Prediction Depression Analysis Framework For Twitter Data Using Genetic Algorithm Based Feature Extraction And Naive Bayes Classifier

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ABSTRACT
Sentiment Analysis and Opinion Mining is a hotspot for testing and the accelerated growth of platforms of social networks. Social media sites like Twitter, Face book and many more play an extremely important role in today's world. Twitter is a micro blogging site offering a vast quantity of data that can be used for numerous opinion analysis purposes, including forecasts, ratings, campaigns, ads, films and so on. Sentiment Analysis is a method for evaluating the positivity or negative of knowledge gathered from massive quantities and classifying it through multiple groups named emotions. This research examines a detailed view of the methodologies used in the classification of sentiments over Twitter data. This research provides a detailed overview of methodologies used in classifying sentiments over Twitter data, presenting a novel approach to depression analysis using advanced techniques such as stop word removal and lemmatization for preprocessing the Twitter data, elite term score, word2vec, and a modified genetic algorithm for feature extraction. The extracted features are then sent to a classifier to classify the tweets as depression or non-depression, and the performance of the MGA-NB model results in high accuracy, sensitivity, and specificity.

Keywords: Twitter data, tweets, sentiment analysis, depression, feature selection, and classification.

1. INTRODUCTION

Social network gives a platform for its users to get and share opinions about all tangibles and intangibles. The users' decisions of buying or accessing a service or product highly depends on those opinions [1]. For an instance, people select a movie based on the reviews available in their social network groups. Current political leaders use social media to communicate with public directly without depend on traditional media. Social media trends highly influence the political campaigns that turns into the success of candidates who utilize the features of social media well [2-4].

Twitter Data Analysis (TDA) handles the data to identify and extract subjective information from the input data and polarity detection deals with the automatic detection of the polarity of the opinions and classifies them based on their contrariety [5]. Plenty of data sources such as blogs, review sites, data sets, or microblogging sites are available. The SA consider different granularity level namely the document, the sentence, and the feature (aspect). In the document-level, Sentiment Analysis (SA) assumes a single opinion for the entire document, but, in the sentence-level, SA expects multiple opinions in the document. Sometimes, a sentence itself contains multiple opinions that lead to aspect-level SA [6-10].

There is a kind of hearing in the dialog that speaks of the perception of a certain item or point of view from all individuals [11-13]. Sense investigation, or, in other words, involves building a gander by building and assembling the item on blog posts, comments, reviews or ratings made by tweets [14]. A couple of emotional experiments can be useful in various ways. For example, in exhibiting, it helps in settling on a choice about the achievement of an advancement fight or new item dispatch, make sense of which types of an item or organization are popular and even perceive which economics like or severely dislike particular features [15].

There are a couple of emotional inquiries. The first conclusion that the word one is assured that the situation in another situation may be viewed as negative [16]. The second test was that people may not even express their perceptions in every environment they are in the same arrangement. Most of the opinions the users will get from feedback or opinion rates to tweet the products through substantial

comments which contain the sentimental key terms [17]. In Sentiment analysis, nevertheless, "the information tweets based on our opinion" is through and through not quite the same as "the taken photograph was bad People can be controlling their announcements.
Most reviews both positive and negative comments in other words the degree sentenced each to a Twitter or blogs such as the easy-to-learn medium, in any case, by dividing the sensible, and, more plausible for a comparative sentence in different results, connect it directly to a human looking for, Positive parse a PC is still troublesome. Sometimes people have to fight for perspectives of different issues to understand what you thought of setting up a short computation [18-20].
Research in depression analysis is driven by the urgent need to address the significant public health burden posed by depression, identified by the World Health Organization as a leading cause of disability worldwide. Early detection is crucial, yet challenging due to depression's complex nature. By developing accurate and efficient analysis methods, researchers aim to enable early intervention, reducing societal burdens. Advancements in technology, including machine learning and wearable sensors, offer new opportunities to enhance analysis. By harnessing these technologies, researchers can develop innovative tools that improve accuracy and accessibility in depression detection, ultimately contributing to personalized medicine and improving mental health outcomes.

