Depression Detection in Reddit Posts Using Natural Language Processing

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Abstract— **In today's digital landscape, social media platforms provide vast repositories of user-generated content, offering unique insights into individuals' emotions and thoughts. This project zooms in on Reddit, a widely used online forum, aiming to discern indications of depression among its users. Through the strategic application of advanced natural language processing techniques, specifically TF-IDF and LIWC, the study meticulously analyzes textual data, uncovering subtle linguistic cues suggestive of depressive states.**

Going beyond surface-level scrutiny, the project integrates sophisticated machine learning models, such as Multilayer Perceptron and Support Vector Machine, to classify posts effectively. These models serve the crucial function of differentiating posts that potentially signal depression from the overwhelming volume of online content. The project's core objective lies in early detection, facilitating timely intervention and support for individuals in distress.

This innovative fusion of linguistic analysis with machine learning methodologies not only signifies a practical approach to mental health screening on digital platforms but also stands as a testament to the evolution of techniques in the realm of natural language processing. Through its systematic methods, the project paves the way for enhanced strategies in identifying and assisting individuals struggling with depression, marking a significant step forward in the field of digital mental health support.

Keywords— Multilayer Perceptron, Support Vector Machine, Term Frequency-Inverse Document Frequency, Linguistic Inquiry and Word Count

I. INTRODUCTION

A common mental health condition that affects millions of people worldwide is depression. Numerous crippling symptoms, including chronic melancholy, losing interest in once-enjoyable hobbies, changes in eating and sleep habits, and even suicidal or self-harming ideas, can result from it. It is essential to identify depression early on and accurately in order to treat and help those who are impacted. Natural language processing (NLP) methods have become increasingly effective in recent years at detecting depression-related signals in textual data, especially from online platforms like Reddit, when combined with text classification algorithms like Multilayer Perceptron (MLP) and Support Vector Machine (SVM).

Millions of people use the well-known social media site Reddit to discuss a variety of subjects, including their individual experiences with mental health. These conversations frequently offer insightful perspectives into the feelings and ideas of those who are struggling with depression. Through the use of NLP tools, academics and medical practitioners can better understand the incidence and subtleties of depression across the online community by extracting useful information from this textual data.

This study investigates the use of NLP techniques and text classification algorithms—more especially, MLP and SVM—to identify depressive symptoms in text data gathered from Reddit. We'll talk about the importance of this strategy, the difficulties in seeing content that could be associated with depression, and the possible advantages of early diagnosis. This study intends to complement current efforts to increase mental health awareness and support by detecting those at risk and providing prompt aid by utilizing machine learning algorithms.

One popular text analysis tool in the fields of computational linguistics and natural language processing (NLP) is Linguistic Inquiry and Word Count (LIWC). The foundation of LIWC is the idea that words have the power to provide information about a person's emotional and psychological states. It groups words according to psychological aspects (including positive and negative emotions, cognitive functions, and social ties) as well as language categories (like pronouns, verbs, and adjectives). It may, for instance, recognise and quantify terms associated with melancholy, anxiety, or personal pronouns in a document.Numerous applications of LIWC analysis have been discovered in the field of depression identification, especially when dealing with online text data like chat logs, blogs, and social media posts.

Words and phrases that express their emotional state are frequently used by depressed people. Words that convey sadness or hopelessness, negative emotional words, and an increase in the use of first-person pronouns are examples of linguistic indicators of depression that LIWC can assist in identifying.By comparing the vocabulary of people with depression to that of people without, researchers can utilize LIWC to build models that can identify depression from text data.Individuals' psychological states can be monitored over time via LIWC analysis. It is possible to detect changes in emotional state or mood by examining the written or spoken content.Understanding how depression develops and how language patterns alter along with it is made easier with the help of this longitudinal investigation. LIWC is a useful tool for assessing how well different depression therapies work. Researchers can learn more about how interventions affect a person's emotional and psychological condition by comparing language patterns before and after therapy.LIWC can be used as a component of a depression early warning system for people who may be at risk. It can identify worrying language trends in their online discussions and offer a chance for prompt intervention.

In natural language processing (NLP), Term Frequency-Inverse Document Frequency (TF-IDF) is a basic idea that is utilized for text analysis and information retrieval. By making it possible to recognise important words or terms that are indicative of a person's mental state, it plays a critical role in the detection of depression. TF counts how often a term appears in a document. A document in the context of diagnosing depression could be any written content, including blog entries and social media posts. Each term is given a score by TF based on how frequently it occurs in the text. A term's TF score increases with the frequency of occurrence.The Inverse Document Frequency (IDF) measures a term's rarity or uniqueness within a set of documents. It is computed by taking the logarithm of the total number of documents divided by the total number of documents that contain the phrase. When a term loses usage throughout the entire document collection, its IDF rises.A term's TF and IDF scores are multiplied to determine its TF-IDF score. The term's significance within a particular document as well as its uniqueness throughout the entire document collection are both reflected in this score.

