International Journal of Multidisciplinary Engineering in Current Research - IJMEC
Volume 9, Issue 8, August-2024, http://ijmec.com/, ISSN: 2456-4265

DEPRESSION DETECTION USING MACHINE LEARNING TECHNIQUES ON TWITTER DATA

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Abstract:
Depression has become a significant issue in today's generation, with the number of individuals affected by depression increasing daily. While some recognize they are dealing with depression, others remain unaware. Additionally, the rise of social media has created a new platform where users express their mental states, often serving as a "diary." Research has explored the use of machine learning algorithms to identify depression through users' social media posts. These algorithms can classify data into depressive and non-depressive categories. This research aims to detect user depression based on their social media content, specifically Twitter posts, using two classifiers: Naïve Bayes and a hybrid model, NBTree. The effectiveness of these classifiers is compared based on accuracy to identify the best method for depression detection. The results indicate that both algorithms perform equally well, showing the same level of accuracy [1,2].

Keywords—*Depression, Social Media, Twitter, Classification, Hybrid, NBTree, Naïve Bayes*

I. Introduction

Depression has emerged as a significant mental health issue, impacting over 264 million individuals globally [1]. Causes of depression may include environmental changes, neurotransmitter imbalances, or genetic factors [2]. While therapy and medication are common treatments, many cases remain undiagnosed due to a lack of awareness, which can lead to self-isolation, erratic behavior, suicidal thoughts, and over-reliance on antidepressants. Untreated depression can impair daily functioning and cause severe harm to both mind and body.

With about 3.8 billion social media users worldwide due to technological advancements [3], platforms like Twitter have become outlets for people to express their emotions and thoughts. These platforms offer valuable insights into users' mental states, which can be analyzed for applications in healthcare and beyond [4]. Twitter, as a micro-blogging site, provides a public forum for users to share brief updates and supports extensive data extraction through its API [6]. Sentiment analysis of tweets can reveal mood states, and machine learning algorithms can classify these sentiments to detect depression [7]. This paper explores depression detection through tweets using Naïve Bayes and a hybrid model called NBTree.

Depression is the most widely recognized sort of physiological or state of mind issue affecting a various number of people the world over. Discouraged individuals are progressively inclined to numerous different issues like sadness, loneliness,

DOI: https://doi-ds.org/doilink/08.2024-67148331

and anxiety. Feature Extraction is one of the most crucial phases in Natural Language Processing for gaining a better knowledge of the context which is to be dealt with. After cleaning the initial text, it must converted it into features that may be utilised for modelling. Because document data cannot be computed, it must be converted into numerical data, such as a vector space model. This transformation operation is commonly referred to as feature extraction of document data. Text Representation, Text Extraction, and Text Vectorization are all terms used to describe Feature Extraction. It is hard for the individuals experiencing gloom to focus on their work, speak with the individuals and significantly more. As a result, recognising depression is critical for the proper evaluation and treatment of a person. A significant amount of relevant data is required to build a depression detection model.

II. Literature Survey

This section provides an overview of depression, reviews existing methods for detecting depression using various machine learning algorithms, and identifies gaps in current research to propose improvements. The discussion is organized into several parts:

A. Overview of Depression

Depression is a prevalent mental health issue that is commonly addressed in health discussions. Untreated depression or ignoring its symptoms can lead to severe consequences, potentially threatening one's life. Depression typically starts from complex interactions among social, biological, and psychological factors, with serious problems potentially developing over time [8]. There are seven types of depression categorized under two main types: clinical depression and bipolar disorder [9]. Clinical depression can last for about two weeks, during which individuals might experience:

1. Feelings of guilt, worthlessness, and helplessness.
2. Changes in appetite leading to weight loss or gain.
3. Suicidal thoughts or attempts.
4. Sleep disturbances, including insomnia or excessive sleep.
5. Persistent sadness nearly every day.
6. Loss of interest in activities and hobbies.

Bipolar disorder, or manic depression, is characterized by extreme mood swings from high (mania) to low (depression) that can last from days to weeks. During manic phases, individuals may exhibit excessive energy, reduced need for sleep, talkativeness, racing thoughts, and poor judgment, often leading to inappropriate behavior.