2. LITERATURE REVIEW

A large number of sentiment analysis (SA) approaches are available in the literature. SA varies depend on the domain they have applied, data sources, tools, and their application. The features are in one of the forms namely bag-of-words, n-grams, POStags, SO, and opinionative words or phrases. Feature selection finds a subset of relevant features from the extracted feature-set in the first phase. Proper text interpretation is an important aspect in SA. A text interpretation method is proposed by [23], that uses a direction-oriented interpretation. The force dynamic model and the path model are the main conceptual models include in their discussion. Various characteristics of subjective information, and similarities and dissimilarities among emotions, and affect feelings have been discussed by [24].
Almansoori, A., et al (2021) [25] explained the effect of the most popular social media platforms may be seen by looking at the number of people who use them. It is quite important in everyday life. The increased popularity of social media as a means of bringing people closer together has opened the way for individuals all over the world to share photographs, sentiments, and videos, posing a significant security risk. Most social media users, on the other hand, are unaware of the underlying security level(s) of their accounts, as well as which elements of these social media should be regarded in the event of a problematic circumstance. The police are putting forth a lot of effort to stop cybercrime in its tracks and lower crime rates. The goal of this study is to learn more about the features of cybercrime on social media and to determine what steps the police should take to combat it.
Phanomtip, A., et al (2021) [26] projected the usage of social media platforms. As a result, these platforms have progressively been ingrained in their everyday lives, influencing their attitudes and behaviours. Although social media platforms were created to exchange information/news and connect relatives and friends, they have also been used to promote false information, conspiracy theories, hate speech, and cyberbullying. Cyberbullying is defined as recurrent bullying that uses digital technology to scare, upset, or shame individuals who are targeted. The negative repercussions of cyberbullying include feeling vulnerable, helpless, embarrassed, alone, sad, or suicidal. Unfortunately, a research found that one-third of pupils had been victims of cyberbullying at some point in their lives.
Singh, A., & Kaur, M. (2020) [27] subjected content-based cybercrime has received a lot of attention. To protect their consumers, web-based social media companies must be able to recognise oppressive content both accurately and competently. The support vector machine (SVM) is a well-known supervised learning model for a variety of classification issues. However, the performance of an SVM model is dependent on the optimal selection of its parameters as well as the data structure. As a result, the goal of this research is to optimise the parameters and feature selection at the same time in order to improve SVM quality.
Singh, A., & Kaur, M. (2020) [28] discussed about researchers that shows increasing interested in content-based cybercrime detection. Cybercrime has evolved into a profit-driven industry that targets online social networks. Cybercriminals seek to benefit from exploiting susceptible places in cyberspace by exploiting human understanding. They pose a hazard to youngsters, particularly teenagers, who are not properly supervised when online. A strong content-based cybercrime detection mechanism is urgently needed to solve this problem.
Despite numerous sentiment analysis (SA) approaches, research gaps persist. Key areas include domain-specific adaptation for handling linguistic nuances, optimizing feature extraction for accuracy, and integrating conceptual models like force dynamic and path models. Challenges also arise in interpreting

ambiguous or sarcastic statements. In cybercrime detection on social media, gaps exist in user education and real-time detection systems development. Advancements in content-based detection methods are needed for identifying malicious content. Understanding social media's long-term impact, especially on cyberbullying and misinformation, is crucial. Targeted research for young user protection, including age-appropriate detection mechanisms, is essential. Addressing these gaps enhances SA and cybercrime detection, promoting user safety and sentiment accuracy.

3. PROPOSED METHODOLOGY

The proposed methodology aims to identify depression through a different approach. The diagram below outlines the proposed methodology.

