency in our findings. The quantitative results section delves deeper into numerical values such as accuracy, precision, and confusion matrices, providing a robust assessment of our system's performance metrics. Graphical analysis further enhances our understanding, offering visual insights into trends and patterns observed in the data. Additionally, the discussion section facilitates a critical reflection on the results, enabling us to elucidate the rationale behind our findings and explore potential avenues for further research and improvement. Overall, this chapter encapsulates the culmination of our project, highlighting the significance of our contributions and paving the way for future endeavors in the field.

Chapter 7

Conclusions & Future Scope

The completion of this project marks a significant milestone in the development of a cognitive recommender system leveraging social media data and visual data analysis. By incorporating both text and image data from users on Reddit, the system demonstrates its potential in identifying individuals with specific mental health conditions, such as depression, anxiety, schizophrenia, autism, bipolar disorder, and borderline personality disorder (BPD). The utilization of advanced techniques, including pre-trained Word2Vec embeddings and Convolutional Neural Networks (CNNs), enhances the system's ability to provide nuanced recommendations tailored to users' mental health states. Additionally, the integration of Synthetic Minority Over-sampling Technique (SMOTE) addresses class imbalance challenges, contributing to the system's robustness. The incorporation of weighed averages effectively combines insights from both textual and visual modalities, providing a holistic understanding of users' mental well-being. Furthermore, Singular Value Decomposition (SVD) facilitates personalized recommendation generation, enabling the system to offer tailored support and resources based on individual user preferences and characteristics.

Looking ahead, there are several avenues for future enhancements and extensions of this project. Firstly, expanding the dataset to encompass a more diverse range of social media platforms could enhance the system's generalizability. Introducing real-time analysis and recommendation features would make the system more dynamic and responsive to users' evolving mental health states. Additionally, incorporating user feedback mechanisms could further refine the recommendation engine, making it more personalized and effective. Exploring collaborations with mental health professionals and integrating additional data sources, such as user demographics, could enrich the system's understanding and contribute to more accurate mental health assessments. Lastly, the deployment of the system in real-world scenarios and conducting extensive user studies would be critical steps in validating its effectiveness and ensuring ethical considerations in mental health applications. Overall, the project lays a foundation for an intelligent and empathetic cognitive recommender system with promising potential for further development and societal impact.

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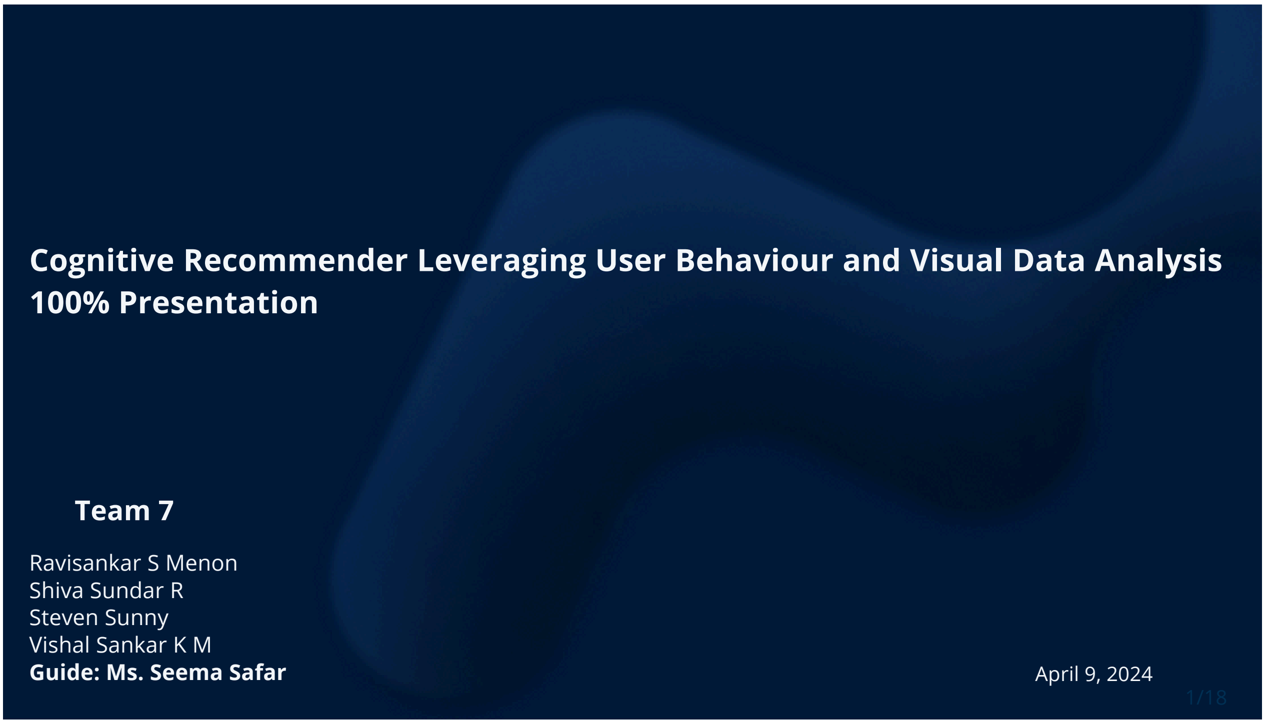
Appendix A: Presentation


Cognitive Recommender Leveraging User Behaviour and Visual Data Analysis
100% Presentation
Team 7
Ravisankar S Menon
Shiva Sundar R
Steven Sunny
Vishal Sankar K M
Guide: Ms. Seema Safar
April 9, 2024
1/18

Overview

Problem Definition

TEAM 7

Problem Definition

- Many individuals share their thoughts and feelings on social media platforms, and some of these posts may contain indicators of mental health concerns such as depression, anxiety, or other conditions. It is important to create a system that can effectively detect these signs to offer timely assistance and support.


Project objective
TEAM 7

Project objective

Develop a comprehensive mental health recognition model that leverages analysis of multi-modal data, and construct an intelligent cognitive recommendation system that tailors its suggestions according to an individual's specific mental health condition.


