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Soft computing and natural language processing to determine the physiological behaviour for analysing mental disorders

Mukesh Chandulal Jain, Dr. Farha Haneef

[1]Oriental University, Indore, Madhya Pradesh, India, mukesh.ch.jain@gmail.com
[2]Oriental University, Indore, Madhya Pradesh, India, farhahaneef2014@gmail.com

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ABSTRACT

Understanding mental health problems and their root causes relies heavily on the interpretation of psychological behavior. This research emphasizes the potential of employing natural language generation (NLG) and machine learning (ML) techniques, such as BERT (Bidirectional Encoder Representations from Transformers) and LDA (Latent Dirichlet Allocation), to identify various psychological behaviors, including depression, loneliness, anxiety, and normal behavior. By scrutinizing and comprehending linguistic features, encompassing syntactic, semantic, and psychological aspects, the algorithms demonstrated remarkable accuracy in predicting psychological behavior and mental disorders. These findings hold significant implications for the field of psychology and mental health by offering novel tools to detect and comprehend psychological disorders. In essence, this study underscores the importance of utilizing advanced computational techniques like NLG and ML to analyze intricate data for determining the mental health of individuals. This approach facilitates new insights into human behavior and aids in developing more precise and effective interventions for psychological disorders. The capability to interpret psychological behavior holds crucial implications for mental health and well-being. Given the prevalence of mental health issues in society, early detection and treatment play a pivotal role in enhancing outcomes. This has motivated us for this research study. By analyzing and interpreting psychological behavior using NLG and ML techniques, the proposed research assists in identifying the early warning signs of mental health problems by understanding the psychological behavior of the target audience.

Keywords: Psychological Analysis; Language Schema; Machine learning; Formal Schema; Translation Skills.

1. INTRODUCTION

Understanding the mental well-being of college students has become an increasingly important concern in today's society. As the pressures and challenges faced by young individuals continue to evolve, it is imperative that we develop effective methods to assess and address mental disorders that may arise during this critical phase of life. In this context, the integration of soft computing and natural language processing (NLP) has emerged as a promising approach for comprehensively analyzing the physiological behavior of college students and identifying potential mental health disorders [1]. College life is a transformative period, characterized by newfound independence, academic rigor, social dynamics, and personal growth. While this phase offers tremendous opportunities for self-discovery and development, it can also expose students to unique stressors and challenges. Balancing academic responsibilities, extracurricular activities, personal relationships, and future uncertainties can take a toll on their mental well-being.

The understanding of psychological behavior is crucial in order to comprehend an individual's mental state. Mental health problems are pervasive in society and affect a substantial portion of the population. Diagnosing and treating these problems can be challenging, as they manifest in various ways and stem from diverse factors [2]. Through the interpretation of psychological behavior, we can gain valuable insights into the root causes of mental health issues and develop effective treatments and therapies that specifically target those causes. Additionally, interpreting psychological behavior can aid in the early identification of potential mental health problems before they worsen [3]. Early detection is pivotal in addressing mental health issues, as prompt identification increases the likelihood of successful intervention [4]. By analyzing and interpreting psychological behavior, we can recognize early warning signs of mental health problems and take appropriate measures to prevent their escalation. Furthermore, the interpretation of psychological behavior can contribute to the reduction of stigma associated with mental health problems [5]. There is often a significant social stigma