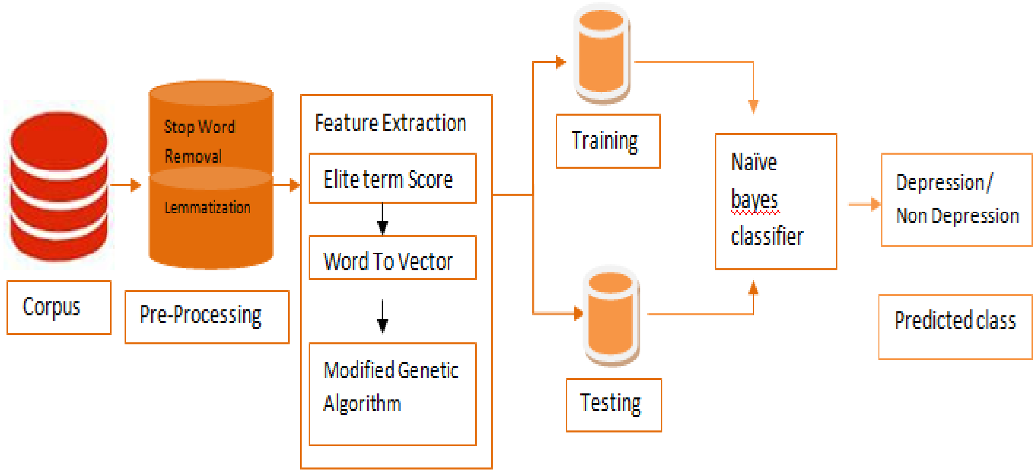

Figure 1. Framework Of Proposed Methodology

3.1. Data pre-processing

Traditional text cleaning methods often concentrate on standard pre-processing processes. An innovative method entails creating a flexible contextual cleaning algorithm that takes into account the distinctive linguistic features linked to sad expressions. This algorithm adaptively modifies cleaning tactics by considering the context, including linguistic subtleties, irony, or encoded language commonly encountered in mental health-related literature.

Stop word Removal

There are words that aren't necessary for activities like classification of sentiment or text categorization, aside from special characters, HTML tags, URLs. Words like I, me, you, he, and others add to the quantity of text data but don't enhance outcomes significantly, thus removing them is a good idea. can utilise a pre-defined collection of stopwords (for example, from Natural Language Tool Kit (NLTK) or another Natural Language Processing (NLP) library) for the task, or it can construct own stopwords depending on specified goal.

Lemmatization

In the context of depression analysis, text normalization plays a vital role in preprocessing textual data to ensure consistency and remove redundancy. Depression-related text data often contains variations of words due to different tenses, plural forms, or other morphological differences. By normalizing these variations to their base or root forms, such as converting "feeling," "feelings," and "felt" to the lemma "feel" the noise in the text is minimized, and the underlying sentiment can be more accurately captured.
This normalization process enhances the effectiveness of sentiment analysis and classification algorithms by providing a standardized representation of depression-related text. It allows for better identification of key sentiments and patterns associated with depression across different textual sources. Overall, text normalization serves as a crucial preprocessing step in depression analysis, enabling more accurate and reliable insights into individuals' mental states and facilitating the development of effective intervention strategies.

3.2. Extraction of features

The unique technique incorporates the acquisition of multi-modal hierarchical embeddings instead of extracting features individually from text, images, and user-related information. This approach systematically incorporates information at several levels of abstraction, effectively capturing intricate connections between textual content, graphic components, and user actions. This enables the program to distinguish complex patterns that could indicate depression across various modalities.

The parameters and depression tweet features are derived from a unique technique that integrates multi-modal hierarchical embeddings, capturing connections between textual content, images, and user actions. The algorithm employs a cross-modal dynamic attention mechanism to adaptively prioritize informative characteristics from each modality. ETS assigns scores to terms based on depression relevance, while Word2Vec maps terms to dense vectors. The MGA optimizes feature selection and combination, and feature fusion integrates information from ETS, Word2Vec, and MGA.

Possible depression tweet features encompass various dimensions of user behavior and content. Textual features may include the frequency of depressive keywords or phrases (e.g., "sad," "lonely," "hopeless"), sentiment analysis scores reflecting negativity (e.g., sentiment score of -0.8 indicating strong negative sentiment), and the use of first-person pronouns (e.g., "I," "me," "myself"). Physiological features might involve the timing and frequency of tweets (e.g., late-night posting or irregular posting patterns), alongside engagement metrics such as interactions with other users (e.g., low frequency of replies or mentions). Behavioral attributes could encompass the topics or themes of tweets (e.g., discussions about loneliness, feelings of despair), linguistic style (e.g., frequent use of negative language, avoidance of future tense), and the frequency of retweets or mentions by other users (e.g., fewer interactions with followers). These features collectively provide insights into users' mental states and may serve as indicators of depression when analyzed comprehensively.

