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Sentiment Analysis of Diabetes Patients' Experiences Using Machine Learning Techniques

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Abstract: Diabetes is a long-term medical disorder that affects blood sugar levels and can cause a variety of related issues, such as heart disease, kidney damage, nerve damage, eye damage and skin ailments. The impact of diabetes on patients' emotional sentiment has not been thoroughly studied, creating a gap in current knowledge on the potential psychological consequences of the disease. This study explores the connection between emotional sentiment and diabetes in an effort to close this knowledge gap. During this study, 215 online forum posts, including patient experiences, problems, routines, and suggestions, were analyzed using two widely used sentiment analysis models, TextBlob and Vader, to investigate whether diabetes affects patients' emotional state. The overall results indicate that diabetes may affect the sentiments of diabetic patients, as observed in their experiences, problems, and suggestions shared as posts on online discussion forums. However, it cannot be conclusively concluded that diabetes always has a significant and directly adverse impact on the sentiments and emotions of diabetic patients. To ascertain whether there is a link between emotions and diabetes, additional in-depth study on the sentiment analysis of patient experiences with diabetes is required, and to identify the specific circumstances under which this association may exist.

Keywords: Diabetes; Sentiment analysis; Machine learning; Patient experiences.

1. Introduction

Diabetes Mellitus is a chronic disease that manifests when either the pancreas fails to generate adequate insulin or when the body is unable to properly use the insulin it produces. Insulin is responsible for regulating blood glucose, is crucial for maintaining healthy blood sugar levels. When diabetes is uncontrolled, hyperglycemia, also known as elevated blood glucose or sugar, frequently occurs and can lead to significant harm to many bodily systems, particularly the nerves and blood vessels over time [1].

According to International Diabetes Federation [2], approximately one in ten adults between the ages of 20-79 are living with diabetes, equating to a staggering 537 million individuals. By 2030, 643 million individuals worldwide (1 in 9 adults) will have diabetes, and by 2045, 784 million adults worldwide (1 in 8 adults) will have the disease. An overwhelming majority of those with diabetes, around 81%, reside in low and middle-income countries. Furthermore, diabetes was the cause of death for 6.7 million individuals in 2021, which translates to one person losing their life every five seconds. An estimated 240 million individuals living with diabetes, which is roughly 44% of the total population affected, remain undiagnosed. It is alarming that about 90% of these people live in low- and middle-income regions. Moreover, the expected cost of diabetes-related healthcare worldwide in 2021 was USD 966 billion, a 316% rise in the last 15 years. It's also crucial to remember that 541 million adults, or about one in ten people globally, have impaired glucose tolerance, which puts them at a high risk of acquiring type 2 diabetes. Last but not least, 68% of adults with diabetes live in the ten countries that have the greatest prevalence of the disease.

Prolonged diabetes duration is linked with a reduction in brain volume, primarily in the gray matter [3]. Welch et al. [4] described that diabetes and its treatment can have a substantial effect on work, social relationships, social abilities, and both physical and emotional health. Neglecting to address the prevalent psychosocial issues experienced by individuals with diabetes can significantly diminish their well-being and adversely affect their social life [5]. According to Egede and Ellis [6], the presence of both diabetes and depression is linked to elevated morbidity and mortality rates, as well as increased healthcare costs. Diabetes may have an impact on a person's personality and emotional state. In addition, diabetes-related fluctuations in blood sugar levels can also affect mood and behavior. Low blood sugar (hypoglycemia) can cause irritability, confusion, and even aggression, while high blood sugar (hyperglycemia) can cause fatigue, difficulty concentrating, and mood swings.

A team of psychologists and psychiatrists from the Joslin Diabetes Centre coined the phrase "diabetic distress" in a peer-reviewed publication in 1995 [7]. These experts used the term "diabetic distress" to describe the difficulties persons with diabetes have in making their psychological adjustments. Diabetes distress, regardless of the form, is the unpleasant emotional or affective experience brought on by managing the demands of diabetes. Diabetes and depression have been reported to be significantly correlated, with depression being linked to poor self-management behaviors, unfavorable clinical outcomes, and higher mortality rates [8]. According to Berry et al. [9], diabetes distress is a reasonable emotional reaction to the potential life-altering consequences of an illness and has been found to have a significant correlation with glycated hemoglobin (HbA1c) levels.