surrounding mental health issues, which can hinder individuals from seeking help when needed [6]. By enhancing our understanding of the underlying causes of mental health problems, we can develop more compassionate and supportive approaches to mental healthcare, thereby diminishing the stigma that surrounds mental illness. The field of mental health has always been a critical area of research and development. The advancement of ML and NLP technologies has paved the way for the use of intelligent algorithms in the analysis and interpretation of psychological behavior [7]. The use of natural language generation (NLG) techniques in combination with machine learning provides a promising approach for the analysis and interpretation of psychological behavior data [8]. NLG refers to the automatic generation of natural language text based on input data, which can be used to generate reports, summaries, or other forms of text-based output. The application of machine learning to the field of psychology and mental health has the potential to revolutionize the way we diagnose and treat mental health disorders [9]. With the help of machine learning, it is now possible to analyze vast amounts of data related to psychological behavior, including speech, text, and other forms of communication. Machine learning algorithms can identify patterns and relationships in these data sets, enabling researchers to develop more accurate models for predicting and diagnosing mental health disorders [10]. Furthermore, machine learning can be used to personalize treatment plans based on an individual's unique psychological behavior patterns. The research proposed a multi-modal neural network model to automatically analyze the textual and visual features of social media data for psychological stress recognition [11]. The research contributed to the development of an effective method for stress detection using NLP techniques. The study presented a new ML approach to predict depression and stress using social media data [12]. The research proposed a novel feature extraction method and an ensemble learning technique to improve the prediction accuracy. The study contributed to the development of a more accurate and efficient method for depression prediction using the data available on social media. The research proposed a deep learning-based method for emotion detection using physiological signals [13]. The study contributed to the development of a more accurate method for emotion detection, which can be considered a useful tool in understanding psychological behavior. The study proposed a deep learning-based approach for detecting depression in social media data [14]. The research contributed to the development of a more effective and accurate method for depression detection using ML and NLP techniques. The research proposed a new ML approach for predicting suicidal ideation in social media data [15]. The study proposed a new feature extraction method and ML-based classification model to improve the prediction accuracy. The research contributed to the development of a more accurate and efficient method for predicting suicidal ideation using social media data.

In [16], the paper provides an overview of the recent advancements in Natural Language Generation (NLG) technology in the field of psychological counseling. It discusses the current state of the art, challenges, and future directions for the use of NLG in mental health counseling. In [17], paper presents an ML-based model for automatic diagnosis of personality disorders using textual data. It uses text processing techniques to extract relevant features from text data and trains a machine learning model to predict the presence of personality disorders. In [18], the paper presents a machine learning model for predicting major depression based on social media data. It uses NLP techniques to analyze social media posts and predicts the presence of depression using ML model. In [19], the article proposes a DL-based approach for automatic detection of mental health status from social media data. It uses NLP techniques and DL algorithms to predict the presence of mental health issues from social media posts.

Impact of content schema on interpretation of psychological behaviour

The influence of content schema on translation abilities can be described in many ways for ascertaining psychological behavior. Translators with a robust content schema have a greater comprehension of domain-specific vocabulary, allowing them to translate the material properly and to analyse the psychological behavior from the gestures and language. It also helps to understand the subtleties of the language for better interpretation of the psychological behaviour. The robust content schemas are more likely to be culturally sensitive, which is essential when translating literature for a particular audience. It comprehends the cultural intricacies of the target language, including conventions, traditions, and values, allowing the machine intelligence based language processing model to generate a suitable translation for interpreting the behaviour. Translating writings with complex subject matter demand an in-depth comprehension of the subject to understand the mental disorders. Translators with a robust content schema are better able to grasp complicated subjects and deliver the required meaning in the target language. A robust content schema also helps translators to express the intended meaning of the original context with more precision. The content schema can understand and comprehend complicated structures, specialist terminology, and cultural allusions, resulting in a better degree of translation accuracy for analysing mental disorders. The translators with a strong content schema are able to work more effectively. This helps to provide faster and more accurate translations of the psychological behaviour, which is advantageous for customers that want rapid response times.

A significant amount of content is always exerted by psychological elements from a conversation [20]. This study focuses primarily on analysing the psychological aspects of psycholinguistics that are relevant to the process of translating or interpreting the variables that impact the adoption of translation skills [21]. To be more explicit, the psychological characteristics that are thought to be contributing variables in selecting translation skills are referred to as language schema, content schema, and formal schema. There is not a great deal of data available on ideas for the translators and interpreters involved in the translation process; nonetheless, there is the possibility that some disclosures regarding mental

health can be provided for the translators and interpreters for analysing psychological behaviour. The use of NLG in combination with machine intelligence can enhance the effectiveness of the analysis and interpretation of psychological behavior data [22].