B. Machine Learning Applications for Detecting Depression via Social Media

Machine learning techniques are used to uncover patterns and insights from data. Previous studies have explored depression detection through Facebook data by analyzing emotional and linguistic styles of language [10]. One study demonstrated that using different kernels in the SVM (Support Vector Machine) algorithm achieved high accuracy for depression detection [11].

In 2016, Nadeem explored the detection of Major Depressive Disorder using Twitter data, comparing Naïve Bayes and SVM algorithms. The results indicated that the Naïve Bayes algorithm performed better than SVM [12].

Additionally, a hybrid machine learning model combining Naïve Bayes and SVM has shown strong

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performance in sentiment analysis tasks for detecting depression on Twitter [13].

Table I summarizes previous research from 2016 to 2020, highlighting various algorithms and their limitations. Most studies have focused on single machine learning algorithms for depression detection and often use one dataset for evaluating accuracy.

Overall, Naïve Bayes has shown superior performance in many studies, but existing research limitations reveal opportunities for developing more effective algorithms and methodologies for depression detection.

III. Pre-Processing & Handling Datasets

To retain current customers and minimize churn, companies often attempt to predict potential churn and respond promptly. Detecting early signs of customer churn helps organizations address issues, satisfy customer needs, and maintain loyalty, thus reducing the costs associated with acquiring new customers. A significant challenge for businesses, especially in the telecommunications sector, is 'customer churn', which occurs when a customer switches from one service provider to a competitor. Existing systems for churn prediction primarily use data mining techniques such as clustering, classification, and association rule mining to model and predict customer churn based on behavioral and attribute data. However, these systems face several disadvantages: they struggle with missing or inconsistent data[12,13], and the predictive results from data mining techniques are not always exact. The algorithms used in these systems are often limited by these issues, making accurate churn prediction challenging.

Proposed System: In contrast, the proposed system utilizes machine learning, a branch of artificial intelligence, to effectively analyze and predict customer churn in the telecommunications industry. By applying algorithms such as the Support Vector Machine (SVM), this system aims to identify patterns in customer behavior that indicate potential churn. Machine learning offers advanced techniques for analyzing customer attrition rates and can measure churn by evaluating the number of customers who cancel their subscriptions over a given period. The SVM algorithm is particularly effective in this context because it can analyze complex data patterns and predict churn with high accuracy. The advantages of this proposed system include its ability to prevent churn through early detection, its cost-effectiveness compared to traditional methods, and its capability to handle large datasets for better predictive performance. The SVM algorithm provides a robust solution for analyzing customer data and predicting churn rates more effectively than previous methods.

While existing systems for detecting depression and predicting customer churn face challenges such as data inconsistencies and limited scope, the proposed system offers a modern, machine learning-based approach to overcome these limitations. By leveraging advanced algorithms and automated analysis, this new system promises a more effective and scalable solution for early detection and intervention in depression, as well as for customer retention in business contexts.

Sentiment analysis is that the maneuver of determinative the emotional tone behind a series of words; would like to appreciate Associate in nursing understanding of the attitudes, opinions, and emotions expressed throughout a text. It's the thanks

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to gauge written or language to work out if the expression is positive, or negative, or neutral. The flexibility to extract sentiment and emotions insights from social knowledge is additionally determined that's being wide adopted by organizations across the globe. This paper focuses on the varied ways used for classifying a given piece of language text in line with the opinions expressed in it. So, on manufacture such perception, machine learning techniques may presumably offer some outstanding selections which are able to assist in examining the distinctive patterns hidden in on-line communication. We have a tendency to tend to tend to aim to utilize machine learning techniques and algorithms for depression detection on social media sites like Twitter.

In recent times, detecting depression using data collected from social network, like audio, video, image or text data, is a growing research field in emotion processing. Data from social media, which includes text data and gifs, emojis, etc., would be used for the analysis and classification processes. An autonomous depression detection system is required due to the complexity of conventional methods based on clinical diagnosis. Using data collected from social media, sentiment levels can be identified and monitored. In this paper, we aim to research on using machine learning & deep learning techniques combined to make a hybrid model. CNN is a technique proven to be efficient in feature extraction combined with Bidirectional LSTM, for contextual learning, both used to apply on the data collected from social media, train the data and obtain efficient results on the level of depressional traits in an individual. It has also been possible to get a reasonably high value of accuracy upon evaluation. The use of AI and machine learning in such systems has greatly assisted in many fields of medical science including psychology analysis.

