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Assessing the Accuracy of Logistic Regression and Bert in Sentiment Analysis and Mental Disorder Classification

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Abstract: *Sentiment analysis leverages machine learning and natural language processing techniques to classify and interpret textual data, identifying sentiments as positive, negative, or neutral. This study explores sentiment analysis in the context of mental health, utilising two models: Logistic Regression and Bidirectional Encoder Representations from Transformers (BERT). The dataset comprises 52 680 unique statements associated with seven mental health statuses, including depression, anxiety and suicidal tendencies. Logistic Regression achieved an accuracy of 72%, while BERT, with its advanced deep learning architecture, demonstrated a significant improvement with an accuracy of 84%. BERT's superior performance is attributed to its bidirectional contextual understanding and attention mechanisms, enhancing its ability to handle complex and nuanced textual information. This study highlights the efficacy of BERT over traditional models in analysing and classifying sentiments related to mental health, underscoring its potential for improving early detection and intervention.*

Keywords: *Sentiment Analysis, Machine Learning, Natural Language Processing, Deep Learning, Mental Health, Contextual Understanding*

1. Introduction

Mental disorders are conditions that affect cognition, emotion, and behavioural control, impairing children's ability to learn and adults' ability to function in their families, businesses, and society as a whole. These medical conditions frequently manifest early in childhood and have a chronic and recurring pattern. Mental disorders contribute significantly to the disease burden due to their high prevalence, early onset, persistence, and limitations [1]. In developed countries, anxiety dis- orders are the most prevalent mental health disorders. They include concerns that are related to structural disorders, neurotic fears, and legitimate actual fears [2]. Fear is an immediate alarm re- sponse to current or imminent risk, actual or perceived, whereas anxiety is a mood state focused on future-oriented concerns, planning for possible unpleasant outcomes [3]. Approximately 3% of the

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worldwide population suffers from bipolar disorders, a severe category of mood disorders marked by the occurrence of both manic or hypomanic episodes and depressive episodes. Although there is a strong family component to many disorders, environmental variables are also quite important [4]. A diverse range of disorders with differing symptoms and probably distinct origins are to- gether referred to as depression. Depressed mood, lack of enjoyment, difficulty paying attention, low energy, disturbed sleep or nutrition, feelings of guilt or worthlessness, and suicidal thoughts are common symptoms. Psychosocial complaints frequently include personality disorders (PD), especially in young adults. PD is associated with low self-esteem, diminished abilities to work and love, and recurrent stressful reactions that drive medical attention [5]. Suicidal ideas, intentions, and attempts are extremely upsetting and are frequently connected to severe sadness, pessimistic future outlooks, and a mental health issue diagnosis [6]. These conditions are all categorised as mental disorders.

Sentiment analysis is a technique that uses machine learning, natural language processing, and computational linguistics to automatically determine the sentiment expressed in text [7], [8]. It typically categorizes opinions as positive, negative, or neutral and can be applied at sentence, document, or feature levels [8]. Common applications include analyzing product reviews, social media content, and public perception of events [7]–[9]. The process involves extracting informa- tion from sentiment-laden words, their context, and linguistic structure [10]. Two main approaches are machine learning and lexicon-based methods [11]. Sentiment analysis aids organizations in decision-making and product improvement [11], [12]. However, challenges persist, such as do- main adaptability, accuracy with limited labeled data, and handling complex sentences [8]. Despite these issues, sentiment analysis remains a valuable tool for mining opinions and emotions across various domains [7].

Natural Language Processing (NLP) is a field of computer science and artificial intelligence fo- cused on enabling computers to understand, interpret, and generate human language [9], [13]. It is crucial for bridging the gap between human communication and machine comprehension, with applications in various domains such as machine translation, text summarising and speech recognition [9], [14]. NLP has evolved from rule-based approaches to advanced techniques like machine learning and deep learning [14]. Its importance is evident in healthcare, where it helps transform unstructured text into structured data for improving patient care and advancing medi- cine [10]. Despite challenges like understanding context and cultural nuances, NLP continues to transform human-computer interactions and find applications in diverse fields, including finance, education, and customer service [15]. Ongoing research aims to address obstacles and advance the field further [10], [16].