Finding particularly noteworthy words and phrases in texts about depression can be facilitated by using TF-IDF. In depressive texts, phrases such as "sadness," "loneliness," or "hopelessness" are likely to have high TF-IDF scores, making them useful markers.TF-IDF can be employed in machine learning models for depression detection in order to identify the most pertinent features (terms) that go towards the categorization. The algorithm can distinguish between depression and non-depressive content more effectively by concentrating on the phrases with the greatest TF-IDF scores.To identify the emotional tone of a document, sentiment analysis can be used in conjunction with TF-IDF. The analysis can help identify depression by highlighting terms with high TF-IDF scores that are also suggestive of unpleasant feelings.

Because MLPs can model non-linear relationships, dynamically learn key features, adapt to the details of the data, and are flexible and scalable, they have various advantages in textual depression identification. MLPs are ideally suited for the complex and non-linear character of textual data since they can capture non-linear relationships in data. MLPs can learn and model the complex linguistic patterns and subtle manifestations of depressive symptoms that are associated with depression identification.

MLPs are skilled at automatically extracting pertinent features from unprocessed text. This is useful in the context of diagnosing depression because they can extract significant language and semantic aspects that might not be obvious or simple to express clearly. Because of its capacity for feature learning, MLPs can adjust to the unique properties of the data. MLPs can be modified and tailored to the specific issue at hand. To optimise the network's performance, researchers and practitioners can create MLP topologies with different counts of layers, neurons, and activation functions. Because of its adaptability, the model may be modified and experimented with, guaranteeing its ability to recognise depression-related patterns.

The effectiveness of SVMs in high-dimensional spaces, their capacity to determine the ideal hyperplane separation, their adaptability in kernel selection, their resilience to overfitting, global optimisation, the sparsity of support vectors, their well-defined margin, their efficiency in binary and multi-class classification, and the ease with which hyperparameters can be adjusted are just a few of the benefits they offer in textual depression detection. Because of these qualities, support vector machines (SVMs) are a useful tool for developing precise and comprehensible models for locating depression indicators in textual data.

Usually, text data is represented as high-dimensional spaces where every distinct word or n-gram is treated as a feature. SVMs can manage the large dimensionality of textual data and are a good fit for this situation. When there are more characteristics (words) than data points (documents), they function very well.The goal of SVMs is to identify the ideal hyperplane for effectively dividing various classes. This refers to identifying the line that reliably separates depressive from non-depressive material in the context of depression detection. This may result in an easily understood decision boundary, which facilitates comprehension of the model's decision-making process.

Compared to certain other machine learning algorithms, SVMs are less likely to overfit, particularly when the number of features (words) is significantly greater than the number of samples. In the detection of depression, where overfitting can result in poor generalization to new data, this robustness is crucial.SVMs identify the decision boundary's worldwide optimal solution. As a result, the model becomes more stable and is less susceptible to fluctuations in the training set or local minima. For reliable findings in depression identification, the model's stability is essential.

II. EXISTING WORK

In the realm of natural language processing and mental health detection on social media, significant strides have been made in recent years. Researchers have diligently explored the intersection of these fields, particularly focusing on identifying signs of depression in online communication.

One prevalent approach has been sentiment analysis, where algorithms analyze the emotional tone of text. However, the intricate nature of depression-related language often eludes simplistic sentiment analysis methods, requiring more nuanced techniques.

Machine learning models have also been employed to detect mental health concerns in online text. These models, similar to the ones proposed in this project, sift through extensive datasets to pinpoint linguistic markers associated with depressive states. While promising, these approaches still face challenges in achieving high accuracy and specificity, especially in capturing the subtleties of mental health-related conversations.

Moreover, the ethical dimensions of automated mental health screening have been a focal point of discussion in existing research. Privacy concerns, consent issues, and potential biases in the data and algorithms have sparked considerable debate, highlighting the need for responsible and ethical practices in this domain.In essence, prior studies have laid the foundation for projects like the one presented here. By drawing from and advancing upon these works, this project seeks to enhance our understanding of mental health indicators in digital communication, contributing to the ongoing efforts to leverage online platforms for mental health awareness and support.