IV. Organisation Consociate

Study for Depression Detection Using Machine Learning: The feasibility study for the depression detection project is a critical phase where the project's viability is evaluated. This phase involves analyzing various factors to ensure that the proposed system will be beneficial and manageable for the organization. The feasibility study is divided into three key considerations.

Economic Feasibility: Economic feasibility examines the financial aspects of the proposed depression detection system to ensure that it is cost-effective for the organization. The cost of implementing machine learning algorithms for depression detection is a significant factor in this study. This includes expenses for hardware, software, and development resources. Fortunately, many machine learning libraries and frameworks are open-source and freely available, which helps keep costs low. The primary expenses will be for high-performance computing resources, data acquisition, and possibly some commercial software licenses for advanced tools. A detailed cost estimate shows that the benefits of early depression detection—such as improved mental health outcomes and reduced long-term healthcare costs—outweigh the initial investment. Thus, the project remains economically viable within the budget constraints.

Technical Feasibility: Technical feasibility assesses whether the proposed system's technical requirements can be met with the available resources. This includes evaluating the hardware and software needs for implementing machine learning algorithms and

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analyzing Twitter data for depression detection. The technical requirements are relatively modest, as modern hardware like an Intel Core i7 processor and 16GB of RAM is sufficient for running complex machine learning models. Python, the chosen programming language, supports a range of libraries for sentiment analysis and classification, such as scikit-learn and TensorFlow, which are well-documented and widely used. Therefore, the system's technical demands are manageable, and there are no significant obstacles to implementing the required technologies. This ensures that the system can be developed with the existing technical resources.

Social Feasibility: Social feasibility evaluates how well the proposed system will be accepted by users and its potential impact on their lives. The system aims to provide a tool for early detection of depression by analyzing Twitter posts, which requires users to engage with the technology and understand its purpose. Educating users about the benefits of this system and ensuring they feel comfortable with the process is crucial. Providing clear documentation, training sessions, and support resources will help users understand how to use the system effectively and feel confident in its application. Additionally, the system must handle sensitive data respectfully, ensuring users' privacy and building trust. Positive user acceptance and proper training will contribute to the system’s success and encourage constructive feedback for further improvements. In summary, the feasibility study for the depression detection system using machine learning addresses economic, technical, and social aspects to confirm that the project is practical and beneficial. Economic feasibility ensures that the system is cost-effective with a clear return on investment. Technical feasibility confirms that the system's requirements are achievable with current technology. Social feasibility focuses on user acceptance and effective training to ensure the system's success.

V. System Architecture & Design Mechanisms

A quantitative study is conducted to train and test various machine learning classifiers to determine whether a twitter account user is depressed, from tweets initiated by the user or his/her activities on Twitter. Data preparation, feature extraction, and classification tasks are performed using various R packages. The classifiers are trained using 10-fold cross validation to avoid overfitting, and then tested on a held-out test set.

System Architecture:

The bubble chart is a simple graphical formalism that can be used to represent a system in terms of input data to the system, various processing carried out on this data, and the output data is generated by this system.

The data flow diagram is one of the most important modelling tools. It is used to model the system components. These components are the system process, the data used by the process, an external entity that interacts with the system and the information flows in the system.