Novelty of Idea and Scope of Implementation
TEAM 7

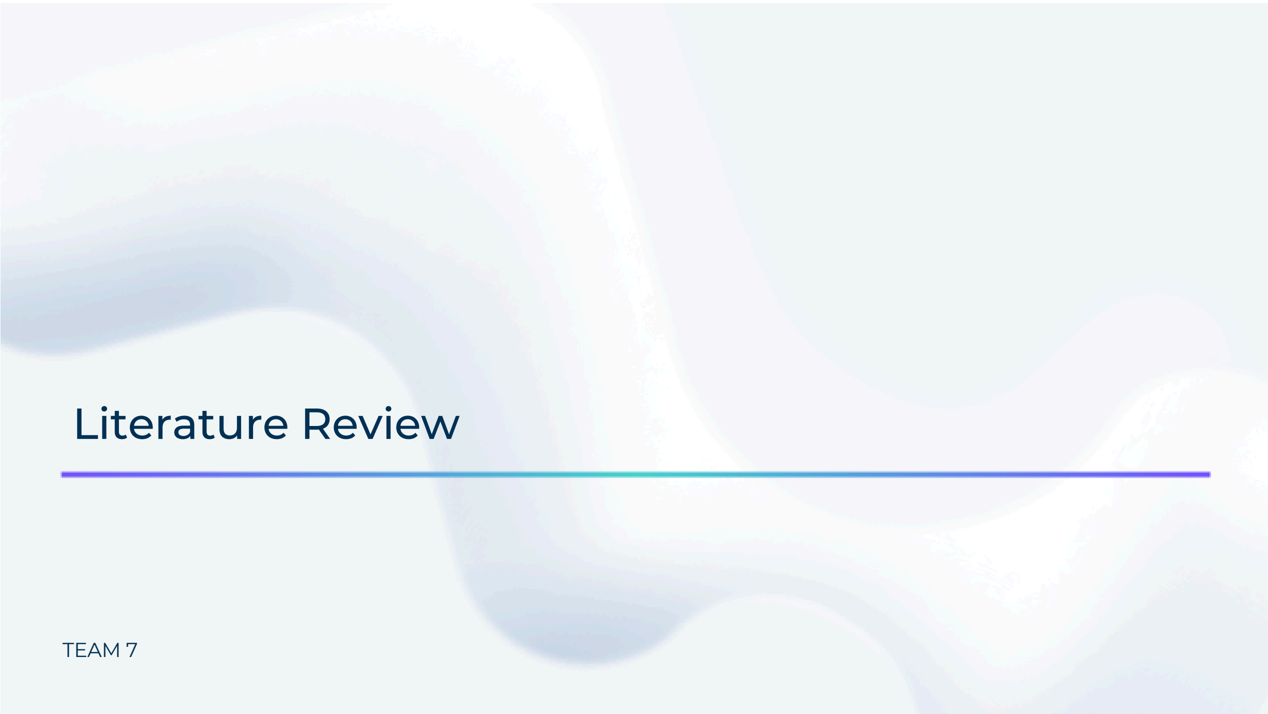
Novelty of Idea and Scope of Implementation

1. Multimodal analysis of image and text data for mental illness classification

2. Cognitive recommender system

This skeletal framework can be used in almost every single social media website.

TEAM 7 8/41


Literature Review
TEAM 7

[1] Depression Intensity Estimation via Social Media: A Deep Learning Approach

- Propose a deep learning-based method to estimate the intensity of depression.
- Design a total of 527 features of five different types to describe each user, which includes emotional, event-triggered, behavioral, user-level, and depression-related features.
- Train a shallow long short-term memory (LSTM) network to predict the depression intensities.

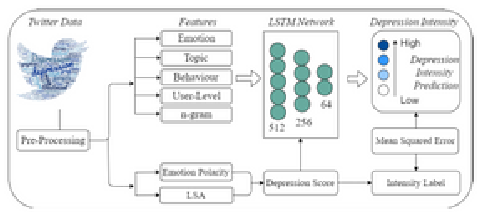
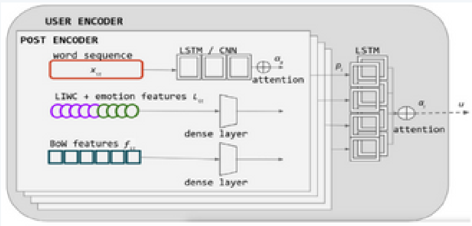


Fig. 3. Overall pipeline of the proposed method.

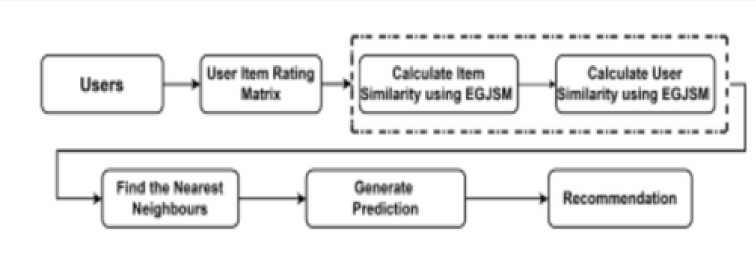
[2] An Emotion and Cognitive Based Analysis of Mental Health Disorders from Social Media Data

- Design and use various deep learning models to automatically predict disorders from social media data.
- The paper proposes the use of a hierarchical attention network as a deep learning model for detecting mental health disorders from social media data.
- The model is designed to capture the hierarchical structure of the language used in social media data and to identify linguistic markers of mental health disorders at different levels of the language, including content, style, and emotions.



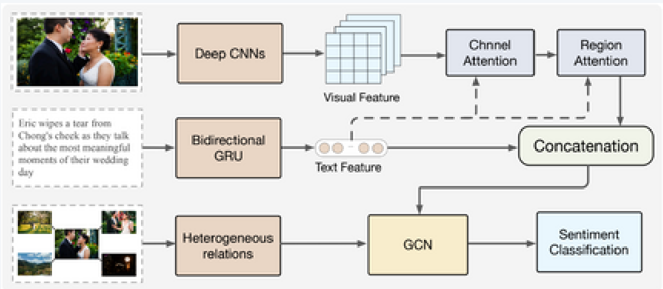
[3] A Cognitive Similarity-Based Measure to Enhance the Performance of Collaborative Filtering-Based Recommendation System

- The objective of this paper is to propose a new similarity measure called the Efficient Gowers-Jaccard-Sigmoid Measure (EGJSM) to enhance the performance of collaborative filtering-based recommendation systems.
- This method is further enhanced by considering cognitive features such as such as feedback, year of release, genre, age etc, to get a method named Cognitive Similarity(CgS) based Recommendation System.