Objectives of the study

- By integrating NLG with machine intelligence, the research seeks to improve the effectiveness of analyzing and interpreting psychological behavior data. This combination can provide valuable insights into the underlying causes of mental health disorders, enabling mental health professionals to make more informed treatment decisions.
- The proposed research intends to utilize NLG techniques to generate natural language text that assists in developing personalized treatment plans. By considering an individual's unique psychological behavior patterns, NLG can contribute to tailoring treatment approaches to specific needs, potentially leading to more effective outcomes.
- The proposed study aims to use NLG to generate comprehensive reports and summaries of patient data. These outputs can be utilized to track the progress of individuals undergoing treatment and to restore the mental health of patients.
- By combining NLG and machine intelligence, the research envisions a transformative impact on the field of mental health. The proposed approach has the potential to revolutionize mental health practices and improve the lives of countless individuals globally.
- The research also seeks to utilize NLG and machine intelligence approaches to interpret psychological behavior, with the broader objective of controlling mental health stigma.

By generating natural language text, NLG techniques can provide insights into the underlying causes of mental health disorders and help mental health professionals make informed treatment decisions. NLG can be used to generate personalized treatment plans that take into account an individual's unique psychological behavior patterns. Additionally, NLG can be used to generate reports and summaries of patient data, which can be used to track progress and make adjustments to treatment plans as needed. In nutshell, the combination of NLG and machine intelligence has the potential to revolutionize the field of mental health and improve the lives of millions of people around the world. Hence, this research is proposing NLG and ML based approaches to interpret the psychological behavior of the persons to analyze their mental state and to control mental stigma in youngsters.

2. PROPOSED METHODS

This research study aims to use the integration of Natural Language Generation (NLG) with machine intelligence to advance the effectiveness of the analysis and interpretation of psychological behaviour. By combining NLG techniques with machine intelligence, this study seeks to provide valuable insights into the underlying causes of mental health disorders. One of the key objectives of this proposed research is to utilize NLG techniques to generate natural language text that can aid in the development of personalized treatment plans. By considering an individual's unique psychological behaviour patterns, NLG has the potential to contribute to tailoring treatment approaches to specific needs. This personalized approach has the potential to greatly improve the quality of care and provide better results for individuals seeking mental health support. The integration of NLG and machine intelligence is envisioned to have a transformative impact on the field of mental health. This proposed approach has the potential to revolutionize mental health practices and improve the lives of countless individuals globally. By harnessing the power of NLG and machine intelligence, mental health professionals can more effectively interpret psychological behaviour. This section elaborates the proposed methodology in a step by step approach.

2.1 Parameters for data collection

The dataset used to determine mental disorders includes various factors that provide insights into an individual's mental health. The prime parameters are illustrated below.

a) **Symptomatology factors:** Information about specific symptoms experienced by individuals is crucial in determining mental disorders [21]. This includes symptoms such as sadness, anxiety, sleep disturbances, irritability, and changes in appetite.
b) **Behavioural patterns:** Observations of behavioural patterns are also considered to identify mental disorders [12]. This includes information on social withdrawal, impulsivity, agitation, self-harm, and substance abuse.
c) **Self-reported assessments:** Questionnaires completed by individuals provide valuable self-reported data about their mental well-being. This assessment includes standardized measures specifically designed to evaluate mental health conditions, such as depression, anxiety, or stress levels.
d) **Medical and family history:** Information about an individual's medical history, including any previous mental health diagnoses can provide context for understanding current mental health concerns [13]. Additionally, family history of mental disorders is taken as binary information "yes" or "no" to indicate potential genetic risk factors.
e) **Life events and stressors**: Significant life events, traumatic experiences, and chronic stressors contribute to the exacerbation of mental disorders [14]. These factors can help assess their impact on an individual's mental health.
f) **Social factors:** The presence or absence of a supportive social network, including family, friends, or community, influence an individual's mental well-being. Data on the quality of social support also provides insights into their

resilience and potential risk for mental disorders.

g) **Demographic information**: Factors such as age, gender, ethnicity, socioeconomic status, and educational background plays a role in determining mental health. Analysing demographic data in conjunction with other factors helps in identifying the patterns and disparities related to specific mental disorders.