III. RESEARCH GAP

In the evolving field of mental health detection using natural language processing and social media data, there are several noteworthy research gaps that require further exploration. One key research gap revolves around the development of fine-grained and interpretable models. While current approaches often yield promising results, they can lack transparency and interpretability. Understanding how these models arrive at their conclusions is critical for building trust and facilitating their integration into real-world mental health support systems. Research efforts in this area could focus on designing models that not only achieve high accuracy but also provide insights into the linguistic cues and features that contribute to their decisions.

Another pressing research gap is the need for studies that investigate the effectiveness of mental health interventions delivered through social media. While there is growing interest in using these platforms for mental health support, there is a dearth of research evaluating the impact of such interventions. Comprehensive studies that assess the efficacy, reach, and long-term outcomes of online mental health support programs are essential for guiding the development of evidence-based interventions and understanding their potential to alleviate mental health challenges.

Furthermore, research on the ethical implications of automated mental health detection and intervention on social media remains a crucial gap. Ensuring user privacy, informed consent, and protection from potential harm or bias is paramount. Ethical frameworks for deploying mental health algorithms on these platforms need to be developed and rigorously examined. Research should explore how these algorithms can coexist with user rights and well-being while respecting the principles of privacy and fairness.

In essence, closing these research gaps is crucial for propelling the field of mental health detection and support on social media to new heights. Prioritizing the understanding of how algorithms work, assessing the real-world impact of online interventions, and grappling with the ethical complexities of automated detection and intervention are imperative steps. By delving into these areas, researchers pave the way for the creation of mental health solutions that are not only technologically advanced but also transparent, impactful, and ethically responsible in the ever-evolving digital landscape.

IV. RELATED WORK

Ethereum is indeed a blockchain-based, open, open-source, decentralized, and peer-to-peer network device that highlights the importance of smart contracts. It offers a distributed Actually turning virtual machine that allows the usage of a worldwide node network to run certain algorithms. Generated licenses in duress and

[1] Suvarna D. Tembhurnikar and Nitin N. Patil introduced a computational approach for topic identification and sentiment analysis specifically tailored for Twitter data. In this study, the authors present the BNgram method, which utilizes n-grams (contiguous sequences of n words) and Bayesian networks.The BNgram method combines these elements to model the relationships between words and the sentiments they convey within Twitter messages. It essentially captures how words and their combinations are associated with specific emotions, thus enabling a more sophisticated understanding of the emotional content embedded in Twitter conversations.

[2] Studies have also delved into various machine learning and natural language processing algorithms to assess their effectiveness in classifying sentiments (positive or negative) within movie reviews. The authors utilize a dataset of IMDB movie reviews to evaluate the performance of algorithms such as Support Vector Machines, Naive Bayes, and others. They measure key sentiment analysis metrics like accuracy, precision, recall, and F1-score to compare the algorithms' classification performance.

[3] Authors Ge Zhan, Ming Wang, and Meiyi Zhan employ sentiment analysis and data visualization techniques to extract and understand the sentiment expressed in user-generated content. To achieve this, the study utilizes Natural Language Processing (NLP) methods to analyze textual data, aiming to detect and categorize sentiments as positive, negative, or neutral. The paper also discusses data visualization tools and techniques to present the sentiment analysis results in a comprehensible manner, providing engineers and data analysts with insights into public opinions. By identifying sentiments and visualizing them effectively, engineers can make informed decisions and improve user experiences in various online platforms.

[4] In this study, NLP methods are used to preprocess and analyze textual content, extracting features and patterns that are indicative of cyberbullying behavior. Machine learning algorithms are then applied to classify text as either cyberbullying or non-cyberbullying. The research discusses the evaluation of these methods, highlighting their effectiveness in identifying harmful online interactions. This work is highly relevant for engineers and data scientists working on content moderation and online safety tools. By leveraging NLP and text analytics, they can develop systems to automatically detect and mitigate cyberbullying, fostering safer online environments and improving user experiences. The paper serves as a technical guide for the implementation of such systems.

[5] In this research, NLP techniques are employed to preprocess and analyze the textual data, extracting linguistic and sentiment features that are associated with depressive states. Machine learning models are then trained on labeled data to classify tweets as indicative of depression or not. The paper discusses the methodology and evaluation of the approach, demonstrating its effectiveness in recognizing potential cases of depression.By applying NLP and machine learning, they can create tools that automatically identify individuals who might be experiencing depression based on their social media activity, enabling timely intervention and assistance.

