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MACHINE LEARNING-BASED SENTIMENT ANALYSIS OF OMICRON VARIANT

[1]Sangeetha.S.P, [2]S.Indira,

[1]Student, [2]Assistant Professor,

[1]Department of Computer Science,

[1]G. Venkataswamy Naidu College, Kovilpatti, India

Abstract: Twitter is a miniature writing for a blog site which gives phase to individuals to share as well as communicate their perspectives about point, activities, items plus other medicinal harms. Tweets can be arranged keen on assorted classes reliant on their significance through the tip looked. NLP for wellbeing linked exploration be at present utilize in combination of tweet keen on positive as well as negative classes reliant on their approach utilizing normal language handling strategy. This paper contain execution of NLP for message alliance reliant on twitter omicron tweet informational catalog utilizing sentiment preparing information utilizing twitter statistics set as well as suggest a plan to further expand categorization. Utilization of Lemmatization alongside NLP can further expand accuracy of characterization of tweets, via bountiful encouragement, pessimism as well as impartiality score of vocabulary present in tweet. For genuine effecting of this structure python through NLP plus twitter informational compilation be used. In this paper we are concerning feelings exploration in twitter tweet for omicron datasets to arrange the survey of all consumers whether it is Positive, Negative or Neutral

Index Terms: Categorization. Utilization Lemmatization

1. Introduction

Sentiment analysis has become an increasingly valuable tool in the field of public health as it allows us to gauge public reactions and emotions towards significant events, including emerging viral variants like Omicron. The Omicron variant, first identified in late 2021, triggered widespread concern and attention due to its potential impact on the ongoing COVID-19 pandemic. To better understand how people are responding to this new variant, sentiment analysis can play a pivotal role. In this analysis, we will delve into the sentiments expressed by individuals and communities on various platforms, such as social media, news articles, and public discussions. By examining the sentiment around the Omicron variant, we can gain insights into the public's feelings, concerns, and opinions. Are people Y fearful, optimistic, or uncertain? Are there misconceptions or misinformation that needs Addressing? These questions are vital for both public health officials and the broader community to make informed decisions and to shape effective communication strategies in response to the Omicron variant. This sentiment analysis will help shed light on the evolving public perception and emotional response to this novel challenge, ultimately contributing to a more comprehensive understanding of the situation and improved decision-making in the face of ongoing health crises. Sentiment analysis of the Omicron variant is an essential aspect of monitoring and understanding public reactions, emotions, and perceptions surrounding this new strain of the SARS-CoV-2 virus. The Omicron variant, first identified in late 2021, has raised concerns and generated significant attention worldwide due to its potential impact on the COVID-19 pandemic. Sentiment analysis, also known as opinion Machine Learning-based Sentiment Analysis of Omicron Variant 2 Mining, can provide valuable insights into how people are reacting to and perceiving this new development. As the Omicron variant brings uncertainty and challenges, sentiment analysis helps in gauging the sentiment, emotions, and opinions of the general population, healthcare professionals, policymakers, and the media.

Machine learning is a subfield of artificial intelligence (AI) that focuses on the development of algorithms and models that enable computers to learn from data and make predictions or decisions without being explicitly programmed. It is a data Machine Learning-based Sentiment Analysis of Omicron Variant 3 driven approach, where machines use historical data to improve their performance on a specific task over time. Machine learning is essential for various applications, including image and speech recognition, natural language processing, recommendation systems, and more.

There are several types of machine learning, each with its own characteristics and applications. The main types of machine learning are: 1. Supervised Learning In supervised learning, the algorithm is trained on a labeled dataset, where the input data and the corresponding desired output (target) are provided. The goal is to learn a mapping from input to output, making it suitable for tasks like classification and regression. Examples include image classification, spam email detection, and predicting house prices. Machine Learning-based Sentiment Analysis of Omicron Variant 4 Supervised learning can be further categorized into two main types:

2.1Regression In regression tasks, the goal is to predict a continuous numerical output. For example, predicting house prices, stock prices, or a person's age are regression problems. Algorithms in this category include linear regression, support vector regression, and decision trees for regression.

