AI-Enhanced Depression Detection and Therapy: Analyzing the VPSYC System

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Abstract- Mental health issues, particularly depression, are prevalent and have significant impacts on individuals and society. The stigma associated with mental health, expensive therapy sessions, and a shortage of mental health professionals contribute to the challenge of addressing this issue. This paper presents VPSYC, a web-based conversational chatbot designed to identify the stage of depression, provide therapy, and evaluate changes in sentiment. Utilizing datasets from Counsel Chat, Empathetic Dialogues, and manually created conversations, the VPSYC system leverages transformer models for effective depression analysis and sentiment evaluation. The study demonstrates the effectiveness of the VPSYC system through both automatic and human evaluations, highlighting its potential to provide accessible and robust mental health support.

I. INTRODUCTION

Depression is a major mental health disorder affecting millions of people worldwide. Despite the availability of treatments, many individuals do not receive adequate care due to various barriers such as social stigma, high costs, and a shortage of mental health professionals. These challenges necessitate innovative solutions to provide accessible mental health support. This paper introduces VPSYC, a conversational chatbot designed to assist individuals experiencing depression by offering therapy sessions and monitoring changes in their mental state.

The VPSYC system is built on advanced natural language processing techniques, employing a transformer architecture to analyze and understand user inputs effectively. By integrating sentiment analysis, the system can track the progress of users' mental health over time, offering personalized support and feedback. This study aims to demonstrate the feasibility and effectiveness of VPSYC as a tool for addressing the gaps in current mental health care services.

Recent advances in Natural Language Processing (NLP) have led to the development of chatbots as a tool for promoting mental well-being. Chatbots can simulate natural conversation, providing support through textual input and output, and have the potential to help alleviate the stigma associated with seeking help for mental health issues.[1]

II. LITERATURE REVIEW

The relationship between language use and the psychological state of the communicator has been a focal point in recent research, particularly in detecting depression through text analysis. This study examines various linguistic markers and their ability to predict depression based on texts written in different genres, such as formal letters and informal holiday notes. Using a representative sample of the Czech adult population, the study found that morphological features of texts could significantly distinguish between depressive and non-depressive individuals. Predictive models developed from these features showed varying degrees of accuracy, with informal texts like holiday letters proving most effective. These findings underscore the potential of linguistic analysis as a tool for early detection of depression, offering insights into the specific language patterns that correlate with depressive states.[2]

Recent advancements in artificial intelligence have shown promising potential in the field of mental health diagnostics, particularly for depression. This systematic review focuses on AI-based methods for diagnosing depression using text data, analyzing various machine learning algorithms and their applications. Key trends identified include the prevalence of natural language processing (NLP) and neural networks (NN) as the primary techniques employed in these studies. The review highlights the effectiveness of these methods in transforming colloquial expressions into objective symptoms and discovering relationships between different types of symptoms. Despite the significant progress, the review emphasizes the need for larger, more comprehensive datasets to improve the reliability and accuracy of these AI models. Future research directions suggested include expanding dataset sizes, exploring unsupervised learning techniques, and extending AI applications to other mental health disorders, thereby enhancing the overall capability and scope of AI in mental health diagnostics.[3]

Automated approaches to depression detection in text data have significantly advanced with the integration of machine learning and natural language processing techniques. This research leverages lexical features, phonesthemes embedding, and the RoBERTa transformer model to identify depression from messages in Telegram groups related to mental disorders. The model underwent rigorous training and achieved promising results, particularly in binary classification and regression tasks. However, challenges remain in real-time monitoring and latency, suggesting a need for further refinement. This study contributes valuable insights into the application of text analysis for mental health assessment and highlights areas for continued improvement to enhance the accuracy and reliability of automated depression detection systems. [4]