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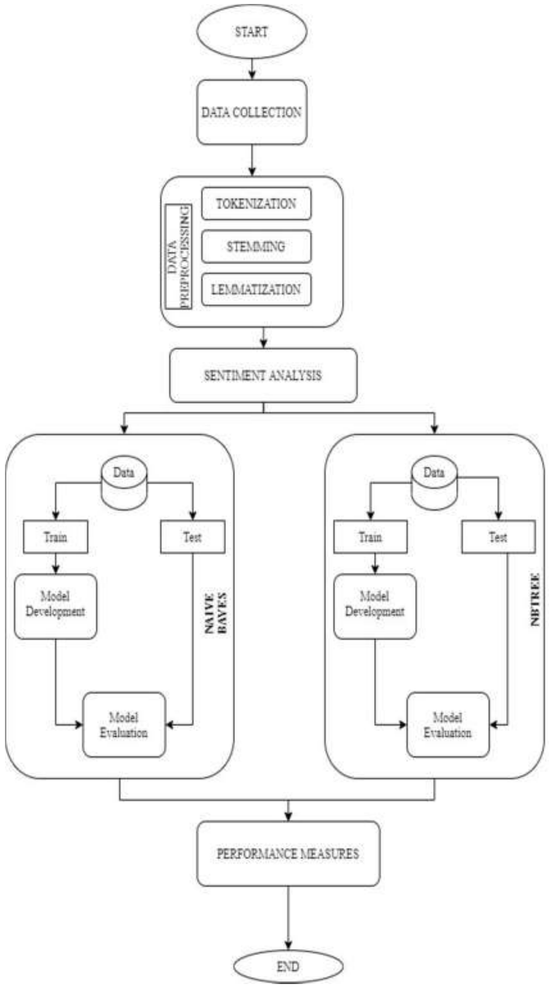

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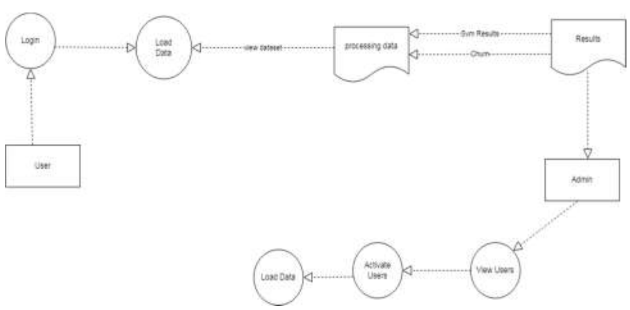
It may be used to represent a system at any level of abstraction. DFD may be partitioned into levels that represent increasing information flow and functional detail.



UML stands for Unified Modelling Language. UML is a standardized general-purpose modelling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group.

The goal is for UML to become a common language for creating models of object oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML.

The Unified Modelling Language is a standard language for specifying, Visualization, Constructing and documenting the artefacts of software system, as well as for business modelling and other non-software systems.

The UML represents a collection of best engineering practices that have proven successful in the modelling of large and complex systems.

The UML is a very important part of developing objects oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

The Primary goals in the design of the UML are as follows: Provide users a ready-to-use, expressive visual modelling Language so that they can develop and exchange meaningful models. Provide extendibility and specialization mechanisms to extend the core concepts. Be independent of particular programming languages and development process. Provide a formal basis for understanding the modelling language. Encourage the growth of OO tools market. Support higher level development concepts such as collaborations, frameworks, patterns and components. Integrate best practices.

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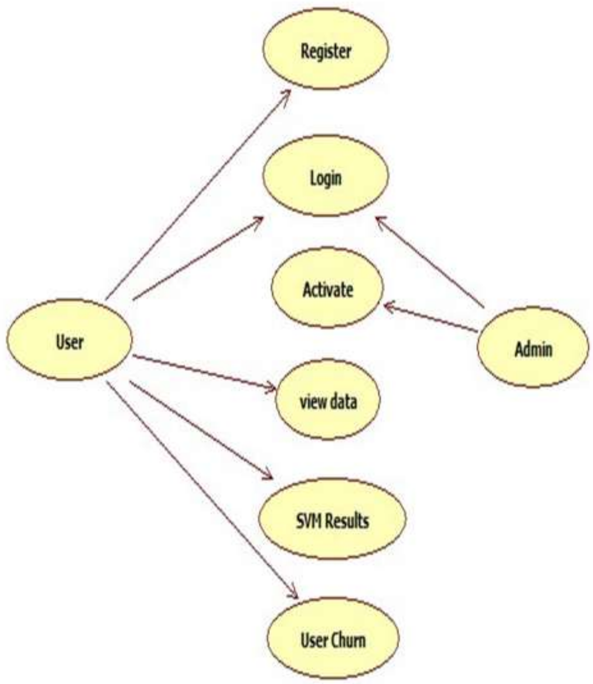