2.1 Natural Language Generation (NLG) for interpretation of mental disorders

NLG is a rapidly developing area of artificial intelligence that involves generating natural language text using automated systems. It involves the use of algorithms that analyse and understand data, which is then translated into human-readable language [19]. NLG has numerous applications in various fields, such as healthcare, customer service, and journalism. In recent years, NLG has gained significant attention in the field of psychology due to its potential in analysing and interpreting psychological behaviour data. The use of machine intelligence s has revolutionized the field of psychology by providing new ways to analyse and understand human behaviour [20]. The NLG techniques have the potential to further enhance this understanding by providing a way to generate human-readable text based on the analysis of psychological behaviour data. This text is then be used to gain insights into human behaviour, develop new therapeutic interventions, and provide support to mental health professionals. NLG exhibits significant impact on psychology during the analysis of clinical data [21]. Clinical data, such as patient notes, can be complex and difficult to interpret, and NLG can provide a way to summarize and make sense of this data. NLG can also be used to provide personalized feedback to patients, helping them to better understand their mental health and develop new coping strategies. The use of NLG in psychology has been explored in this research to exploit its potential to revolutionize the field of psychology and to provide new insights and therapeutic interventions for mental health.

NLG is used with the aid of **LDA (Latent dirichlet allocation)** to interpret psychological behaviour:

Step 1: Data Collection and Pre-processing

The first step is to collect data in the form of text or speech from the individual. This data is collected from various sources, such as social media posts, emails, chat messages, or transcribed speech. Once the data is collected, it needs to be pre-processed to remove any irrelevant or sensitive information [22], such as personally identifiable information or profanity. This pre-processing step can also involve converting the data into a standardized format and cleaning it up to remove any spelling or grammatical errors.

Step 2: Feature Extraction

The next step is to extract linguistic features from the pre-processed data. This involves identifying and extracting different linguistic patterns and styles from the text, such as word choice, sentence structure, and use of metaphors [23]. There are various techniques and algorithms available for feature extraction, such as part-of-speech (POS) tagging, named entity recognition (NER), and sentiment analysis. We have used POS method in our research study.

Step 3: Linguistic Style Analysis (LSA)

Once the linguistic features are extracted, the next step is to perform LSA to interpret psychological behavior. This involves analyzing the linguistic features and patterns to identify specific traits or characteristics of the individual, such as their personality, cognitive processes, and emotional state. There are various techniques available for LSA, and we have used machine intelligence approaches for analysis such as LDA and BERT. The LSA is a valuable tool for interpreting psychological behavior from language, as it provides a detailed understanding of an individual's linguistic style and patterns of language use [24]. By analyzing an individual's language in this way, it can help identify potential mental health issues, cognitive processes, and personality traits, which can inform treatment and interventions.

Step 4: NLG for Reporting and Interpretation

Once the LSA is completed, the final step is to use NLG to generate reports and summaries that interpret the results of the analysis in a way that is easy to understand for psychologists and mental health professionals. This involves using ML algorithms to generate natural-sounding human language that summarizes the linguistic features and patterns of the individual and provides insights into their psychological behaviour. These reports are customized based on the specific needs of the psychologist or mental health professional and can include recommendations for interventions and treatments. The NLG is a powerful tool for interpreting psychological behaviour from language by using LSA. The psychological behaviour can be analysed to draw further inferences regarding the mental ailments.

2.2 LDA based approach

The objective here is to develop a model based on LDA to identify and determine mental disorders. LDA is a statistical topic modeling technique that can uncover latent topics within a collection of data. In this study, LDA is applied to analyze psychological behavior data and identify patterns related to different mental disorders.

- Theme identification: The LDA-based model is employed to identify latent themes within the psychological behavior data. By analyzing the content, structure, and patterns of the data, the model can uncover underlying topics that are associated with various mental disorders such as depression, loneliness, anxiety or normal behaviour.

Let D be the dataset consisting of N samples, each represented by a textual description D_i.

Each sample D_i is associated with a corresponding label L_i, where $L_i \in$ {depression, loneliness, anxiety, normal}.

The LDA model aims to discover underlying topics in the textual data and their distribution across the dataset.

The number of topics/themes, denoted by K, is predefined.

Let θ_i denote the topic distribution for the i^{th} document, D_i.

Let φ_k denote the word distribution for the k^{th} topic, where $k \in \{1, 2, ..., K\}$.

- Model Parameters:

Θ represents the set of topic distributions, $\{\theta_1, \theta_2, ..., \theta_n\}$.
Φ represents the set of word distributions for each topic, $\{\varphi_1, \varphi_2, ..., \varphi_K\}$.