The global coronavirus pandemic has significantly impacted mental health, exacerbating symptoms of depression among individuals. The necessity for timely identification and intervention for depression has led to the development of AI-based systems that analyze social media activity, specifically tweets, to detect depressive states. Recent advancements involve employing deep learning models such as CNN, LSTM, and Bidirectional LSTM for emotion classification. These models focus on identifying emotions like sadness, fear, anger, and joy, with a particular emphasis on sadness as a critical indicator of depression. The implementation of an ensemble model combining CNN, LSTM, and Bidirectional LSTM has shown to maximize the recall metric, improving the accuracy of depression detection. The efficacy of these models is demonstrated through their application on datasets, achieving better results than previous models and proving their utility in real-time data analysis. This approach not only facilitates early detection and intervention for depression but also offers insights into the emotional states conveyed through social media posts, enhancing mental health support during and after crisis periods. [5]

The detection of depression through facial expression recognition has garnered significant attention in the field of deep learning due to the rise of big data and the prevalence of mental health issues. Using Convolutional Neural Networks (CNN), along with tools like OpenCV and Haar Cascade Classifier, researchers have developed systems capable of distinguishing between depressed and non-depressed individuals based on facial imagery. The creation of a novel dataset comprising 5000 images of both depressed and non-depressed faces has been crucial for training and evaluating these models. The proposed architecture combines CNN with Haar Cascade Classifier to achieve an accuracy of 81%, a precision of 87%, and a recall of 88%. This system demonstrates a robust performance, surpassing various other models and techniques previously employed for depression detection, highlighting the potential of deep learning applications in mental health diagnostics and the importance of innovative data collection methods for enhancing model accuracy and reliability. [6]

The detection of depression from textual data has been increasingly explored due to the growing influence of social media and the significant mental health challenges faced globally. Utilizing advanced machine learning techniques, researchers have developed models capable of identifying depressive symptoms from user-generated content on platforms like Twitter. This study employs Long-Short Term Memory (LSTM) networks and Recurrent Neural Networks (RNN) with two hidden layers, focusing on early detection of depression through text analysis. The proposed model, trained on a dataset of tweets, achieves a high accuracy of 99%, outperforming traditional frequency-based deep learning models by reducing the false positive rate. By leveraging techniques such as One-Hot encoding and Principal Component Analysis (PCA) for feature extraction, the model effectively captures the semantic nuances of depressive language, demonstrating the potential of RNN and LSTM architectures in mental health diagnostics. This research highlights the feasibility and efficiency of automated depression detection systems, offering a valuable tool for early intervention and mental health support.[7]

Deep learning techniques have been increasingly utilized for detecting depression through social media analysis. This study presents a novel Multi-Aspect Depression Detection with Hierarchical Attention Network (MDHAN) using Twitter data. The proposed method involves preprocessing tweets by tokenization, punctuation removal, stop-word removal, stemming, and lemmatization. Feature selection is optimized using Adaptive Particle Swarm and Grey Wolf Optimization methods. The MDHAN architecture effectively classifies tweets into depressed and non-depressed categories, achieving an impressive accuracy of 99.86%. This method outperforms existing models like CNN, SVM, and MDL, demonstrating superior precision and reduced execution time. The findings highlight the potential of advanced deep learning models in enhancing the accuracy and efficiency of depression detection from social media data, contributing significantly to mental health diagnostics. [8]

The study leverages lexicon-based sentiment analysis for detecting depression through social media platforms. By formulating a classification function and developing an enhanced depression diagnostic system, the researchers aimed to provide individuals with an online tool to assess their mental health status. The system achieved a precision of 77% and an F1-score of 74%, validated by clinical psychologists. It was observed that individuals with depression tend to use more offensive and aggressive language. This research highlights the importance of early detection and the potential of using social media data to identify depressive symptoms, offering a valuable tool for mental health monitoring and support. [9]

III. RESEARCH METHODOLOGY

The development of the VPSYC system required a meticulous approach to gather and prepare a comprehensive dataset that would enable effective training and evaluation of the chatbot. Ensuring the diversity and relevance of the data was paramount to creating a robust model capable of understanding and responding to a wide range of user inputs. This section outlines the data collection and preprocessing methods used to achieve these goals.