Diabetic patients' care should prioritize their physical, psychological, social, and economic welfare [10]. Elevated levels of HbA1c have been observed to have a correlation with various physical symptoms such as hyperglycemia, as well as negative mood states like dissatisfaction, depression, tension, and fatigue, ultimately resulting in poorer overall well-being [11]. Sentiments and emotions may become evident in written documents since the selection of words, tone, and overall writing style utilized by the writer can indicate their emotional state during the writing process. Diabetes has a significant psychological impact on patients, and their written experiences reflect their mentality and sentiment.

Sentiment analysis, commonly referred to as opinion mining, is the technique of examining text, voice, or other forms of communication to ascertain the author's emotional tone or attitude towards a specific topic or subject. It involves identifying and extracting subjective information from the text using computational methods such as machine learning, natural language processing (NLP), and others. Sentiment analysis attempts to categorize a text's sentiment as either positive, negative, or neutral. The outcomes of sentiment analysis can be used to track brand reputation, gauge public opinion, and even predict customer behavior. Sentiment analysis has many uses in many different fields, including E-Commerce [12], politics [13,14], education [15] and social media analysis [16, 17]. In recent years, sentiment analysis has been increasingly used in the healthcare [18] field to gain insights into patient experiences and improve the quality of care. However, to date, no significant study has examined the impact of diabetes on patients' sentiments by analyzing their experiences, problems, routines, and suggestions.

The goal of this study is to bridge a gap in the current understanding of diabetic patients' sentiments by utilizing machine learning techniques to perform sentiment analysis on their shared experiences, routines, problems, and suggestions. By analyzing the sentiments expressed in written documents, it is possible to identify the impact of diabetes on patients' emotional states. The study hypothesizes that analyzing the sentiment of diabetic patients' feelings, experiences, and suggestions can provide valuable insights into how diabetes affects their sentiments. The motivation behind this study is to better understand how diabetes affects patients' sentiments. By analyzing patients' sentiments in experiences, healthcare providers can develop tailored interventions that improve the quality of life for patients and support their overall well-being.

2. Related Work

Over the years, several studies have investigated the impact of diabetes on patients, including their physical health, psychological well-being, and overall quality of life. This section provides a comprehensive overview of the existing work on the subject, with an emphasis on studies that have analyzed the effect of diabetes on patients. Gabarron et al. [19] conducted an analysis of the sentiment expressed in messages related to diabetes that were posted on Twitter. To carry out this study, messages were extracted from the Twitter standard API that were specifically related to Type 1 and Type 2 diabetes. The findings of the study revealed that tweets that mentioned Type 2 diabetes and did not contain emojis had a significantly more negative sentiment as compared to tweets that included emojis. Conversely, tweets that were related to Type 1 diabetes and included emojis had a significantly more positive sentiment and were less negative compared to tweets that did not include any emojis.

A meta-analysis was carried out by Lustman et al. [20] to look into any possible connections between depression and inadequate glycemic control. Effect sizes (ESs) were calculated, statistical analysis was carried out on the aggregate data, and 24 trials were chosen for study using meta-analytic techniques. According to the study's findings, depression and hyperglycemia are related in people with type 1 or type 2 diabetes.

The potential relationship between typical personality features and differences in glycemic control was investigated by Lane et al. [21] using data from a clinical trial of a stress management intervention in 105 individuals with type 2 diabetes. The study discovered that patients with lower baseline average blood glucose levels tended to score higher on the personality trait of neuroticism as well as on a number of particular features such anxiety, angry hostility, sadness, self-consciousness, and vulnerability. Conversely, these patients tended to score lower on the trait of altruism. The study found that personality factors may provide new insights into variations in glycemic control in patients with type 2 diabetes and that the propensity to feel fewer negative emotions and to prioritize the needs of others over one's own may be a risk factor for poor glycemic control.