- Model Inference:

The topic distribution, θ_1, for each document D_i is inferred using Bayesian inference methods, such as variational inference.
The word distribution, φ_k, for each topic is estimated using statistical estimation technique.

- Mental disorder classification: The identified topics are linked to specific mental disorders. The model assigns probabilities or scores to each topic, indicating the likelihood of a particular mental disorder being present based on the observed topics in the data.
  - To classify a new document, D_{new}, its topic distribution, θ_{new}, is inferred using the learned model parameters.
  - The predicted label, Y_{new}, for the new document can be determined based on the highest probability topic(s) in θ_{new}.
  - Training and Evaluation:
  - The LDA model is trained using a labeled dataset, where the true labels are used to guide the learning process.

- Diagnostic tool development: The LDA-based model is used to develop a diagnostic tool that can assist mental health professionals in identifying and diagnosing mental disorders. By inputting psychological behavior data into the model, it generates predictions regarding the presence of specific mental disorders.
- Validation: The effectiveness of the LDA-based model is assessed through validation processes. This involves comparing the model's predictions with established diagnostic criteria to determine its reliability in determining mental disorders.

By utilizing LDA as a basis for the model, this research aims to provide a novel approach to identifying the mental disorders based on the analysis of psychological behavior data.

2.3 BERT based prediction of psychological behavior

The objective here is to develop a BERT-based model for identifying psychological disorders and classifying them into four categories: depression, loneliness, anxiety, and normal behavior. BERT is a pre-trained language model that can understand the context and meaning of text. The BERT-based model is used for the prediction of psychological behavior. The model uses the power of Bidirectional Encoder Representations from Transformers (BERT), a state-of-the-art language representation model, to capture the contextual information and semantic relationships within psychological behavior data.
The dataset is compiled that includes text samples and descriptions as mentioned earlier in this paper, related to individuals' psychological behavior. The dataset is labeled with the four target classes.
Let's denote our input dataset as $D = \{(x_1, y_1), (x_2, y_2), \ldots\ldots (x_n, y_n)\}$ where $x_1$represents the input text sequence and y_1 represents the corresponding psychological behavior label. Each input text sequence xi is tokenized into a sequence of tokens $[x_1, x_2, \ldots\ldots x_m]$ using BERT's tokenizer.
BERT consists of a multi-layer transformer architecture that incorporates a self-attention mechanism, enabling the model to capture dependencies between different words in the input sequence. The self-attention mechanism allows each token to attend to all other tokens, capturing both local and global contextual information. Formally, let's denote the BERT model as F, which takes an input sequence $[x_1, x_2, \ldots\ldots x_m]$ and outputs a sequence of hidden states$[h_1, h_2, \ldots\ldots h_m]$. Each hidden state hi captures the contextual representation of the corresponding tokenx_1.
To perform the prediction of psychological behavior, we introduce a task-specific prediction layer on top of BERT. The prediction layer is typically a feed-forward neural network with two fully connected layers followed by a Softmax activation function.
Let's denote the prediction layer as G, which takes the hidden states$[h_1, h_2, \ldots\ldots h_m]$ as input and outputs the predicted probabilities for each class label. The predicted probability distribution is given by$P(y_1|x_1) = G([h_1, h_2, \ldots\ldots h_m])$, where $P(y_1|x_1)$ represents the probability of predicting label y_1 given the input sequence x_1.
The pre-trained BERT has to be fine-tuned using the prepared dataset. This process involves training the model on the balanced dataset of classifying psychological behavior into the four designated classes. Fine-tuning adapts the general language understanding capabilities of BERT to the specific classification task for determining mental disorders.
The fine-tuned BERT model is utilized to extract relevant features from the textual input. BERT is able to capture both syntactic and semantic information, allowing for a comprehensive representation of the psychological behavior descriptions.
During the training phase, we employ a cross-entropy loss function to optimize the model parameters. The loss is calculated as the negative log-likelihood of the true label distribution. The model parameters are updated using backpropagation and gradient-based optimization algorithms such as Adam. To make predictions on an unseen data, we feed the input sequence through the BERT model, obtain the hidden states, and pass them to the prediction layer. The