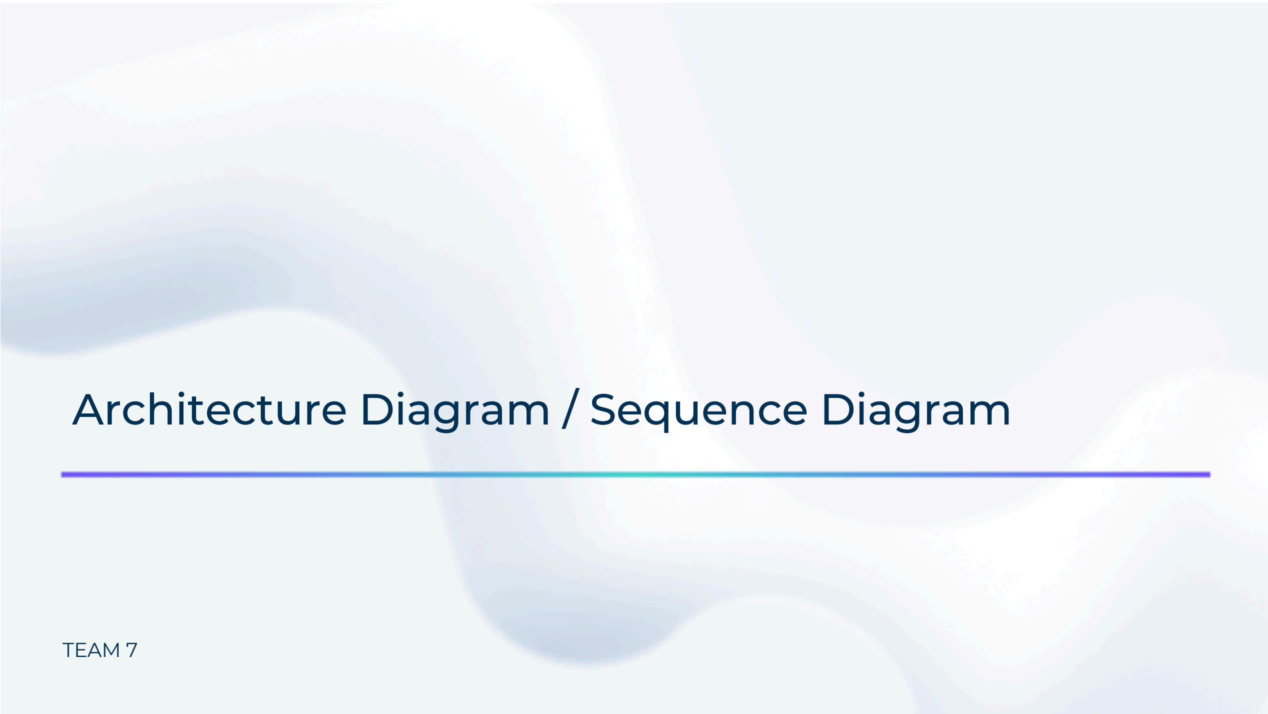
[4] Social Image Sentiment Analysis by Exploiting Multimodal Content and Heterogeneous Relations

- An attention-based multimodal sentiment classification system that takes into account both visual data and text data.
- This method has 4 components: single modal representation learning, progressive dual image-text attention, heterogeneous relations fusion, and sentiment classification.

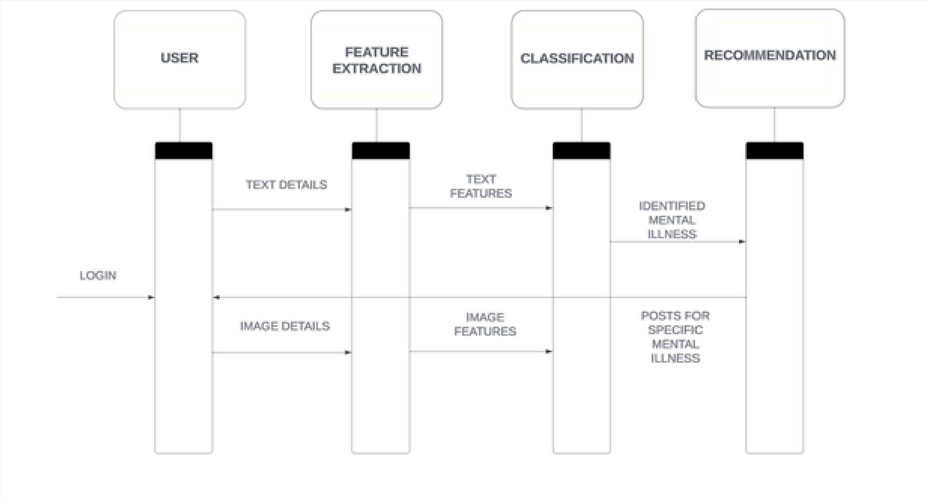



Methodology
TEAM 7

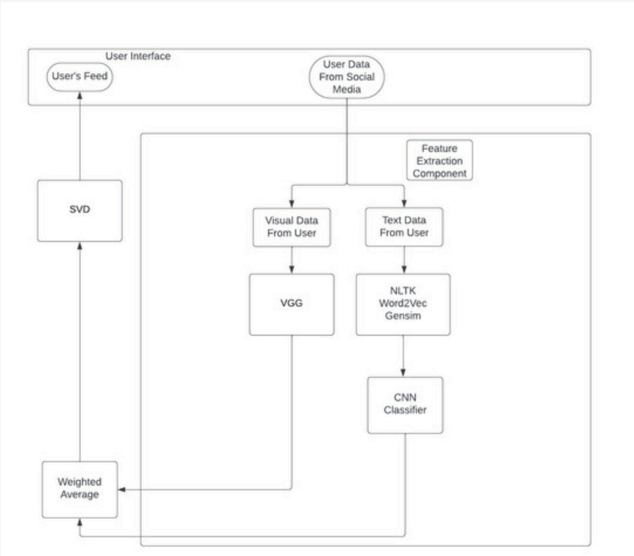
- Use NLTK library, Porter Stemmer and word2vec API to extract text features.
- Predict the mental illness of the user using CNN using only the text features (Depression, Anxiety, Borderline Personality Disorder, Autism, Schizophrenia, Bipolar).
- Do sentiment analysis on the image using VGG and get three sentiments - positive, negative, and neutral.
- Combine the three sentiments and get a final image sentiment.
- Combine the results of the textual prediction and image sentiment using weighed averages, and get the final probability of a user having a certain mental illness of one among-(Depression, Anxiety, Borderline Personality Disorder, Autism, Schizophrenia, Bipolar).
- Pass the mental illness along with the user's age, gender, and location to the SVD(Single Value Decomposition) recommendation system. Using these details recommend the user positive posts to help them combat their mental illness.