The ability to recognize, comprehend, and control one's own and other people's emotions is known as emotional intelligence (EI), and it is seen as a critical skill for success in both personal and professional setting. Pérez-Fernández et al. [22] investigated the correlation between emotional intelligence (EI) and biological and psychological factors in individuals with Type 1 and Type 2 diabetes. The results revealed that low levels of EI are negatively linked with HbA1c levels. The EI, on the other hand, has a positive effect on glycemic control, anxiety, and quality of life. The study found no discernible change in EI between those with diabetes and those in good health. Moreover, greater EI scores are linked to better psychological outcomes, including increased life satisfaction, wellbeing, and marital status. Conversely, lower levels of EI are associated with diabetes-related anxiety and distress.

Jacobson et al. [23] conducted a review-based study that suggests that diabetes, particularly type 1 diabetes, could increase the likelihood of patients developing depressive disorders. A molecular mechanism connecting the metabolic changes brought on by diabetes to changes in brain structure and function may be responsible for this risk. Another study [24], identified a significant increase in depression rates among diabetic patients, particularly in the elderly. Clinically relevant depressive disorders affect around 20-30% of diabetes patients, with 10% being diagnosed with major depression disorder. Additionally, those who already have depression appear to be more likely to also acquire diabetes mellitus, and depression itself can make diabetes' glycemic control problems worse, increasing the risk of complications and unfavorable outcomes. In contrast, better glycemic management is typically linked to a reduction in depressed symptoms.

Bergner and Goldberger [25] examined a number of potential pathways that would account for the epidemiological data between diabetes mellitus with sudden cardiac mortality. Silent myocardial ischemia, autonomic nervous system dysfunction, abnormal cardiac repolarization, hypoglycemia, a hypercoagulable state brought on by diabetes, diabetic cardiomyopathy, and impaired respiratory response to hypoxia and hypercapnia are a few potential causes that could be to blame for the higher incidence of sudden cardiac death in people with diabetes mellitus. The study's findings support the hypothesis that diabetes mellitus increases the risk of sudden cardiac death.

3. Materials and Methods

The aim of this study is to perform sentiment analysis on diabetic patients' shared experiences, routines, problems, and suggestions in order to better understand the impact of diabetes on patients' emotional states and to provide valuable insights into how diabetes affects their sentiments, which can be used to develop tailored interventions to improve the quality of life and overall well-being of patients. The methodology followed during the study is shown in Figure 1.

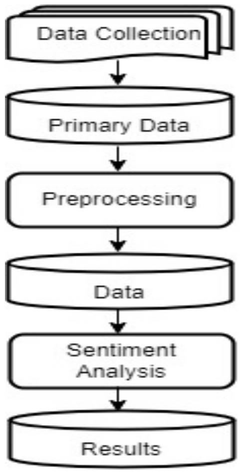

Figure 1. Research Methodology

During the study, data was collected from different online sources between January 14th and 16th, 2023, where diabetic patients shared their experiences, problems, suggestions, and other comments. Initially, 538 posts were collected, but 312 were excluded, leaving 215 that were ultimately selected for analysis. Out of these 215, 66 were selected from 'comments.medicinenet.com', 3 were extracted from 'diabetes.co.uk', 138 were taken from 'diabetesdaily.com', 2 were taken from 'feedspot.com' and 6 were extracted from 'diabetescare.net'.

Before checking the sentiments, the detailed preprocessing was performed on collected data. In which, all the text was converted in lowercase form and then accented character were removed from the text by using Unidecode package of Python. Similarly, the regular expressions were defined through which the non ascii characters were removed from the data. To remove the dimensionality of data the contraction was expanded and punctuations were removed.

The data underwent parts of speech tagging, lemmatization, and stop words elimination with the aid of spaCy, which is a Python and Cython-based open-source software library for advanced natural language processing.

There are various models that can be used for sentiment analysis in machine learning. Pretrained sentiment analysis models refer to machine learning models that have undergone training on vast amounts of data to forecast the sentiment (positive, negative, or neutral) of a specific text or sentence. These models have already acquired the knowledge of the typical patterns and attributes associated with each sentiment category. For the present study, TextBlob and VADER were used for sentiment analysis.