A. Data Collection

The dataset used for training and evaluating the VPSYC system consists of three primary sources:

a. Counsel Chat

A collection of 5,000 therapy conversations providing real-world interactions between therapists and clients. This dataset is valuable for understanding natural conversation flows in therapy sessions.

b. Empathetic Dialogues

A dataset containing 20,000 conversations specifically designed to capture a wide range of empathetic responses. This dataset helps in training the chatbot to respond empathetically to various emotional cues.

c. Manually Created Conversations

An additional 15,000 conversations crafted to enhance the dataset's diversity. These conversations include various scenarios and responses to ensure the chatbot can handle a broad spectrum of interactions effectively.

The final dataset comprised 40,000 therapy and empathetic conversations, providing a robust foundation for training the chatbot. Data preprocessing involved cleaning the text data by removing any irrelevant information, normalizing text for consistency, and tokenizing the text to prepare it for model training. Special attention was given to maintaining the context and emotional tone of the conversations to ensure the chatbot's responses are contextually relevant and empathetic.[10]

DATASET	DETAILS
Counsel Chat	5,000
Empathetic	20,000

Manual Creation	15,000

Table 1: Dataset Division

B. Data Preprocessing

Data preprocessing involved cleaning the text data by removing any irrelevant information, normalizing text for consistency, and tokenizing the text to prepare it for model training. Data preprocessing includes data cleaning, normalization, transformation, feature extraction, and selection, which are crucial steps to ensure the quality and reliability of the data used in machine learning tasks. [11] Special attention was given to maintaining the context and emotional tone of the conversations to ensure the chatbot's responses are contextually relevant and empathetic.

C. Depression Analysis

The VPSYC system utilizes the Patient Health Questionnaire (PHQ-9) to assess the severity of depression. The PHQ-9 is a widely used clinical tool consisting of nine questions, each scored from 0 to 3, resulting in a total score ranging from 0 to 27. Based on the total score, depression is categorized into five stages: None, Mild, Moderate, Moderately Severe, and Severe.This study confirms that PHQ-9, which has been proven to be a useful screening test for depression, is an effective diagnostic tool in mobile assessments, as well as in primary care and clinical settings.[12]

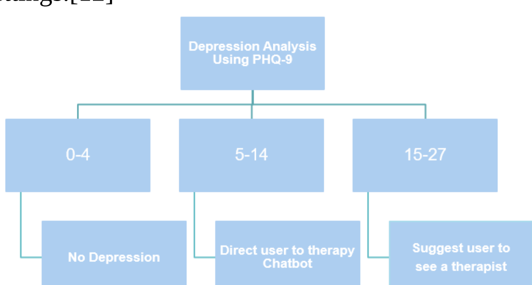

Fig.1: Depression Analysis

D. Model Selection and Training

During the experimentation phase, various models, including Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, were tested. However, the transformer model outperformed the others due to its ability to process sentences as a whole, capture long-term dependencies, and leverage parallel processing. As noted, transformer based models exhibit better performance when compared to Neural network based models and LSTM based models. [13] Additionally, deep learning methods have shown better performance compared to traditional machine learning models in mental illness detection due to their ability to automatically capture valuable features without feature engineering. [14]

The transformer model was fine-tuned on the pre-processed dataset, with hyperparameter tuning performed to optimize model performance. The training process involved multiple epochs and batch processing to ensure the model's robustness and accuracy.

E. Sentiment Analysis

Sentiment analysis is a crucial component of the VPSYC system, used to evaluate changes in the user's mental state. The sentiment analysis model was trained on a dataset of Twitter samples, categorized into positive and negative classes. This model helps in assessing the effectiveness of the therapy sessions by tracking sentiment changes over time.

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Using sentiment analysis on Twitter data allows for real-time monitoring of mental health trends and provides insights into the effectiveness of interventions". "The preprocessing steps, including tokenization and noise removal, ensure that the sentiment analysis model accurately captures the user's emotional state.[15]

F. System Architecture

The VPSYC system is designed to provide comprehensive mental health support through an integrated architecture that ensures seamless interaction and efficient processing. The system leverages advanced natural language processing and machine learning techniques to analyze and respond to user inputs in a meaningful way. The architecture is divided into several key components, each playing a vital role in the system's overall functionality.