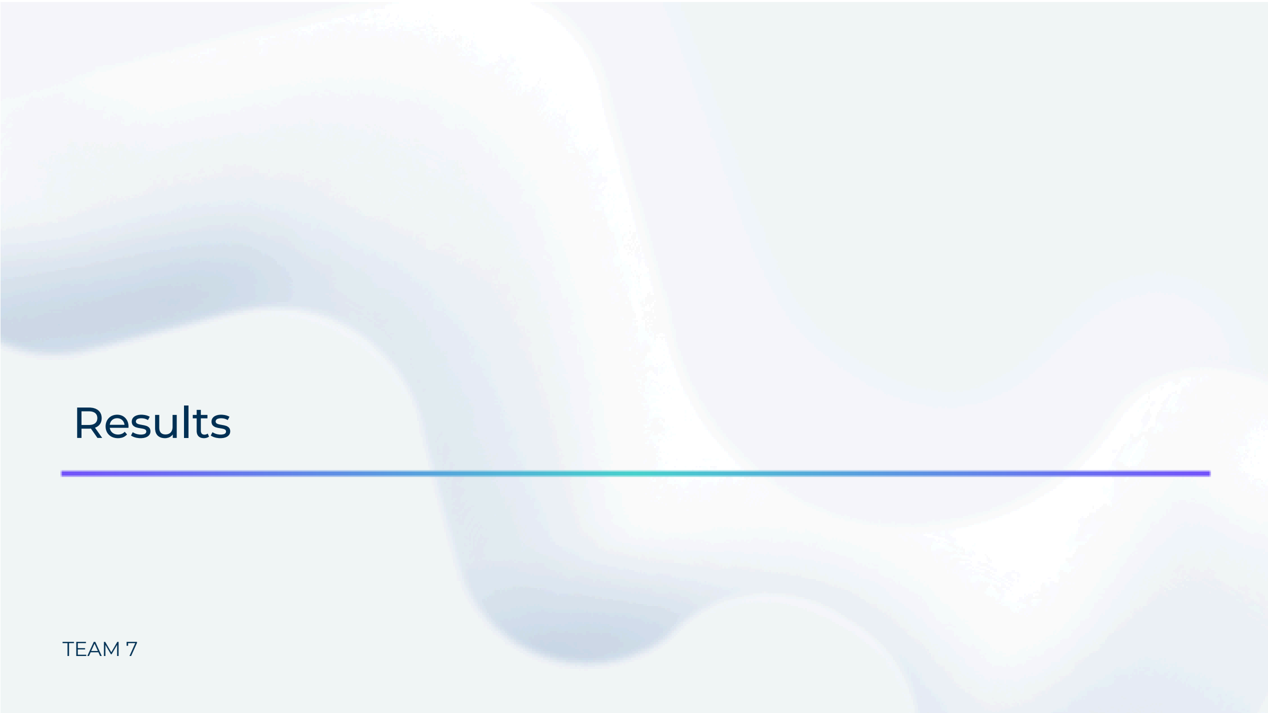

Architecture Diagram / Sequence Diagram
TEAM 7

Sequence Diagram



Architecture Diagram




Results
TEAM 7

30 Percent Results

1. Used NLTK library, Porter Stemmer and word2vec API to extract features.

2. Mental disorder classification based on textual data using CNN.

30 Percent Results

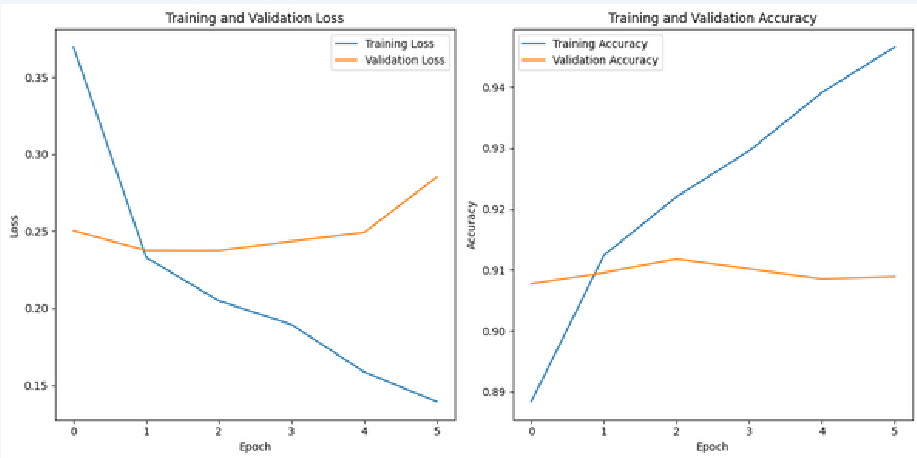


Figure: Anxiety-Accuracy and Loss

30 Percent Results

```
Accuracy: 0.9118
Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.96      0.94     26380
           1       0.88      0.77      0.82      9246

    accuracy                           0.91     35626
   macro avg       0.90      0.86      0.88     35626
weighted avg       0.91      0.91      0.91     35626
```

Figure: Anxiety - Evaluation Metrics

60 Percent

1. Image captioning and Sentiment Analysis

2. Compared different models - ViT, Blip, Senticap

3. Finalised on Blip

60 Percent

60 Percent

```
[{'label': 'NEU', 'score': 0.9629542231559753}]
['a brown and white cow and a black and white cow']
```

Figure: Output-Using ViT

```
a photograph of a couple of animals that are running in the dirt
No model was supplied, defaulted to distilbert-base-uncased-finetuned-sst-2-english an
Using a pipeline without specifying a model name and revision in production is not rec
there are two animals that are fighting in the dirt
emoji is not installed, thus not converting emoticons or emojis into text. Install emo
[{'label': 'NEG', 'score': 0.8495825529098511}]
```

Figure: Output-using Blip

60 Percent

60 Percent

```
a photograph of a man holding a gun in his hand
No model was supplied, defaulted to distilbert-base-uncased-finetuned-sst-2-english an
Using a pipeline without specifying a model name and revision in production is not rec
arafed man holding a gun in his hand and screaming
emoji is not installed, thus not converting emoticons or emojis into text. Install emo
[{'label': 'NEG', 'score': 0.9499502778053284}]
```

Figure: Output-using Blip

Results

- Concatenation of textual and visual sentiment for mental illness classification.