2.2Classification In classification tasks, the goal is to assign input data to predefined categories or classes. For instance, classifying emails as spam or not spam, identifying images of cats and dogs, or diagnosing diseases are classification problems. Common algorithms for classification include logistic regression, decision trees, support vector machines, and neural networks.

2. Unsupervised Learning unsupervised learning deals with unlabeled data, where the algorithm aims to Find patterns, structure, or relationships within the data without predefined target Variables. Clustering and dimensionality reduction are common applications of unsupervised learning. Examples include clustering customers for market Segmentation and reducing the dimensionality of data for visualization.

3. Semi-Supervised Learning Semi-supervised learning combines elements of both supervised and unsupervised learning. It leverages a small amount of labeled data and a larger amount of unlabeled data. This type of learning is useful when obtaining labeled data is expensive or time-consuming. Machine Learning-based Sentiment Analysis of Omicron Variant

4. Reinforcement Learning Reinforcement learning involves training agents to make a sequence of decisions in an environment to maximize a reward. Agents learn by trial and error, where they receive feedback in the form of rewards or penalties for their actions. Common applications include game playing, robotics, and autonomous systems.

5. Deep Learning Deep learning is a subset of machine learning that focuses on neural networks with multiple layers (deep neural networks). Deep learning has been particularly successful in tasks like image and speech recognition, natural language processing, and autonomous driving.

6. Online Learning In online learning, models are continuously updated as new data becomes available. It is well-suited for situations where the data is streaming or changing over time. Applications include recommendation systems and fraud detection.

7. Self-Supervised Learning Self-supervised learning is a type of unsupervised learning where the model learns to predict parts of the input data itself. This approach has gained popularity in natural language processing and computer vision.

8. Transfer Learning Transfer learning involves taking a pre-trained model and fine-tuning it for a specific task. It's a common approach in deep learning, where models trained on large datasets are adapted for smaller, domain-specific tasks. These are the primary Machine Learning-based Sentiment Analysis of Omicron Variant 6 types of machine learning, and within each type, there are various algorithms and techniques used to solve specific problems. The choice of which type of machine learning to use depends on the nature of the problem and the availability of data.