Traditional feature fusion approaches frequently utilize fixed weights to merge information from many modalities. The algorithm presents a novel approach by incorporating a cross-modal dynamic attention mechanism. This mechanism adaptively modifies the influence of each modality according to the contextual information of the data. The purpose of this attention mechanism is to be trained to prioritize the most informative characteristics from each modality for a given input. This training enhances the system's ability to adapt to different user actions and expressions.

Let X be the input dataset containing textual, physiological, and behavioral data samples, represented as $X=\{x_1,x_2,...,x_n\}$, where each xi is a feature vector with dimensions d. The ETS algorithm assigns scores to terms in the textual data based on their relevance to depression. Let Si denote the elite term score for term i in the vocabulary. We can represent the ETS process as:

$$S_i = \frac{\text{Frequency of Term}}{\text{Total Terms}} \quad (1)$$

The Word2Vec algorithm maps each term i in the vocabulary to a dense vector representation V_i in R^m, where m is the embedding dimension. Let W be the word embedding matrix, where $W=[V_1,V_2,...,V_n]$. The Word2Vec process transforms the input textual data into embedded feature vectors:

$$x_i^{''} = \text{Word2Vec}(x_i, W) \quad (2)$$

The MGA optimizes the selection and combination of features extracted by ETS and Word2Vec. Let $F=x_1^{'}, x_2^{'},.......,x_n^{'}]$ be the feature matrix after Word2Vec transformation. The MGA iteratively selects features from F based on their fitness and combines them to form a new feature vector:

$$x_i^{'''} = \text{MGA}(F) \quad (3)$$

Feature fusion integrates information from different sources, combining the feature vectors obtained from ETS, Word2Vec, and MGA. Let $F_{fusion}=[x_1^{''}, x_2^{''},.......,x_n^{''}]$ be the fused feature matrix. The feature fusion process can be represented as:

$$xi''' = \text{Feature}_{\text{Fusion}}(x_i^{'}, x_i^{''}) \quad (4)$$

3.3. Classification

The extracted features are then sent to a Naïve-Bayes classifier to classify the tweets as depression or non-depression. Naïve-Bayes classifiers are probabilistic classifiers. This classification systems are based on the application of Bayes' theorem with a clear independent assumption among the different features. Let's suppose that there's an x_1 to x_n dependent vector and 'y' type variable. In relation to Bayes:

$$p(y)|x_1, \dots\dots, x_n = \frac{P(y)P(x_1,......,x_n|y)}{P(x_1,......,x_n)} \quad (5)$$

Now in relation to assumption

$$P(y, x_1, \dots\dots, x_i - 1, x_i + 1, \dots, x_n) = P(x_i|y) \quad (6)$$

This function becomes for any i,

$$P(x_1, \dots\dots.., x_n) = \frac{P(y)\prod_{i=1}^{n} P(x_i|y)}{P(x_1,......,x_n)} \quad (7)$$

$P(x_1,\ldots,x_n)$is constant on the given input, the classification rules can be applied:

$$\hat{y} = P(y) \prod_{i=1}^{n} P(x_i|y) \quad (8)$$

And for approximation use Maximum-A-Posterior estimation P(y) and P (xi | y).

4. RESULT AND DISCUSSION

The dataset used in this context is the sentiment140 dataset, a comprehensive collection of 1,600,000 tweets obtained through the Twitter API. Each tweet in the dataset is meticulously annotated with sentiment polarity, categorizing tweets into negative, neutral, or positive sentiments denoted by values 0, 2, and 4 respectively. The dataset consists of six essential fields for each tweet entry: "target" indicates the sentiment polarity, "IDs" uniquely identifies each tweet, "date" provides the timestamp of when the tweet was posted, "flag" denotes the query associated with the tweet (defaulting to NO_QUERY if none exists), "user" contains the username of the Twitter account posting the tweet, and "text" encapsulates the actual content of the tweet, showcasing sentiments or opinions expressed by users. With its diverse and meticulously labeled data, the sentiment140 dataset serves as a valuable resource for sentiment analysis tasks, enabling researchers to develop and evaluate models adept at detecting sentiment nuances in natural language expressions across social media platforms like Twitter.