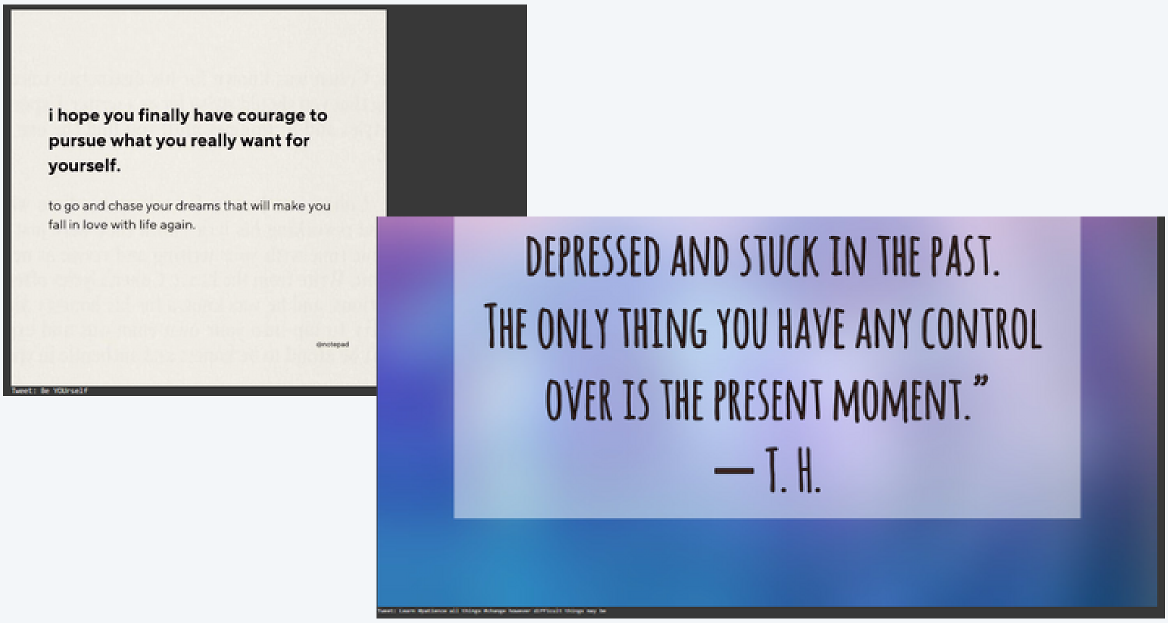
- Cognitive Recommender System which recommends based on the detected mental illness and other features like age, gender, and location.

28/41

```
Depression: [0.9971008]
Anxiety: [0.82449937]
Autism: [0.38835335]
Bipolar: [0.8854489]
BPD: [0.07889745]
Schizophrenia: [0.03657173]
```

```
Combined Sentiment for Depression: 0.81872916
Combined Sentiment for Anxiety: 0.6979082
Combined Sentiment for Autism: 0.392606
Combined Sentiment for Bipolar: 0.74057287
Combined Sentiment for BPD: 0.17598686
Combined Sentiment for Schizophrenia: 0.14635886
```

```
Negative: 0.26240238547325134
Neutral: 0.2834213972091675
Positive: 0.4541761875152588


Negative: 0.09409192204475403
Neutral: 0.21921756863594055
Positive: 0.6866905689239502


Negative: 0.05345390737056732
Neutral: 0.15646040439605713
Positive: 0.7900857329368591


Negative: 0.5722560286521912
Neutral: 0.2590740919113159
Positive: 0.1686699390411377


Negative: 0.4913267195224762
Neutral: 0.10025561600923538
Positive: 0.40841761231422424


Negative: 0.40252885222435
Neutral: 0.28328362107276917
Positive: 0.31418749690055847
```


i hope you finally have courage to pursue what you really want for yourself.
to go and chase your dreams that will make you fall in love with life again.
@notepad
DEPRESSED AND STUCK IN THE PAST.
THE ONLY THING YOU HAVE ANY CONTROL OVER IS THE PRESENT MOMENT.”
— T. H.