prediction layer outputs the predicted probabilities for each class label, allowing us to classify the psychological behavior of the input text sequence.
The extracted features are inputted into a classification layer, which maps the features to the four target classes: depression, loneliness, anxiety, and normal behavior. The model is then make predictions based on these learned representations, assigning each input to one of the four classes.
The performance of the BERT-based model is evaluated using appropriate metrics. This assessment provides insights into the model's effectiveness in classifying psychological disorders. The BERT-based prediction model offers several advantages, including its ability to capture the contextual semantics of psychological behavior data and its flexibility to handle various text sequences of different lengths.
By using the power of NLG and machine intelligence, this research aims to develop a robust and accurate model for identifying and classifying psychological disorders into the specified categories. The outcomes of this study can contribute to improved diagnostic processes and targeted interventions in the field of mental health.

3. RESULTS AND INTERPRETATIONS

The dataset used for training in this research possesses several key characteristics that contribute to its relevance for understanding psychological behavior. Firstly, the dataset was carefully curated to include a diverse range of text-based data that is directly related to psychological behavior. This includes sources such as therapy sessions, online forums, or social media interactions, which capture authentic and real-world expressions of individuals' psychological experiences. By incorporating such a varied dataset, the research study aims to capture a wide spectrum of psychological behavior, allowing for a comprehensive analysis. Additionally, the dataset includes annotations that categorize the psychological behavior into relevant classes, such as depression, loneliness, anxiety, and normal behavior. These labels enable the supervised training of machine learning algorithms, allowing them to learn patterns and associations between linguistic features and specific psychological conditions. The labeled dataset thus provides a foundation for training the algorithms to accurately interpret and classify psychological behavior based on known categories.
NLG and ML methods such as LDA and BERT are used to identify psychological behavior from linguistic analysis. Linguistic style analysis is a technique that has been used with NLG to analyze language and identify patterns associated with psychological behavior of individuals. When evaluating ML algorithms for identifying psychological behavior from linguistic analysis, it is important to use appropriate evaluation metrics such as accuracy, precision, recall, F1 score, AUROC, and confusion matrix. The choice of evaluation metrics is made based on our goals of the analysis. The schema networks in our mind are based on the premise that we have a comprehensive grasp of a large amount of information in source and target languages.
The diversified factors such as transplantation, extension, substitution, explanation, combination, transliteration, pictographic translation, conversion, amplification, and omission at the lexical level, and amplification, omission, restructuring, conversion, combination, division, mixture, and embedding at the syntactic level, can be skilfully adopted by the machine intelligence based model because these factors have influence on the choices of the psychological behaviour of an individual . The dataset has target variables such as depression, loneliness, anxiety and normal behaviour.

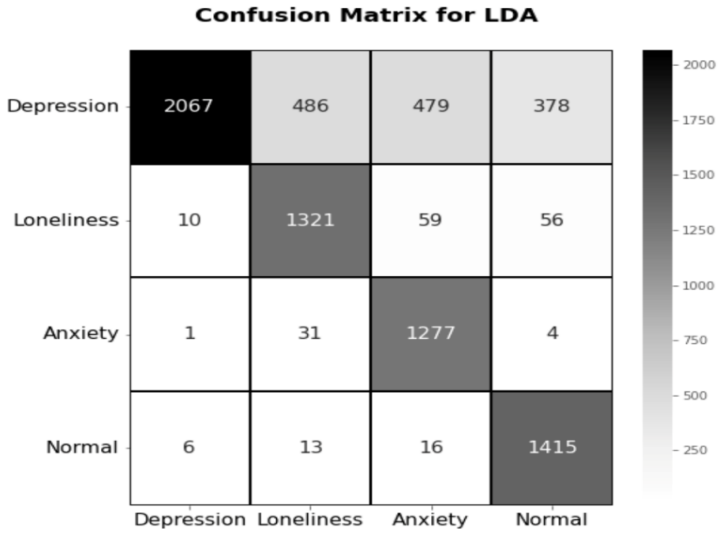

Figure 2. Confusion matrix for LDA based identification of psychological behaviour

Two ML approaches LDA and BERT are devised for the linguistic analysis and the results are shown for LDA based identification of psychological behaviour based on four target variables as shown in Figure 2. The LDA based model is able to predict the results with great accuracy by classifying the psychological behaviour into four classes such as depression, loneliness, anxiety and normal behaviour. The person is suffering from mental conditions if the classification does not fall under normal category. For all other classes, the person needs assistance from a psychiatrist or healthcare professional.