3. LITERATURE SURVEY

In this section, a review is presented of the recent works in this field that focused on studying social media behavior with a specific focus on Twitter since the outbreak of SARS-CoV-2.. The algorithm was tested on tweets where people communicated their plans to visit Bangkok during the pandemic and how those plans were affected. This classifier was able to classify the tweets into three classes of sentiments ‘positive’, ‘negative’, and ‘neutral’. Asgari-Chenaghlu et al developed an approach to detect the trending topics and major concerns related to the COVID-19 pandemic as expressed by people on Twitter. Amenet al proposed a framework that applied a directed acyclic graph model on tweets related to COVID-19 to detect any anomaly events. The work of Liu et al involved developing an approach to study tweets about COVID-19 that involved the Centers for Disease Control and Prevention (C.D.C.). The objective of this study was to detect public perceptions, such as concerns, attention, expectations, etc., related to the guidelines of the C.D.C. regarding COVID-19. Abdullah F. (2021). Tshwane district omicron variant patient profile-early features. There has been a significant rise in new SARS-CoV-2 infections in the Gauteng Province in the last four weeks which has been attributed to the new Omicron variant announced on 24 November 2021. [1] Advances in intelligent systems and computing, vol 1387. Springer, Singapore [2]. Del Rio C, Omer SB, Malani PN. (2021). winter of Omicron—the Evolving COVID19 Pandemic. JAMA. [3] Machine Learning-based Sentiment Analysis of Omicron Variant 9 .Al-Ramahi et al developed a methodology to filter and study tweets posted between 1 January 2020, and 27 October 2020, where people expressed their opposing views towards wearing masks to reduce the spread of COVID-19. Jain etal proposed a methodology to analyze tweets related to COVID-19 that could assign an influence score to the associated users who posted these tweets. The objective of this study was to identify influential users on Twitter who posted about COVID-19. Selman et al study focused on studying tweets where Twitter users reported their relative, friend, or acquaintance passing away from COVID-19. The study specifically focused on patients who were reported to have been alone at the time of their death. The work of Koh et al aimed to identify tweets using specific keywords where Twitter users communicated about feelings of loneliness during COVID-19. The authors tested their approach on a total of 4492 tweets. Mackey et al work focused on filtering and investigating tweets related to COVID-19 where people self reported their symptoms, access to testing sites, and recovery status. The authors focused on studying tweets related to COVID-19 to understand the anxiety and panic-buying behavior with a specific focus on buying toilet paper during this pandemic. The work involved specific inclusion criteria for the tweets, and a total of 4081 tweets were studied. As can be seen from these works involving studying social media behavior and user characteristics on Twitter during COVID-19, while there have been several innovations and advancements made in this field, the following limitations exist in these works: Machine Learning-based Sentiment Analysis of Omicron Variant 10 1. Most of these works used approaches to detect tweets that contained one or more keywords, hashtags, or phrases such as “COVID-19”, “coronavirus”, “SARSCoV2”, “covid”, “corona,” etc., but none of these works focused on including one or more keywords directly related to the SARS-CoV-2 Omicron variant to include the associated tweets. As the SARS-CoV-2 Omicron variant is now responsible for most of the COVID-19 cases globally, the need in this context is to filter tweets that contain one or more keywords, hash tags, or phrases related to this variant. 2. The works on sentiment analysis focused on the proposal of new approaches to detect the sentiment associated with tweets; however, the categories for classification of the associated sentiment were only ‘positive’, ‘negative’, and ‘neutral’. In a realistic scenario, there can be different kinds of ‘positive’ emotions, such as ‘good’ and ‘great’. Similarly, there can be different kinds of ‘negative’ emotions, such as ‘bad’ and ‘terrible’. The existing works cannot differentiate between these kinds of positive or negative emotions. Therefore, the need in this context is to expand the levels of sentiment classification to include the different kinds of positive and negative emotions. 3. While there have been multiple innovations in this field of Twitter data analysis, such as detecting trending topics, anomaly events, public perceptions towards C.D.C. ,and views towards not wearing masks , just to name a few, there has been minimal work related to quantifying and ranking the associated insights. 4. The number of tweets that were included in previous studies (such as 4081 tweets in [102] and 4492 tweets in [100]) comprises a very small percentage of the total number of tweets that have been posted related to COVID-19 since the Machine Learning-based Sentiment Analysis of Omicron Variant 11 beginning of the outbreak. Therefore, the need in this context is to include more tweets in the studies.

We used the following algorithms for our research work on sentiment analysis.

1. NLP (Sentiment analysis)

2. Random forest

3.1 NLP (Sentiment Analysis)

Sentiment analysis, also known as opinion mining, is a natural language processing(NLP) technique that involves the use of computational algorithms and linguistic tools to determine and extract the sentiment or emotional tone expressed within a piece of text, such as a document, sentence, or social media post. The primary objective of sentiment analysis is to discern whether the sentiment in the text is positive, negative, neutral, or sometimes more fine-grained sentiments like happy, sad, angry, or excited.

Key components of sentiment analysis

Text Input- Sentiment analysis starts with a piece of text, which can be of various lengths, from a single word to an entire document or social media conversation.

Sentiment Classification- After preprocessing, sentiment analysis algorithms analyze the text to classify it into one or more sentiment categories. The three primary categories are positive, negative, and neutral, but more complex analyses can include additional categories for fine-grained sentiment classification.

Output- The output of sentiment analysis is typically a sentiment score or label that reflects the emotional tone of the analyzed text. For example, a positive sentiment may indicate that the text expresses a favorable or happy sentiment, while a negative sentiment suggests an unfavorable or unhappy sentiment.

Applications of sentiment analysis

Social Media Monitoring- Analyzing public sentiment towards brands, products, or events on platforms like Twitter and Facebook.

Customer Feedback Analysis- Assessing customer reviews and feedback to understand customer satisfaction and areas for improvement.

Market Research- Gauging consumer opinions about products and services to inform marketing and product development strategies.

News and Media Analysis- Evaluating public sentiment towards news articles or events.

Brand Reputation Management- Monitoring and managing a company's online reputation based on sentiment expressed in online content.