TextBlob is a Python library that is used for natural language processing tasks such as part-of-speech tagging, noun phrase extraction, and sentiment analysis. It provides a simple and intuitive API for working with text data. TextBlob uses the Pattern library under the hood, which includes a pre-built sentiment analysis module. The sentiment analysis module uses a machine learning approach based and is trained on a large corpus of data. TextBlob is widely used for sentiment analysis [26, 27].

VADER (Valence Aware Dictionary and sEntiment Reasoner) is a lexicon-based sentiment analysis tool that uses a pre-built sentiment lexicon to evaluate the sentiment of a given text or sentence. The sentiment lexicon contains words and phrases that are labeled with their sentiment polarity (positive, negative, or neutral) and intensity scores. VADER also uses rules-based heuristics to handle cases such as negations, intensifiers, and emojis. The output of VADER includes four sentiment scores: positive, negative, neutral, and compound, which is a normalized score that combines the three other scores. VADER is a widely used sentiment analysis tool [28, 29].

The results of sentiment analysis obtained after the preprocessing of data were further analyzed with SPSS (version: 25) and the visualization of results were performed with R (version 4.2.3). The overall results of study are presented in section 4.

4. Results

The study aims to analyze diabetic patients' shared experiences, routines, problems, and suggestions to understand diabetes' emotional impact and provide insights on its effect on their sentiments. The 215 posts of diabetic patients were analyzed for sentiment using TextBlob and Vader, and the results are shown in Table 1.

Table 1. Result of Sentiment Analysis

Statistics	TextBlob		Vader
	Polarity	Sensitivity	Score
Mean	0.04	0.49	-0.05
Median	0.05	0.51	0.00
Std. Dev	0.19	0.18	0.60
Range	1.45	0.95	1.96
IQR	0.20	0.20	1.09
Skewness	-0.53	-0.85	0.11
Kurtosis	2.95	1.10	-1.32

Out of 215 posts, TextBlob identified 119 as positive, 77 as negative, and 19 as neutral. Meanwhile, Vader recognized 106 posts as negative, 95 as positive, and classified 14 posts as neutral. To provide a clearer illustration, the results are presented using graphical plots (Figure 2).

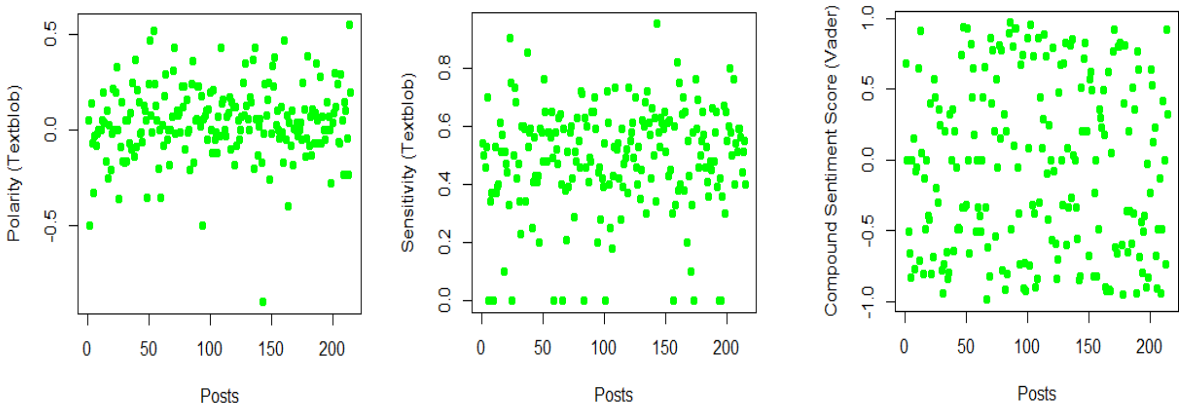

Figure 2. Results of Sentiment Analysis

The graphical plots clearly illustrate the variation observation in polarity, sensitivity and compound sentiments score. To facilitate further analysis, normality tests were carried out and the obtained results are displayed in Table 2.