[6] In their work "Depression Detection by Analysing Social Media Posts of User," Al Asad, N., Pranto, M. A. M., Afreen, S., and Islam, M. M. describe their thorough approach for identifying depression through social media post analysis. The study begins with the gathering of data from many social media platforms, using publicly available textual data from sites such as Facebook, Twitter, and Reddit, without naming the sources. The gathered data is then put through preparation to make sure it is clean and ready for analysis. This includes text tokenization, stop word removal, lemmatization or stemming, and the removal of special characters. Then, using methods like the Bag of Words (BoW) model or Term Frequency-Inverse Document Frequency (TF-IDF) to transform the text into a format appropriate for machine learning, the researchers extract features from the preprocessed data. Next, the data is labelled as depressive or non-depressive, using techniques such as manual annotation or, if available, the use of self-reported labels. Though the study doesn't say which specific algorithms are utilised, machine learning is at the centre of the process. Support Vector Machines (SVM), Multinomial Naive Bayes, and deep learning methods such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) are popular options for text classification problems.

[7] A thorough methodology for identifying depression from speech data is presented in the research "Natural Language Processing Methods for Acoustic and Landmark Event-Based Features in Speech-Based Depression Detection" by Huang, Z., Epps, J., Joachim, D., and Sethu, V. To improve the accuracy of depression diagnosis, the research methodology combines landmark event-based characteristics with natural language processing (NLP) techniques. Speech samples from people with a range of depression symptoms are recorded as part of the data gathering process. From these speech recordings, acoustic characteristics like pitch, intensity, and speech rate are retrieved, and landmark events like pauses and changes in

speaking tempo are also recognised and measured. The speech's linguistic content is examined using the NLP component, with a particular emphasis on its syntactic and semantic components. The combination of these characteristics enhances the depression detection system's overall effectiveness by enabling the model to identify linguistic and emotional clues. The process is then applied to machine learning models to categorise people into depressive and non-depressive groups using support vector machines (SVMs) or neural networks.

[8] The paper, titled "MHA: a Multimodal Hierarchical Attention Model for Depression Detection in Social Media" by Li, An, Cheng, Zhou, Zheng, and Hu (2023), introduces an innovative approach for detecting depressive tendencies in social media users. Leveraging a Multimodal Hierarchical Attention (MHA) model, the study integrates text, image, and auxiliary information, utilizing attention mechanisms both within and between modalities to effectively identify relevant data. By incorporating features such as emotional content, posting patterns, and social interactions, the model generates a comprehensive feature set for each user. The application of attention mechanisms enhances the model's ability to focus on crucial information within modalities and assign varying importance to different modalities, ultimately improving the accuracy of depressive tendency classification. This study contributes significantly to the field, offering a systematic and promising method for addressing the challenging task of detecting depressive tendencies in social media users (Li et al., 2023).

[9] In their paper titled "Depression Screening in Humans with AI and Deep Learning Techniques," Wani, ELAffendi, Shakil, Imran, and Abd El-Latif (2022) address the crucial task of early depression detection on social media platforms. They emphasize the wealth of sensitive social signals related to depression present in online content, which, if harnessed effectively, can aid in the identification of individuals at risk. To tackle the limitations of existing depression detection models, the authors propose an innovative approach employing artificial intelligence (AI) and deep learning (DL) techniques. Their model utilizes hybrid feature-based behavioral-biometric signals, integrating advanced methods like Word2Vec and term frequency-inverse document frequency (TF-IDF) models into a convolutional neural network (CNN) and long-short term memory (LSTM) architecture. The study's dataset, sourced from various online social network platforms including Facebook, Twitter, and YouTube, is the first of its kind and contributes significantly to the field. The experiments demonstrate the effectiveness of their approach, with the hybrid (CNN + LSTM) models achieving remarkable accuracy rates of 99.02% and 99.01% for Word2Vec LSTM and Word2Vec (CNN + LSTM) models, respectively. These results outperform existing approaches on key performance measures, making this study a significant advancement in the realm of AI-driven depression detection on social media platforms (Wani et al., 2022)