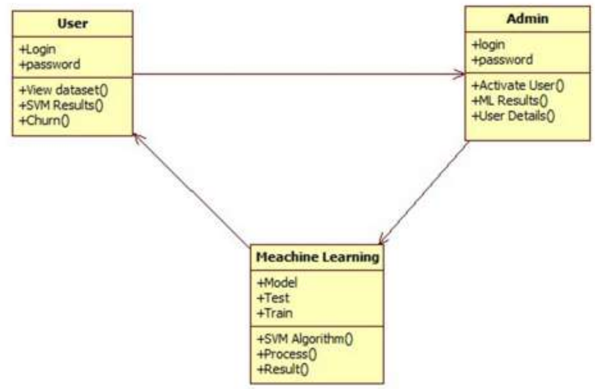
A use case diagram in the Unified Modelling Language (UML) is a type of behavioural diagram defined by and created from a Use-case analysis.

Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases.

The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

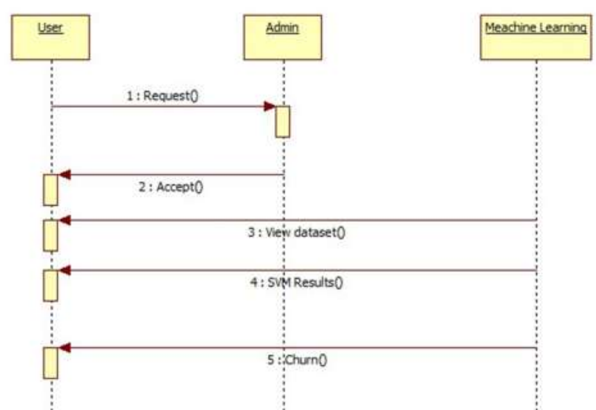
Class Diagram:

In software engineering, a class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among the classes. It explains which class contains information.



Sequence Diagram:

A sequence diagram in Unified Modelling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams



Activity Diagram:

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control.

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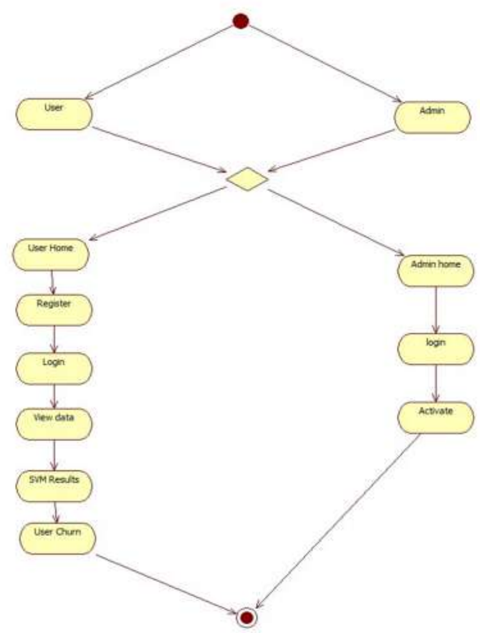

VI. Modules of Twitter API Into Training

User: The User begins by registering on the platform with a valid email and mobile number for future communication. After registration, the Admin must activate the user account before the user can log into the system. Once activated, the user can log in and upload Twitter data for analysis, ensuring the data format aligns with the required structure for processing. The user can upload datasets of Twitter posts that match the specified columns for sentiment analysis, such as tweet text and sentiment labels. The User can also add new data to the existing dataset through the web interface provided by our Django application. On the web page, the user can select the "Classification" option to execute sentiment analysis algorithms, which will calculate and display Accuracy, F1-Score, Recall, and Precision based on the chosen algorithms. The user can also choose the "Prediction" option to input a new tweet or text review and receive sentiment analysis results indicating whether the text is positive, negative, or neutral.

Admin: The Admin logs in using their credentials to manage user accounts and oversee system operations. Admin responsibilities include activating new user accounts so that users can access the system. The Admin has access to the overall system data and can view and manage all datasets uploaded by users. Admin can also access the "Results" section of the web interface where the performance metrics of various machine learning algorithms are displayed, including Accuracy, F1-Score, Precision, and Recall. After all algorithms are executed, the Admin can review the overall performance metrics on the web page to determine which algorithm performed best in detecting depression based on sentiment analysis.