Table 2. Result of Normality Tests

Model	Parameter	Kolmogorov-Smirnov			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
TextBlob	Polarity	0.080	215	0.002	0.963	215	0.000
	Sensitivity	0.093	215	0.000	0.938	215	0.000
Vader	Sentiment	0.100	215	0.000	0.934	215	0.000

Non-normality was detected in the polarity and sensitivity identified by TextBlob, as well as in the sentiments identified by the VADER, as determined by both the Kolmogorov-Smirnov and Shapiro-Wilk tests.

The one-sample Wilcoxon signed-rank test conducted on the TextBlob Polarity and the VADER compound sentiment score identified significant differences in the sentiments of posts for TextBlob Polarity (T-value = 0.50, Median = 0.05, $p < 0.05$) and VADER score (T-value = 0.50, Median = 0.51, $p < 0.05$). Similarly, the one-sample Wilcoxon signed-rank test conducted on the TextBlob sensitivity identified no significant difference in the analyzed posts of diabetic patients for TextBlob Sensitivity (T-value = 0.50, Median = 0.0, $p = 0.76$). Two different sentiment analysis techniques were used, and their correlation is shown using a scatterplot (Figure 3).

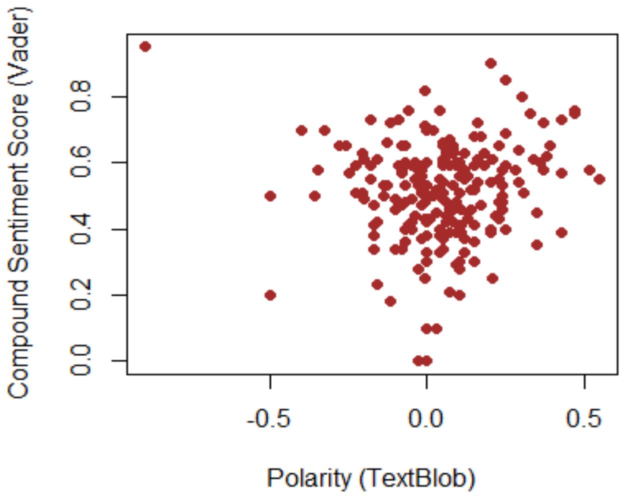

Figure 3. Scatterplot of Correlation

The scatterplot clearly illustrates the association between the scores. Figure 4 shows the bean plots created for the visual representation of sentiment score, sensitivity, and polarity.

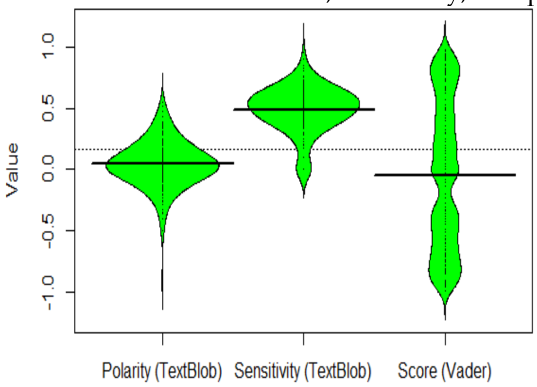

Figure 4. Bean Plots of Results

The density curve illustrated by the bean plots clearly and concisely represents the results obtained from the sentiment analysis of posts made by diabetic patients. The performance of TextBlob and VADER is also analyzed during the study, and the results are shown in Table 3.

Table 3. Classification Report

Model	Description	Precision	Recall	F1-Score	Support
	Negative	0.49	0.53	0.51	88
	Positive	0.66	0.62	0.64	127
TextBlob	Accuracy			0.59	215
	Macro Avg	0.58	0.58	0.58	215
	Weighted Avg	0.59	0.59	0.59	215
	Negative	0.66	0.89	0.75	88
	Positive	0.90	0.68	0.77	127
VADER	Accuracy			0.76	215
	Macro Avg	0.78	0.78	0.76	215
	Weighted Avg	0.80	0.76	0.76	215

The results presented in the classification report indicate that the performance of TextBlob and VADER is highly effective in recognizing sentiment within the dataset. The overall and cumulative findings reveal that, for TextBlob, precision stood at 0.66, recall at 0.62, and an F1-score of 0.64. Similarly, VADER demonstrated strong performance on the study's dataset, achieving precision, recall, and F1-score values of 0.90, 0.68, and 0.77, respectively.