Performance metrics are quantitative measures used to assess the effectiveness and efficiency of a model or system in solving a specific task or problem. In the context of depression analysis or any machine learning task, performance metrics provide valuable insights into how well the model performs in classifying instances as depressive or non-depressive. Key performance metrics include accuracy, which measures the overall correctness of the model's predictions; specificity measures the proportion of true negative instances correctly identified by the model, and sensitivity measures the proportion of actual positive cases correctly identified as positive by the model.

The confusion matrix is used to evaluate the performance of a MGA-NB model. It provides a summary of the predictions made by the model against the actual true labels of the data. The matrix is typically structured as follows:

Predicted Class	**Actual Class**
Positive	TP (True Positives)
Negative	FP (False Positives)

TP = True Positive (Correctly Predicted as Depression)
TN = True Negative (Incorrectly Predicted as non-depression)
FP = False Positive (Incorrectly Predicted as Depression)
FN = False Negative (Correctly Predicted as non-depression)

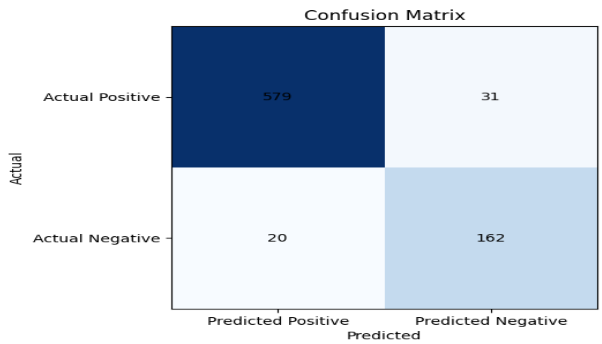

Figure 2. Confusion Matrix

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (10)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (11)$$

Table 1. Comparison of Accuracy, Specificity, Sensitivity

Epoch	Accuracy		Specificity		Sensitivity	
	NB	MGA-NB	NB	MGA-NB	NB	MGA-NB
50	80.86	93.22	0.786	0.898	0.81944	0.944672
100	80.89	93.8	0.789	0.901	0.77546	0.935927
150	79.95	93.23	0.806	0.91	0.85688	0.935108
200	81.59	93.16	0.821	0.934	0.79596	0.933194
250	80.05	93.56	0.875	0.965	0.87897	0.966611

Comparison of Accuracy

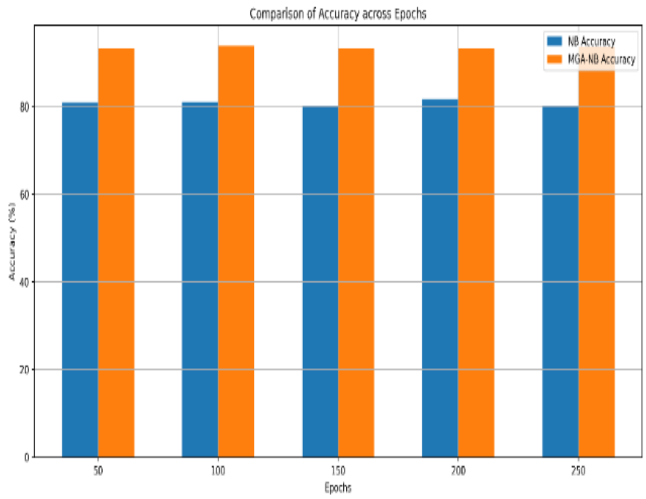

Figure 3. Comparison of Accuracy

Across all epochs, the MGA-NB model consistently achieves higher accuracy compared to the NB model. The MGA-NB accuracy ranges from 93.16% to 93.80%, whereas the NB model's accuracy fluctuates between 79.95% and 81.59%. This demonstrates that MGA-NB significantly improves classification performance over the NB model.