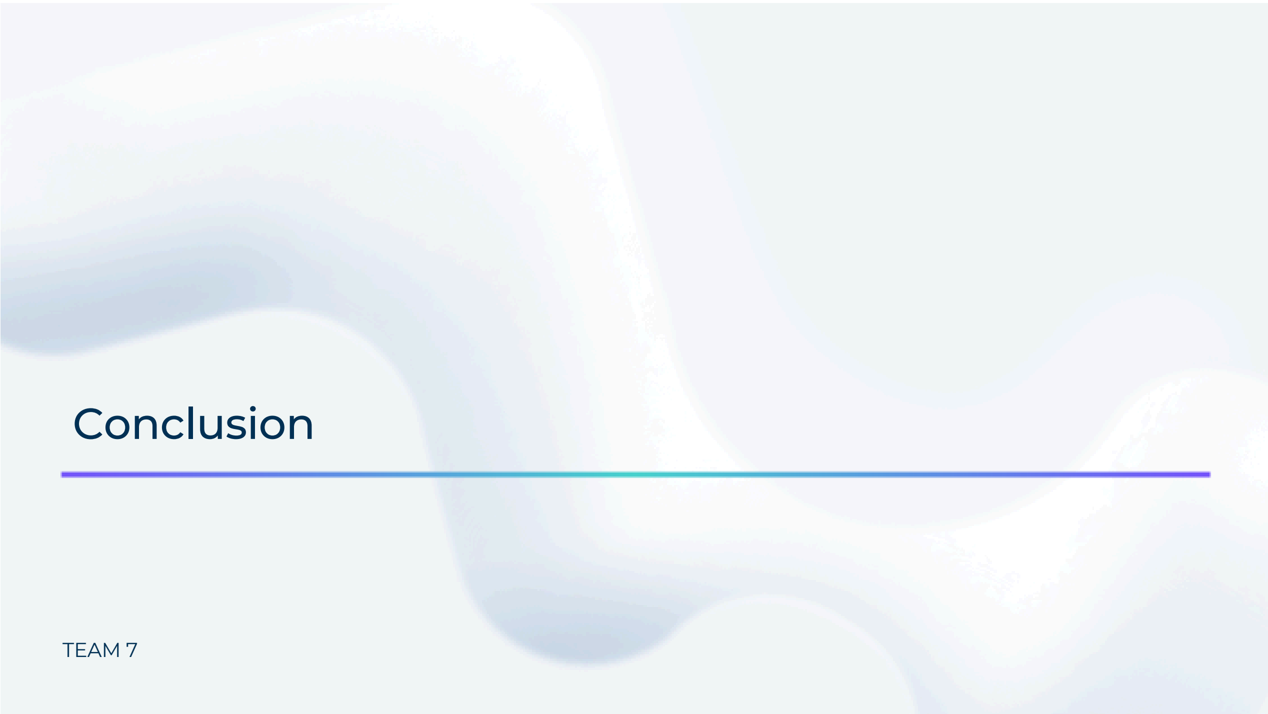
30/41

Work Division

TEAM 7

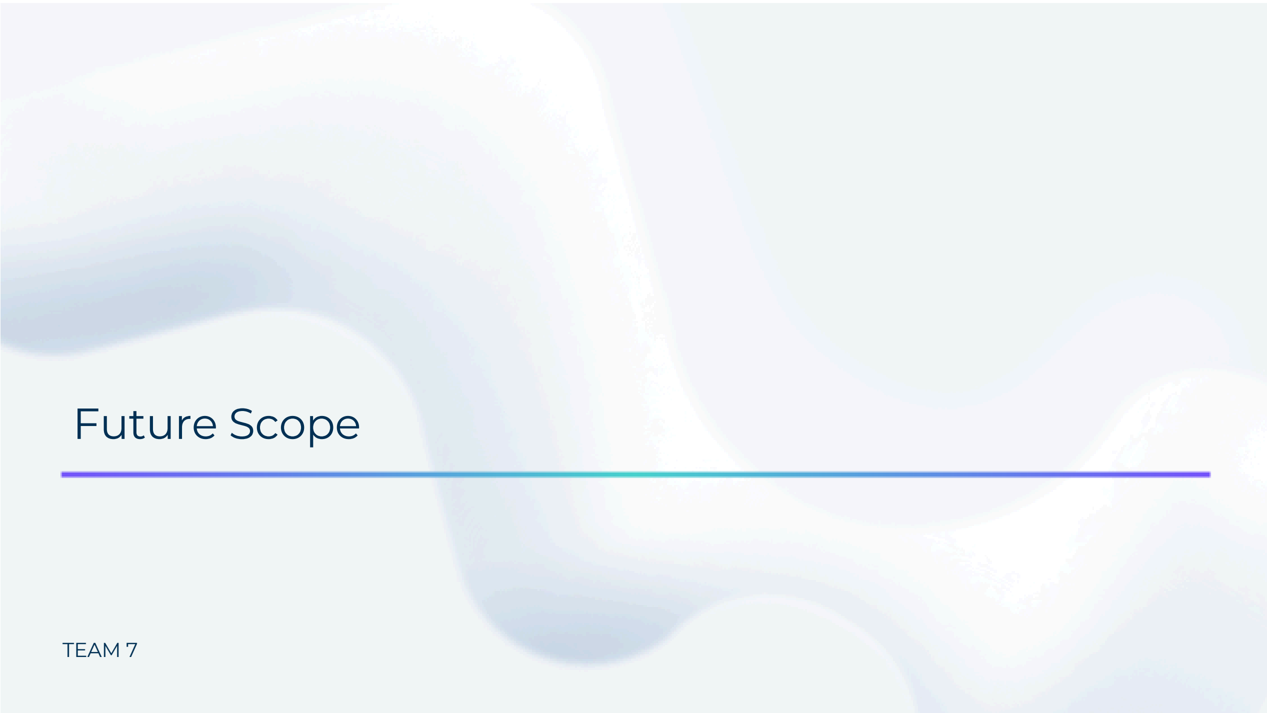
Task Distribution

1. Ravisankar S Menon - Text Classification, Recommendation System
2. Shiva Sundar R - Text Classification, Concatenating System
3. Steven Sunny - Testing, Result Analysis, Dataset Collection
4. Vishal Sankar K M - Image Sentiment Analysis, Concatenating System


Conclusion
TEAM 7

Conclusion

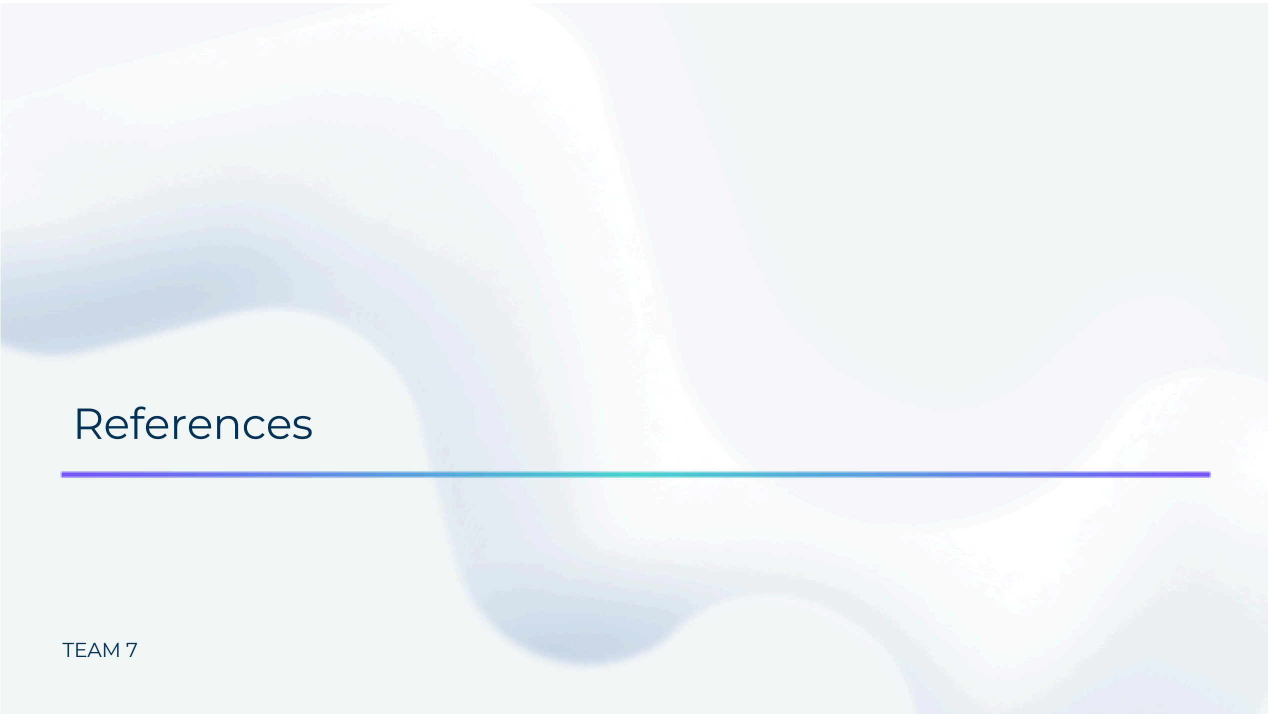
Our goal is to develop a machine learning model which can analyze the social media posts of a user(using their images and texts), and to use that to detect the presence of mental illnesses and to recognize the specific mental illness. We further plan to create a recommendation system which can recommend posts to help them through their specific mental illness.