Data Preprocessing: Data preprocessing involves preparing raw Twitter data for machine learning tasks. The data, which consists of tweets and their associated sentiment labels, is cleaned and transformed for analysis. This includes removing irrelevant information, handling missing values, and converting data into a suitable format for analysis. Techniques used in preprocessing include noise reduction, missing data imputation, and normalization of text data. The preprocessing steps also include tokenization, removing stop words, and stemming or lemmatization to prepare the data for feature extraction and model training. Proper preprocessing ensures that the data is ready for effective machine learning model development.

Social media channels, such as Facebook, Twitter, and Instagram, have altered our world forever.

People are now increasingly connected than ever and reveal a sort of digital persona. Although social media certainly has several remarkable features, the

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demerits are undeniable as well. Recent studies have indicated a correlation between high usage of social media sites and increased depression. The present study aims to exploit machine learning techniques for detecting a probable depressed Twitter user based on both, his/her network behavior and tweets. For this purpose, we trained and tested classifiers to distinguish whether a user is depressed or not using features extracted from his/her activities in the network and tweets. The results showed that the more features are used, the higher are the accuracy and F-measure scores in detecting depressed users.

This method is a data-driven, predictive approach for early detection of depression or other mental illnesses. This study's main contribution is the exploration part of the features and its impact on detecting the depression level.

Text pre-processing is applied to all documents. First, a corpus is created and tweets in each document are tokenized. Next, normalization is applied, where all characters are turned to lower case and punctuations, retweets, mentions, links, unrecognized emoji's, and symbols are removed. Usually, normalization includes removing stop words, such as first-person pronouns like "I," "me," and "you," but when removing stop words, we keep the firstperson pronouns. Later, stemming is applied and a document term matrix (DTM) is created for each account.

The matrix indicates the frequency of words in each tweet, where each row indicates a document of tweets and each column indicates all words used in all accounts.

Support Vector Machines is an algorithm that determines the most effective call boundary between vectors that belong to a given cluster (or category) and vectors that don't belong thereto. It will be applied to any reasonably vectors that inscribe any reasonably knowledge.

In the SVM rule, we have a tendency to tend to plot each data item as some extent in n-dimensional space (where n is varying of choices you have) with the price of each feature being the price of a particular coordinate. Naïve Bayes Classifier Sentiment analysis could be a field dedicated to extracting subjective emotions and feelings from text. One common use of Sentiment Analysis is to work out if a text expresses negative or positive feelings. Written reviews area unit nice datasets for doing Sentiment Analysis as a result of they usually go with a score which will be wont to train a rule.

Naive mathematician classifiers are heavily used for text classification and text analysis Machine Learning classification. Although it's moderately straightforward, it usually performs still the maximum amount a lot of difficult solutions.

Machine Learning: In this module, the preprocessed Twitter data is split into training and test datasets, typically with the data used for training and for testing. The cleaned data is then subjected to various machine learning classifiers, such as Naïve Bayes and a hybrid model like NBTree. The performance of these classifiers is evaluated based on metrics such as Accuracy, Precision, Recall, and F1-Score. The results are displayed on the web page to allow comparison between algorithms. The classifier with the highest performance metrics is selected as the best model for detecting depression from Twitter data.

VII. Conclusion

From the above discussion, it is clear that detecting depression is a critical issue that spans across various

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domains, including mental health and technology. As mental health problems continue to rise globally, it becomes imperative for organizations to develop effective methods for identifying and addressing depression. Machine learning techniques offer promising solutions for this challenge by leveraging large-scale social media data to detect signs of depression. The focus of this report has been on exploring the potential of machine learning algorithms, particularly Naïve Bayes and the hybrid model NBTree, for analyzing Twitter data to detect depressive symptoms. By applying sentiment analysis to tweets, these algorithms can classify text data into depressive or non-depressive categories with significant accuracy. The comparison of these algorithms demonstrates that both methods are effective in their own ways, offering valuable insights into depression detection. Ultimately, this report highlights how machine learning can advance depression detection and improve mental health support through innovative approaches and advanced analytical tools.

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