The complex clinical presentations and overlap of symptoms make diagnosing mental disorders difficult. Misdiagnosis can occur when distinct conditions share similar symptoms, and the pro- cedure is made more challenging by knowledge gaps. Therefore, in order to enhance the diagnosis process, cutting edge technologies like artificial intelligence are making their way into contemporary healthcare. Intelligent systems are able to accurately detect mental disorders, which helps with diagnosis, treatment, and patient recovery. As AI technology develops, it will assist healthcare professionals in early illness detection and customised treatment plans based on patient character- istics.

The goal of this paper is to examine how advanced Neural Networks adapted specifically for Natural Language Processing are effective in classifying mental disorders from patient complaints. The BERT model is compared with a traditional Logistic Regression model which is based on statistical methods.

2. Methods and Materials

The data used was compiled and curated from various sources. The dataset is an amalgamation of raw data from various openly accessible sources, cleaned and compiled and can thus be used as a resource for sentiment analysis and other Natural Language Processing (NLP) tasks. The dataset is created by amalgamating data from different sources available on Kaggle, a platform for the exchange of datasets and other related resources. The entire dataset is also available on Kaggle.

The dataset consists of two variables, a statement and status, which is a target variable. The statement is a textual string consisting of a variable length statement. The status is mental disorder or condition that the patient making the statement was diagnosed with. The initial assignment of statuses for a given statement was made by a mental health professional. The dataset is composed of 52680 unique statements each corresponding to one of seven statuses. The complete list of statuses and their prevalence in the dataset is shown in Table 1.

Table 1: Statuses and their proportion in the dataset

Status	Distribution	Proportion
Normal	16342	31.02%
Depresion	15404	29.24%
Suicidal	10652	20.22%
Anxiety	3841	7.29%
Bipolar	2777	5.27%
Stress	2587	4.91%
Personality disorder	1077	2.04%
Total	52680	100%

The distributions of labels is also depicted graphically in Figure 1.

Before the model development the dataset validity was confirmed and it was ensured that the data within is applicable for the given task. Following this step, the dataset was divided into two subsets, the training set which consisted of 80% of total number of samples and the validation set, which consisted of the remaining 20%.

For classification of the statements two models were developed. First model is Logistic Regres- sion, which is a statistical Machine Learning (ML) model. Second model that was used in this study is Bidirectional Encoder Representations from Transformers (BERT), which is a deep learn- ing model based on transformer architecture.

Logistic Regression is a statistical model commonly used for binary classification tasks.

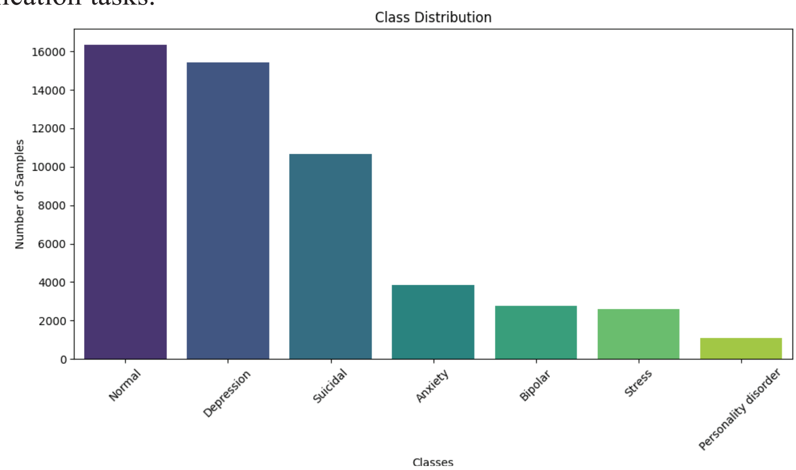

Figure 1: Class distribution within the dataset

It uses a logistic function to model a binary dependent variable. For sentiment analysis, the model can be trained to predict whether a given text expresses a positive or negative sentiment. Logistic Regression models the probability that a given input belongs to a particular class. It starts with a linear combination of input features:

$$z = \beta_0 + \beta_1 X_1 + \beta_2 x_2 +, \dots, +\beta_n x_n \tag{1}$$

Where β_0 is intercept term, $\beta_1, \beta_2, \dots, \beta_n$ are coefficients for features and $x_1, x_2, \dots$ x_n are fea- tures. In this particular case, the features list and the features themselves are extracted using Term Frequency Inverse Document Frequency method from the input text.