Future Scope
TEAM 7

Future Scope

- Improve the recommendation system
- Find a better way combine textual and image data
- Find more training data
- Improve upon image analysis

36/41


References
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Status of paper publication

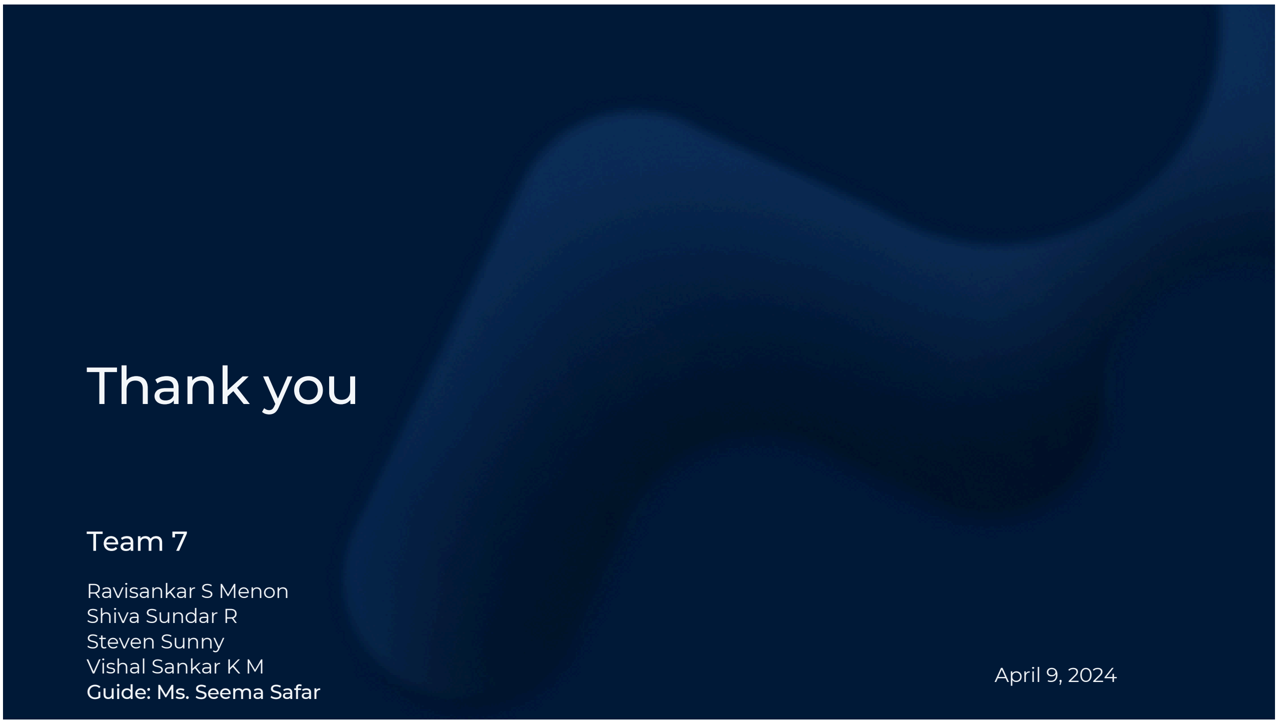
TEAM 7

Status of paper publication

4th IEEE International Conference on Signal Processing, Informatics, Communication and Energy Systems 2024

Submission Date : May 10, 2024

Notificaton of Acceptance: June 28, 2024


Thank you
Team 7
Ravisankar S Menon
Shiva Sundar R
Steven Sunny
Vishal Sankar K M
Guide: Ms. Seema Safar
April 9, 2024

Appendix B: Vision, Mission, Programme Outcomes and Course Outcomes

Vision, Mission, Programme Outcomes and Course Outcomes

Institute Vision

To evolve into a premier technological institution, moulding eminent professionals with creative minds, innovative ideas and sound practical skill, and to shape a future where technology works for the enrichment of mankind.

Institute Mission

To impart state-of-the-art knowledge to individuals in various technological disciplines and to inculcate in them a high degree of social consciousness and human values, thereby enabling them to face the challenges of life with courage and conviction.

Department Vision

To become a centre of excellence in Computer Science and Engineering, moulding professionals catering to the research and professional needs of national and international organizations.

Department Mission

To inspire and nurture students, with up-to-date knowledge in Computer Science and Engineering, ethics, team spirit, leadership abilities, innovation and creativity to come out with solutions meeting societal needs.

Programme Outcomes (PO)

Engineering Graduates will be able to:

1. Engineering Knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

2. Problem analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

3. Design/development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

4. Conduct investigations of complex problems: Use research-based knowledge including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

5. Modern Tool Usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

6. The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal, and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

7. Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

8. Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

9. Individual and Team work: Function effectively as an individual, and as a member or leader in teams, and in multidisciplinary settings.

10. Communication: Communicate effectively with the engineering community and with society at large. Be able to comprehend and write effective reports documentation. Make effective presentations, and give and receive clear instructions.

11. Project management and finance: Demonstrate knowledge and understanding of engineering and management principles and apply these to one's own work, as a member and leader in a team. Manage projects in multidisciplinary environments.

12. Life-long learning: Recognize the need for, and have the preparation and ability to engage in independent and lifelong learning in the broadest context of technological change.

Programme Specific Outcomes (PSO)

A graduate of the Computer Science and Engineering Program will demonstrate:

PSO1: Computer Science Specific Skills
The ability to identify, analyze and design solutions for complex engineering problems in multidisciplinary areas by understanding the core principles and concepts of computer science and thereby engage in national grand challenges.

PSO2: Programming and Software Development Skills
The ability to acquire programming efficiency by designing algorithms and applying standard practices in software project development to deliver quality software products meeting the demands of the industry.

PSO3: Professional Skills
The ability to apply the fundamentals of computer science in competitive research and to develop innovative products to meet the societal needs thereby evolving as an eminent researcher and entrepreneur.

Course Outcomes (CO)

Course Outcome 1: Model and solve real world problems by applying knowledge across domains (Cognitive knowledge level: Apply).

Course Outcome 2: Develop products, processes or technologies for sustainable and socially relevant applications (Cognitive knowledge level: Apply).

Course Outcome 3: Function effectively as an individual and as a leader in diverse teams and to comprehend and execute designated tasks (Cognitive knowledge level: Apply).

Course Outcome 4: Plan and execute tasks utilizing available resources within timelines, following ethical and professional norms (Cognitive knowledge level: Apply).

Course Outcome 5: Identify technology/research gaps and propose innovative/creative solutions (Cognitive knowledge level: Analyze).

Course Outcome 6: Organize and communicate technical and scientific findings effectively in written and oral forms (Cognitive knowledge level: Apply).