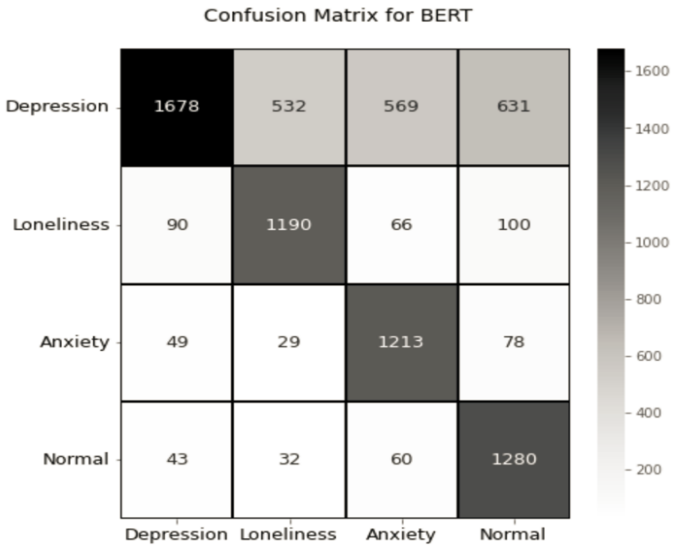

Figure 3. Confusion matrix for BERT based identification of psychological behaviour

BERT is a powerful ML algorithm that is particularly well-suited for tasks that involve understanding the context and meaning of text. BERT is used for a variety of tasks related to psychological behaviour, such as personality prediction, sentiment analysis, and emotion detection but in our study it is making the linguistic analysis for identifying the psychological problems in individuals and Figure 3 shows that BERT is able to predict the classes of mental states very well with great accuracy of 95%.

Figure 4 illustrates the precision, recall, and F1-scores obtained by the BERT and LDA models for classifying psychological disorders. The precision value for BERT is 0.91, indicating that out of all the instances predicted as positive, 91% were correctly classified. Similarly, the precision value for LDA is 0.94, indicating a slightly higher accuracy in correctly identifying psychological disorders. The recall score measures the model's ability to identify all the positive instances correctly. BERT achieved a recall score of 0.88, indicating that it correctly identified 88% of all positive instances for psychological disorders. On the other hand, LDA achieved a higher recall score of 0.93, indicating a better ability to capture a larger proportion of positive instances. The F1-score combines precision and recall into a single metric, providing a balanced evaluation of the model's overall performance. BERT achieved an F1-score of 0.9, representing a harmonic mean of precision and recall. LDA, on the other hand, obtained an F1-score of 0.93, indicating a better balance between precision and recall.

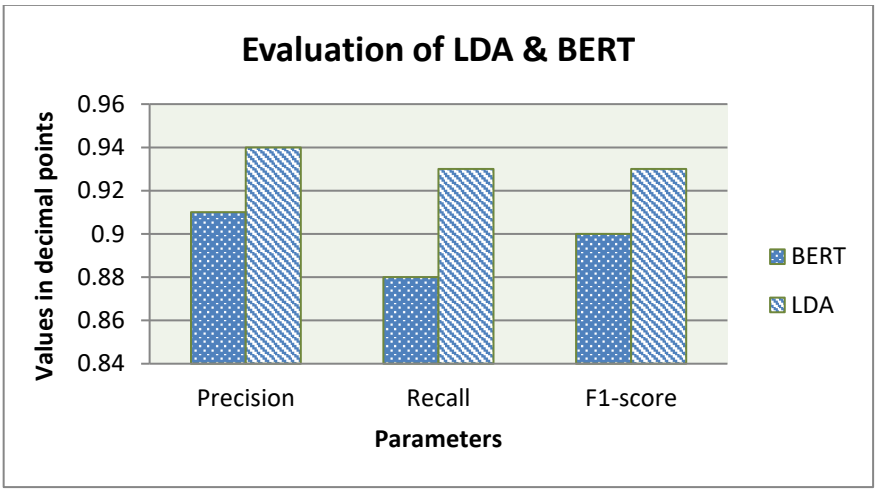

Figure 4. Evaluation of performance of LDA and BERT

These scores suggest that both BERT and LDA models are performing well in classifying psychological disorders, with LDA generally demonstrating slightly higher precision, recall, and F1-scores compared to BERT. It is worth noting that the precision, recall, and F1-scores are key evaluation metrics that assess the performance of the models in correctly classifying psychological disorders. Higher scores indicate better accuracy and effectiveness in identifying the target psychological disorders. The NLP and ML are the powerful tools for identifying psychological behaviour from linguistic analysis