To map linear function to probability sigmoid function is used:

$$\sigma(z) = \frac{1}{1+e^{-x}} \tag{2}$$

The output of the $\sigma(z)$ is a value between 0 and 1 represented the probability a statement is mapped to particular class, in this case a status.
The parameters β are estimated by maximising the log-likelihood function:

$$L(\beta) = \sum_{i=1}^{m} \left[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i) \right] \tag{3}$$

Where m is the number of samples in the training set, y_i is the actual label of i-th sample, and $y\hat{}_i$ is predicted probability of the i-th sample for a given status. The goal is to find β which maximises log-likelihood function, which is preformed using Gradient Descent optimisation algorithm.
BERT is a deep learning model based on the Transformer architecture. Unlike traditional models, BERT reads text bidirectionally, enabling it to understand the context of a word by looking at both its left and right surroundings. It is pre-trained on a large corpus of text and can be fine-tuned on specific tasks. BERT is a deep neural network, consisting of multiple layers of transformers, each having Multi-Head Self-Attention Mechanism which allows the model to focus on different parts of the input sequence at the same time. The transformers in BERT model are specifically designed to understand the context in the natural language. The transformer architecture of BERT model consists of only the encoder-decoder part, meaning that it can process input data and capture contextual information simultaneously.
The use of Transformers in BERT model is significant because it enables the use previously men- tioned Self-Attention Mechanism which allows the model to weigh the importance of every word in a sentence compared to all other words. This is achieved using Softmax function whcih convert vector of raw scores for an input into a probability distribution over classes. The attention score α can be represented as:

$$\alpha(Q,K,V) = \sigma\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{4}$$

Where Q are queries, a current word that is being evaluated, K are keys, which potential candid- ates in the sequence that can provide relevant information to the query, V the actual values that need to be aggregated, in other word the status that is associated with the statement, and d_k is the dimensionality of the keys. The σ is Softmax function which is used to convert raw values from queries and keys into probabilities.
Given a vector of scores $z = [z_1, z_2, \ldots, z_n]$ Softmax function produces a probability distribution $\sigma(z) = [\sigma_1, \sigma_2, \ldots, \sigma_n]$ where:

$$\sigma_i(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}} \tag{5}$$

In the Attention mechanism, the softmax function ensures that the sum of attention weights across all positions in the sequence is 1. This normalization allows the model to distribute its focus across different parts of the sequence based on their relevance to the current query.

3. Results and Discussion

BERT represents a significant advancement over traditional models like Logistic Regression for sentiment analysis, particularly in complex and sensitive areas such as mental health. While it offers superior accuracy and contextual understanding, it comes with increased computational
demands and less interpretability. Choosing between these models depends on the specific re- quirements of the task, the availability of computational resources, and the importance of inter- pretability.
BERT, with its deep architecture and attention mechanism, has a much higher expressive power than Logistic Regression. It can model a wide variety of language phenomena, including word order, syntax, and semantics, which are crucial for accurately understanding and classifying senti- ment.

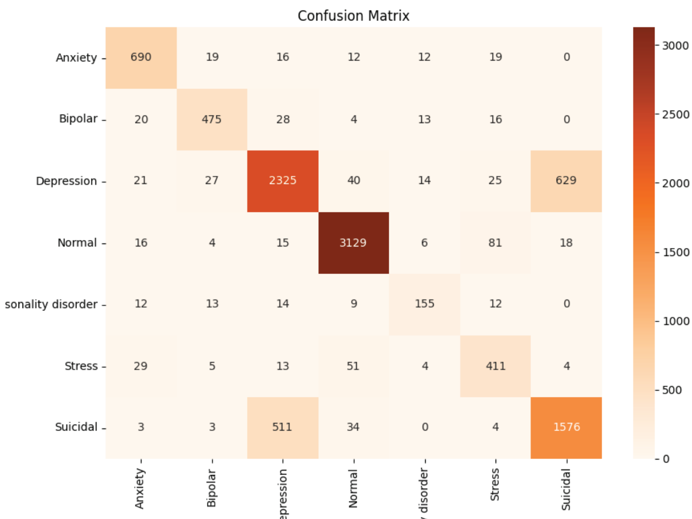

Figure 2: Confusion matrix for BERT model

After training the Logistic Regression model on the training dataset the accuracy of 72% percent was achieved. Using the BERT model on the other hand resulted in the significant improvement in terms of accuracy, which was 84%.