V. METHODOLOGY

After meticulously collecting data from diverse online sources such as blogs and Reddit, the dataset, comprising 1460 instances, underwent a series of preprocessing steps to ensure consistency and quality. These steps included the removal of extra line breaks, reduction of multiple consecutive periods (ellipses) to a single space for readability, elimination of non-alphanumeric characters, stripping leading and trailing spaces, and normalizing spaces. These measures standardized the textual format, resulting in a meticulously cleaned dataset ready for in-depth analysis. For accurate labeling, documents were categorized into "Depression" (Y) and "Non-Depression" (N) classes based on their directory paths. Documents within directories containing "non_depression" were labeled as "Non-Depression," while those within directories containing "depression" were labeled as "Depression." This meticulous labeling process ensured each document's association with the appropriate class label, a crucial step for training and evaluating the text classification models. Linguistic Inquiry and Word Count (LIWC) analysis was employed as a complementary feature engineering step to enhance the text classification task. LIWC, a tool quantifying linguistic and psychological aspects of text, provided a deeper understanding of emotional and psychological content within the textual data. Relevant LIWC categories were selected, covering a wide range of emotional and psychological states, enriching the dataset with nuanced insights. To integrate LIWC analysis with traditional TF-IDF (Term Frequency-Inverse Document Frequency) features, the text data underwent TF-IDF vectorization, capturing the importance of specific words and word combinations in the documents. The vectorization considered bigrams (ngram_range=(2, 2)) and limited features to the top 100. Simultaneously, LIWC analysis was performed using the Empath library, generating numeric values representing the presence and intensity of each selected LIWC category within the document. These TF-IDF and LIWC-derived features were then horizontally concatenated, creating a feature matrix that captured both textual patterns and emotional/psychological dimensions. For model building, two powerful machine learning models were utilized: the Multilayer Perceptron (MLP) Classifier and the Support Vector Machine (SVM) Classifier. The MLP Classifier, an artificial neural network with two hidden layers (64 and 32 neurons), was trained on the combined TF-IDF and LIWC features. Model optimization involved backpropagation and gradient descent techniques. Simultaneously, the SVM Classifier, employing a linear SVM classifier, was trained on standardized TF-IDF and LIWC features. Notably, the SVM Classifier demonstrated superior performance, achieving an accuracy of 94.8% on the testing data. The implementation utilized various Python libraries, including os, glob, re, scikit-learn, and Empath, to handle tasks such as data organization, text preprocessing, feature extraction, and machine learning model training.

After training, the MLP Classifier achieved an accuracy of 92% on the testing data, indicating its ability to effectively classify text documents as either depression-related or non-depression-related.

To further optimize the MLP classifier's performance, hyperparameter tuning was performed using a grid search approach. Various combinations of hyperparameters, including the number of neurons in the hidden layers and the activation function, were explored.

The grid search identified the best combination of hyperparameters, leading to a slight improvement in accuracy to approximately 92.4%.

VI. CONCLUSION and FUTURE WORK

Both models demonstrated strong performance in detecting depression-related content in textual data. The choice between the MLP and SVM classifiers may depend on specific requirements, including model complexity and interpretability. Our research has produced noteworthy outcomes in the field of depression identification from textual data on Reddit. To extract pertinent information from the text, we combined feature engineering techniques: TF-IDF vectorization and Linguistic Inquiry and Word Count (LIWC) analysis. Multilayer Perceptron (MLP) and Support Vector Machine (SVM), in particular, proved to be reliable machine learning models for categorization. The MLP classifier performed admirably, with an accuracy of 92%; we were able to significantly improve its performance to about 92.4% by tweaking its hyperparameters. On the test data, the SVM classifier achieved an astounding accuracy of 94.8%, surpassing the performance of the MLP. These findings highlight how effective it is to identify depression-related information in textual data by integrating linguistic analysis with conventional Natural Language Processing (NLP) and machine learning techniques. The high classification accuracy both classifiers were able to obtain indicates that our technique has the potential to be a very useful tool for early depression detection and support. This study adds to the ongoing efforts to raise awareness of mental health issues and emphasizes the potential benefits of using cutting-edge natural language processing (NLP) and machine learning techniques to better identify and treat mental health problems in the digital era.

In this project, we employed a TF-IDF vectorizer with a 2-gram (bi-gram) range to capture word combinations. To gain a more nuanced understanding of text patterns, future work can explore the use of different n-gram ranges, including Unigrams(1-grams), Trigrams (3-grams) and beyond. While the Multilayer Perceptron (MLP) Classifier has shown promising results in this project, RNNs can capture sequential dependencies in text data and may improve the model's ability to understand the context of posts. Future work can involve fine-tuning LIWC categories and considering additional categories based on domain-specific knowledge or linguistic research. A more extensive and domain-specific LIWC lexicon could improve the model's linguistic analysis. Class imbalance, where one class (e.g., "depression found") is significantly smaller than the other, can affect model performance. Future work should explore techniques to address class imbalance, such as oversampling, undersampling, or using advanced algorithms like Synthetic Minority Over-sampling Technique (SMOTE). Enhancing the interpretability and explainability of the model's predictions is crucial, especially in healthcare and mental health applications. Techniques such as LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations) can be applied to provide insights into the model's decision-making process.

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