The schema in psycholinguistics mainly refers to the knowledge existing in human beings' minds. Schemata are a group of "interactive knowledge structures" or "building blocks constituting cognitive ability" stored in long-term memory in the form of hierarchy. In the process of translating and interpreting, the language schema, content schema, and formal schema in SL and TL need to be activated to understand the source language and then comprehend the meaning of the

source and familiarise themselves with the available knowledge reflected in source language before transferring them into target variables. The use of NLG and ML for analyzing psychological behavior from linguistic analysis can provide valuable insights into human behavior, and has the potential to improve our understanding and treatment of psychological disorders.

4. DISCUSSION

The study employed NLG, BERT, and LDA techniques to identify and understand psychological behavior related to mental disorders, specifically focusing on four classes: depression, loneliness, anxiety, and normal behavior. By using NLG and machine intelligence-based methods such as BERT and LDA, the study aimed to enhance the analysis and interpretation of psychological behavior data. The findings of the study hold significant implications for the field of psychology and mental health. The results demonstrated that NLG and machine learning techniques, namely BERT and LDA, yielded accurate and reliable predictions of psychological behavior through linguistic analysis. The study utilized a diverse range of linguistic features, including syntactic, semantic, and psychological features, to train the ML algorithms BERT and LDA. Evaluation of the models was performed using standard metrics, including precision score, accuracy, and confusion matrix.

BERT achieved a commendable recall score of 0.88, indicating its ability to correctly identify 88% of positive instances for psychological disorders. On the other hand, LDA outperformed BERT with a higher recall score of 0.93, indicating its superior capability in capturing a larger proportion of positive instances in psychological behavior categorization. By harnessing the potential of NLG and machine intelligence techniques like BERT and LDA, we have gained deeper insights into human behavior and effective interventions for psychological disorders. The utilization of these techniques holds promise for advancing the field of psychology and mental health, facilitating early detection of mental health problems. However, further research and validation on larger and more diverse datasets will be performed in future to enhance the generalizability and robustness of these models for real-world applications.

5. CONCLUSION

In conclusion, the study has utilized NLG and machine intelligence based techniques such as BERT and LDA to identify psychological behavior based on four classes: depression, loneliness, anxiety, and normal behavior. BERT and LDA are utilized for analyzing and interpreting psychological behavior data in order to identify and understand mental disorders. The findings of the study have important implications for the field of psychology and mental health. The study outcome suggests that the use of NLG and machine learning can provide accurate and reliable predictions of psychological behavior from linguistic analysis. The study uses a variety of linguistic features to train the ML algorithms LDA and BERT, including syntactic, semantic, and psychological features. The algorithms are evaluated using standard evaluation metrics such as precision score, accuracy, and confusion matrix. The study highlighted the potential of NLG and machine intelligence based techniques, such as BERT and LDA, in enhancing the analysis and interpretation of psychological behavior data. BERT achieved a recall score of 0.88, indicating that it correctly identified 88% of all positive instances for psychological disorders and LDA achieved a higher recall score of 0.93, indicating a better ability to capture a larger proportion of positive instances of psychological behaviour categorization. LDA has obtained an F1-score of 0.93, indicating a better balance between precision and recall. The result outcome suggests that both BERT and LDA models are performing well in classifying psychological disorders. In future, we will attempt to use more diverse and large datasets to analyze the robustness of the proposed models for real world applications of psychological disorders.

6. COMPLIANCE STATEMENTS

Conflicts of interest: The authors have no conflicts of interest to declare.
Ethical Approval: Not applicable for this research study.
Data Accessibility: Data is accessible through a valid request.

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