Appendix C: CO-PO-PSO Mapping

CO-PO AND CO-PSO MAPPING

	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11	PO 12	PSO 1	PSO 2	PSO 3
CO 1	2	2	2	1	2	2	2	1	1	1	1	2	3		
CO 2	2	2	2		1	3	3	1	1		1	1		2	
CO 3									3	2	2	1			3
CO 4					2			3	2	2	3	2			3
CO 5	2	3	3	1	2							1	3		
CO 6					2			2	2	3	1	1			3

3/2/1: high/medium/low

JUSTIFICATIONS FOR CO-PO MAPPING

MAPPING	LOW/MEDIUM/ HIGH	JUSTIFICATION
100003/ CS722U.1-PO1	M	Knowledge in the area of technology for project development using various tools results in better modeling.
100003/ CS722U.1-PO2	M	Knowledge acquired in the selected area of project development can be used to identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions.

100003/ CS722U.1-PO3	M	Can use the acquired knowledge in designing solutions to complex problems.
100003/ CS722U.1-PO4	M	Can use the acquired knowledge in designing solutions to complex problems.
100003/ CS722U.1-PO5	H	Students are able to interpret, improve and redefine technical aspects for design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
100003/ CS722U.1-PO6	M	Students are able to interpret, improve and redefine technical aspects by applying contextual knowledge to assess societal, health and consequential responsibilities relevant to professional engineering practices.
100003/ CS722U.1-PO7	M	Project development based on societal and environmental context solution identification is the need for sustainable development.
100003/ CS722U.1-PO8	L	Project development should be based on professional ethics and responsibilities.
100003/ CS722U.1-PO9	L	Project development using a systematic approach based on well defined principles will result in teamwork.
100003/ CS722U.1-PO10	M	Project brings technological changes in society.

100003/ CS722U.1- PO11	H	Acquiring knowledge for project development gathers skills in design, analysis, development and implementation of algorithms.
100003/ CS722U.1- PO12	H	Knowledge for project development contributes engineering skills in computing & information gatherings.
100003/ CS722U.2- PO1	H	Knowledge acquired for project development will also include systematic planning, developing, testing and implementation in computer science solutions in various domains.
100003/ CS722U.2- PO2	H	Project design and development using a systematic approach brings knowledge in mathematics and engineering fundamentals.
100003/ CS722U.2- PO3	H	Identifying, formulating and analyzing the project results in a systematic approach.
100003/ CS722U.2- PO5	H	Systematic approach is the tip for solving complex problems in various domains.
100003/ CS722U.2- PO6	H	Systematic approach in the technical and design aspects provide valid conclusions.
100003/ CS722U.2- PO7	H	Systematic approach in the technical and design aspects demonstrate the knowledge of sustainable development.

100003/ CS722U.2-PO8	M	Identification and justification of technical aspects of project development demonstrates the need for sustainable development.
100003/ CS722U.2-PO9	H	Apply professional ethics and responsibilities in engineering practice of development.
100003/ CS722U.2-PO11	H	Systematic approach also includes effective reporting and documentation which gives clear instructions.
100003/ CS722U.2-PO12	M	Project development using a systematic approach based on well defined principles will result in better teamwork.
100003/ CS722U.3-PO9	H	Project development as a team brings the ability to engage in independent and lifelong learning.
100003/ CS722U.3-PO10	H	Identification, formulation and justification in technical aspects will be based on acquiring skills in design and development of algorithms.
100003/ CS722U.3-PO11	H	Identification, formulation and justification in technical aspects provides the betterment of life in various domains.
100003/ CS722U.3-PO12	H	Students are able to interpret, improve and redefine technical aspects with mathematics, science and engineering fundamentals for the solutions of complex problems.

100003/ CS722U.4- PO5	H	Students are able to interpret, improve and redefine technical aspects with identification formulation and analysis of complex problems.
100003/ CS722U.4- PO8	H	Students are able to interpret, improve and redefine technical aspects to meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.
100003/ CS722U.4- PO9	H	Students are able to interpret, improve and redefine technical aspects for design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
100003/ CS722U.4- PO10	H	Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools for better products.
100003/ CS722U.4- PO11	M	Students are able to interpret, improve and redefine technical aspects by applying contextual knowledge to assess societal, health and consequential responsibilities relevant to professional engineering practices.
100003/ CS722U.4- PO12	H	Students are able to interpret, improve and redefine technical aspects for demonstrating the knowledge of, and need for sustainable development.
100003/ CS722U.5- PO1	H	Students are able to interpret, improve and redefine technical aspects, apply ethical principles and commit to

		professional ethics and responsibilities and norms of the engineering practice.
100003/ CS722U.5-PO2	M	Students are able to interpret, improve and redefine technical aspects, communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.
100003/ CS722U.5-PO3	H	Students are able to interpret, improve and redefine technical aspects to demonstrate knowledge and understanding of the engineering and management principle in multidisciplinary environments.
100003/ CS722U.5-PO4	H	Students are able to interpret, improve and redefine technical aspects, recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.
100003/ CS722U.5-PO5	M	Students are able to interpret, improve and redefine technical aspects in acquiring skills to design, analyze and develop algorithms and implement those using high-level programming languages.
100003/ CS722U.5-PO12	M	Students are able to interpret, improve and redefine technical aspects and contribute their engineering skills in computing and information engineering domains like

		network design and administration, database design and knowledge engineering.
100003/ CS722U.6- PO5	M	Students are able to interpret, improve and redefine technical aspects and develop strong skills in systematic planning, developing, testing, implementing and providing IT solutions for different domains which helps in the betterment of life.
100003/ CS722U.6- PO8	H	Students will be able to associate with a team as an effective team player for the development of technical projects by applying the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.
100003/ CS722U.6- PO9	H	Students will be able to associate with a team as an effective team player to Identify, formulate, review research literature, and analyze complex engineering problems
100003/ CS722U.6- PO10	M	Students will be able to associate with a team as an effective team player for designing solutions to complex engineering problems and design system components.
100003/ CS722U.6- PO11	M	Students will be able to associate with a team as an effective team player, use research-based knowledge and research methods including design of experiments, analysis and interpretation of data.

100003/ CS722U.6-PO12	H	Students will be able to associate with a team as an effective team player, applying ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
100003/ CS722U.1-PSO1	H	Students are able to develop Computer Science Specific Skills by modeling and solving problems.
100003/ CS722U.2-PSO2	M	Developing products, processes or technologies for sustainable and socially relevant applications can promote Programming and Software Development Skills.
100003/ CS722U.3-PSO3	H	Working in a team can result in the effective development of Professional Skills.
100003/ CS722U.4-PSO3	H	Planning and scheduling can result in the effective development of Professional Skills.
100003/ CS722U.5-PSO1	H	Students are able to develop Computer Science Specific Skills by creating innovative solutions to problems.
100003/ CS722U.6-PSO3	H	Organizing and communicating technical and scientific findings can help in the effective development of Professional Skills.