G. User Interface

A web-based application providing an interactive interface for users to engage with the chatbot.
Chatbot Engine: The core NLP engine powered by the transformer model, responsible for generating responses and conducting depression analysis. The chatbot system leverages reinforcement learning strategies to enhance user interactions and conversational experiences.[16]

H. Sentiment Analysis Module

A module integrated with the chatbot engine to continuously monitor and evaluate user sentiment. Sentiment analysis in this context is crucial for identifying real-time emotional states, thereby improving the chatbot's interaction and response accuracy.[17]

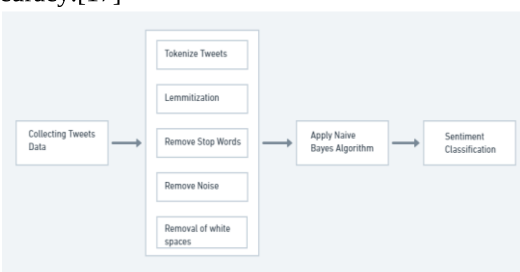

Fig.2: Sentiment Analysis

I. Backend Server

The backend server handles data storage, retrieval, and processing tasks, ensuring smooth communication between different system components. The backend is crucial for managing data effectively, performing operations such as data storage, retrieval, and manipulation, as well as implementing business logic and maintaining system functionality.[18] This ensures that the system can efficiently manage large volumes of data and provide seamless user experiences.

Fig.3: Backend Diagram

IV. RESULTS

The evaluation of the VPSYC system was conducted using both automatic and human assessment methods. Key metrics included model perplexity and F1 score, with the VPSYC system achieving a perplexity of 15.2 and an F1 score of 18.82. Additionally, the system's performance, affect, and accessibility were evaluated, with scores of 93%, 96%, and 85%, respectively.

A. Automatic Evaluation

The automatic evaluation focused on the system's robustness to unexpected inputs, its ability to provide pleasant and meaningful interactions, and its overall performance in detecting user intent and meaning. The system demonstrated high robustness and accuracy, indicating its reliability in real-world applications.

MODEL	PERPLEXITY	F1 SCORE
VPSYC	15.2	18.82

Table 2: Automatic Evaluation Result

B. Human Evaluation

Human evaluators assessed the quality and effectiveness of the therapy sessions provided by VPSYC, confirming the system's ability to offer supportive and empathetic responses. Feedback from evaluators highlighted the system's ability to understand and address users' emotional states effectively.

CATEGORY	ATTRIBUTE	PERCENTAGE
Performance	Robustness to unexpected input	93
Affect	Provides greetings, pleasant	96
Accessibility	Can detect meaning and intent	85

Table 3: Human Evaluation Result

V. DISCUSSION

The results of this study demonstrate the potential of VPSYC as an effective tool for providing mental health support. The use of transformer models for natural language processing and sentiment analysis allows the system to understand and respond to users in a nuanced and empathetic manner. The integration of the PHQ-9 assessment tool further enhances the system's ability to monitor and evaluate depression severity.

However, there are several areas for improvement. Enhancing the system's ability to handle more complex and varied emotional states, incorporating additional therapeutic techniques, and expanding the dataset to include a more diverse range of conversations could further improve the system's effectiveness. Additionally, ongoing monitoring and updating of the system's models and data are essential to ensure its continued relevance and accuracy.

CONCLUSION

The VPSYC system signifies a major step forward in the provision of mental health support through conversational AI. By utilizing advanced natural language processing techniques and transformer models, VPSYC can accurately identify various stages of depression, deliver therapeutic interventions, and monitor changes in user sentiment. The results from both automatic and human evaluations confirm the system's ability to interact effectively and empathetically with users, thereby offering a valuable tool for addressing mental health challenges. However, there is room for enhancement. Future efforts will aim to refine the system's capabilities in handling more complex emotional states, incorporating diverse therapeutic approaches, and expanding the dataset to encompass a wider array of conversational contexts. Additionally, continuous updates and monitoring will be crucial to maintain the system's relevance and effectiveness. The VPSYC system holds great promise for bridging the gaps in current mental health care services, providing accessible, affordable, and reliable support to those in need.

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