Sentiment analysis, a natural language processing technique, has emerged as a valuable tool for classifying mental disorders, particularly in the context of social media data. Recent studies have explored its application in detecting depression, anxiety, and other mental health issues [17], [18]. By analyzing text from social media posts and online communications, sentiment analysis can provide insights into individuals' emotional states, enabling early detection and intervention for mental health problems [19]. The COVID-19 pandemic has heightened the importance of this
approach, as increased social media usage and isolation have led to a rise in mental health concerns [20]. Researchers have employed various machine learning and deep learning methods, including lexical approaches and Naive Bayes models, to classify sentiments related to mental health [17]. Some studies have achieved promising results, with accuracy rates reaching up 89% in detecting mental disorders using multi-labeled deep-learning models [18]–[20].
Recent studies have explored the effectiveness of BERT for sentiment analysis.

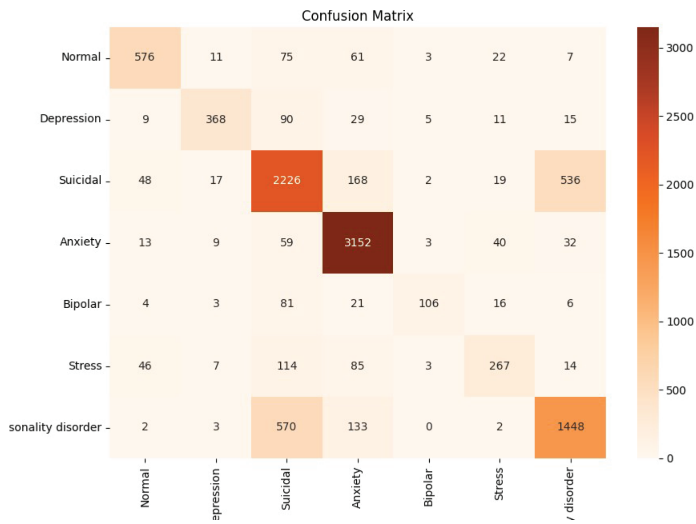

Figure 3: Confusion matrix for Logistic Regression model

Traditional statistical models, including Logistic Regression have been successfully used for sentiment analysis [21]. BERT outperforms traditional models like Naive Bayes in binary and multi-class sentiment classification tasks on Twitter data [22]. When compared to other transformer-based models like DistilBERT and RoBERTa, BERT demonstrates superior performance in analyzing sentiments in movie reviews and tweets [23]. BERT's ability to capture sentimental relations, including word negations and intensifications, makes it more effective than basic machine learning and deep learn- ing models for classifying user textual data [24]. In a comprehensive comparison of sentiment analysis techniques, including lexicon-based models, logistic regression, LSTM, and BERT, the pre-trained BERT model exhibited undisputed superiority in sentiment classification performance, as measured by accuracy, precision, recall, and F1 score [25].

4. Conclusion

This study highlights the significant advantages of using advanced deep learning models like BERT for sentiment analysis, particularly in the context of mental health. While Logistic Regres- sion provides a solid starting point with an accuracy of 72%, BERT greatly improves performance, achieving an accuracy of 84%. This improvement is due to BERT's advanced features, including its ability to understand text in both directions and its attention mechanisms that capture more nuanced details.

Recent research has shown that BERT outperforms traditional models, such as Logistic Regression and Naive Bayes, in sentiment analysis tasks. For example, BERT excels in classifying sentiments
in social media posts and movie reviews, outperforming other transformer-based models like Dis- tilBERT and RoBERTa. BERT's ability to handle complex sentiment details, like word negations and intensification, makes it more effective than simpler models.

In various comparisons, BERT consistently shows superior performance across important metrics such as accuracy, precision, recall, and F1 score. This makes it a valuable tool for analysing men- tal health-related text and improving early detection and intervention strategies. Future research should focus on integrating BERT into real-world mental health monitoring systems, adapting it to different languages and datasets, and addressing any challenges related to its computational demands and interpretability.

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