5. Discussion

The goal of this study is to analyze the sentiments of diabetic patients by utilizing machine learning techniques to perform sentiment analysis on their shared experiences, routines, problems, and suggestions. The hypothesis is that by analyzing the sentiment of diabetic patients' feelings, experiences, and suggestions, valuable insights can be gained into how diabetes affects their emotions. To achieve this objective, a total of 215 online posts made by diabetic patients were analyzed using two popular sentiment analysis techniques.

The overall sentiment analysis performed with TextBlob identified 35.81% of posts as negative, 8.84% as neutral and 55.35% as positive. While, Vader, classified the sentiments of 49.3% of post as negative, 6.51% as neutral, and 44.19% as positive. TextBlob identified more posts as positive compared to negative, while Vader identified more posts as negative compared to positive. The precision, recall, and F1-score for both TextBlob and VADER reflect their strong performance in sentiment analysis of the dataset, implicitly affirming the accuracy and reliability of the results obtained.

The overall results described that diabetes may affects the sentiments of diabetic patients observed in the experiences, problems and suggests by patients as posts on the online discussion forum. However, it can't be concretely concluded that diabetes has always a strong and directly negative impact on the sentiments and emotions of diabetes.

This study presents a unique approach to understanding the emotional experiences of diabetic patients by performing sentiment analysis on the experiences, problems, and suggestions they shared online. Through this analysis, valuable insights were gained into how diabetes affects the emotional well-being of patients, shedding new light on this important aspect of their lives. However, there are several threats to the validity of this research: i) the study only obtained data from popular online discussion forums on diabetes, which may not be representative of the entire population of diabetic patients, ii) the study did not consider the age, gender, nationality, type of diabetes, or any other factor of the participants, which could influence the results, iii) the study may have only included a certain type of participant, such as those who are more active on online forums or those who are more likely to express their emotions online, iv) the study only included participants who chose to participate in online forums, which may not be representative of the broader population of diabetic patients, v) participants may have expressed certain sentiments or emotions that they believed were more socially acceptable or desirable, rather than their true feelings, v) the study only analyzed messages from a certain time period, which may not be representative of the sentiments and emotions of diabetic patients at other times, vi) the sentiment analysis may not have accurately captured the sentiment of messages due to ambiguity or sarcasm in the language used, and vi) the study's findings may not be generalizable to other populations of diabetic patients or to those who do not use online forums.

Based on the results of this study, several potential directions for future work can be identified. Firstly, future research could investigate the emotional experiences of diabetic patients in greater depth, taking into account demographic factors such as age, gender, and type of diabetes. Additionally, it would be valuable to compare the emotional experiences of diabetic patients with those of other patient populations, in order to identify similarities and differences in emotional needs across different patient groups. Secondly, future research could focus on developing targeted interventions to support the emotional well-being of diabetic patients. This might involve developing online resources, such as support groups or educational materials, that specifically address common emotional concerns experienced by diabetic patients. Finally, further analysis of sentiment data from other sources, such as social media platforms or online health forums, could provide a more comprehensive understanding of diabetic patients' emotional experiences. By combining data from multiple sources, future research could identify patterns and trends in emotional experiences that are not apparent from analyzing data from a single source.

6. Conclusions

Diabetes is a chronic metabolic disorder that can lead to a range of complications, including cardiovascular disease, neuropathy, nephropathy and retinopathy, making it a significant public health challenge worldwide. This study analyzed experiences, problems, routines, and suggestions shared by diabetes patients on online forums to investigate whether diabetes affects the sentiment of patients. The study suggests that diabetes may have a negative impact on the emotional state of diabetic patients, which is evident from the sentiment analysis of their online posts. Nonetheless, it cannot be definitively established that diabetes consistently and directly exerts a negative influence on the emotional sentiments of diabetic individuals. There may be other factors such as personal circumstances, age, and support systems that may also play a role in influencing their emotional state. Further research is required to determine how demographic and lifestyle factors, such as age, socioeconomic status, race and ethnicity, gender, health behaviors, and mental health, influence the attitudes of diabetic patients.

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