Comparison of Specificity

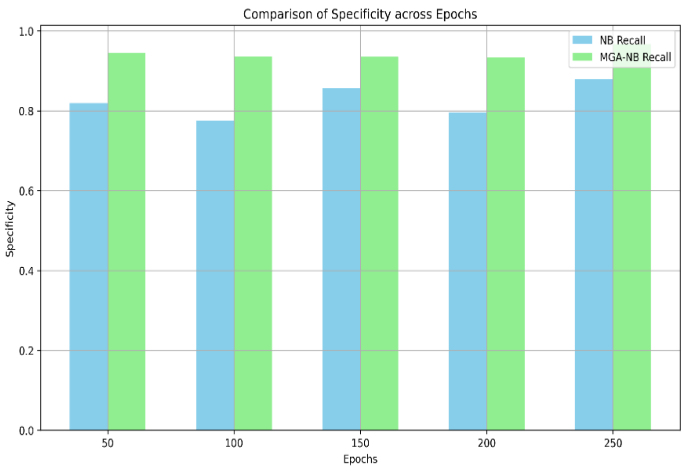

Figure 4. Comparison of Specificity

The MGA-NB model consistently outperforms the NB model in specificity across all epochs. Specificity measures the ability to correctly identify non-depressive cases,and the results show that MGA-NB has higher specificity,ranging from 0.898 to 0.965, compared to the NB model's range of 0.786 to 0.875, showcasing a significant improvement in classification performance.

Comparison of Sensitivity

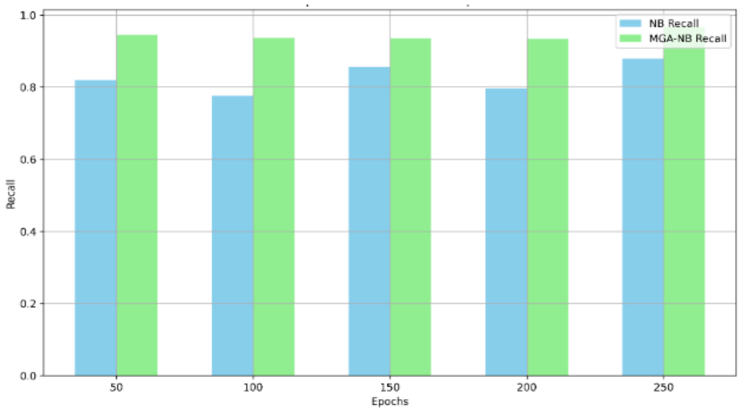

Figure 5. Comparison of Sensitivity

The MGA-NB model consistently exhibits higher sensitivity compared to the NB model across all epochs. MGA-NB sensitivity ranges from 0.933194 to 0.966611, while NB sensitivity ranges from 0.775463 to 0.878968. This indicates that MGA-NB is significantly better at identifying true positives, thus improving its ability to correctly detect relevant instances.

5. CONCLUSION

This research introduces an innovative framework for depression analysis leveraging advanced sentiment analysis techniques applied to Twitter data. Through the integration of methods such as Elite term score, word2vec, and a modified Genetic Algorithm for feature extraction, the study endeavours to refine the accuracy of depression detection. Employing a Naïve Bayes (NB) classifier and feature fusion strategies, the framework demonstrates promising outcomes in categorizing sentiments related to depression. By addressing the societal challenges associated with mental health disorders, the proposed methodology offers potential applications in early intervention and personalized treatment plans, contributing significantly to the field of mental health analysis. However, further exploration is warranted to enhance the robustness of the approach, including the incorporation of additional machine learning algorithms and ethical considerations surrounding mental health analysis on social media platforms.

However, future exploration in to involve the integration of deep learning models such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs) to uncover more intricate patterns within social media data. Additionally, the incorporation of multimodal data sources, including text, images, and user interactions, could provide a more comprehensive understanding of individuals' mental states.

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