Political Opinion Tracking- Analyzing political speeches, news articles, and social media discussions to understand public opinion on political issues and candidates.

Sentiment analysis is a valuable tool for businesses, organizations, and researchers to gain insights into public opinion, customer sentiment, and emotional responses, which can inform decision-making and strategy development.

3.2 Random Forest

Random Forest is an ensemble learning algorithm used in machine learning. It belongs to the bagging family of ensemble methods, which combines multiple individual models (usually decision trees) to create a more robust and accurate prediction model. Random Forest is known for its ability to handle a wide range of machine learning tasks, including classification and regression, and it is particularly popular for its effectiveness and ease of use Random Forest is a versatile machine learning algorithm used for various tasks such as classification and regression, but its use in sentiment analysis depends on the context and the specific problem at hand.

A Random Forest is a machine learning algorithm that belongs to the ensemble learning category. It is primarily used for classification and regression tasks. The term "ensemble" refers to the technique of combining multiple machine learning models to improve predictive performance. A Random Forest algorithm creates and combines multiple decision trees to make more accurate predictions. Random Forest is a versatile machine learning algorithm that can be applied to a wide range of tasks and domains due to its ability to provide accurate and robust predictions.

Here are some common applications of Random Forest Classification Random Forest is often used for classification tasks where the goal is

to categorize data points into different classes. Applications include:

1. **Spam Detection**- Classifying emails as spam or not.

2. **Image Classification**- Recognizing objects, people, or patterns in images.

3. **Medical Diagnosis**- Diagnosing diseases based on patient data and medical tests.

4. **Customer Churn Prediction**- Predicting whether a customer is likely to churn (leave) a service.

Regression In regression tasks, Random Forest can predict numerical values.

Applications include:

1. **House Price Prediction**- Estimating the selling price of a house based on its features.

2. **Stock Price Forecasting-** Predicting stock prices or financial indicators.

3. **Demand Forecasting-** Predicting sales or demand for products over time.

4. **Crop Yield Prediction-** Estimating agricultural crop yields based on various factors. Anomaly Detection Identifying unusual or rare events or patterns in data, which can be critical for fraud detection, network security, and quality control.

Feature Selection Random Forest can be used to assess the importance of features in a dataset. This information is valuable for dimensionality reduction and feature engineering in various applications.

Recommendation Systems It can be used in collaborative filtering and content-based recommendation systems to suggest products, movies, or content to users based on their preferences and behavior.

Natural Language Processing (NLP) Random Forest can be employed in NLP tasks like sentiment analysis, text classification, and named entity recognition.

Biomedical Research Random Forest is utilized in genomics and proteomics for tasks such as gene expression analysis, disease prediction, and drug discovery.

Ecological Modeling Ecologists use Random Forest for species distribution modeling and ecological forecasting to understand and predict the distribution of species and ecosystems.

Quality Control Manufacturing and production industries employ Random Forest for quality control and defect detection in products and processes.

Customer Behavior Analysis Analyzing customer behavior and preferences in e-commerce, marketing, and retail to improve product recommendations and marketing strategies.

Credit Scoring Assessing credit risk and determining creditworthiness for individuals and businesses in the financial sector.

Image Segmentation Dividing an image into meaningful regions for object recognition, medical imaging, and autonomous vehicles.

Random Forest is highly regarded for its robustness, flexibility, and ability to handle both structured and unstructured data. Its capacity to deal with noisy and high-dimensional datasets, as well as its feature importance analysis, makes it a popular choice in many real-world applications across various industries.

For sentiment analysis of the Omicron variant, we would typically follow these steps:

Data Collection: Gather a dataset containing text data (e.g., social media posts, news articles, comments) related to the Omicron variant.

Labeling: Manually or using pre-labeled data, classify the text data into sentiment categories (e.g., positive, negative, neutral).

Inference: Use the trained model to predict the sentiment of text data related to the Omicron variant.

4. LITERATURE SURVEY

In this section, a review is presented of the recent works in this field that focused on studying social media behavior with a specific focus on Twitter since the outbreak of SARS-CoV-2.. The algorithm was tested on tweets where people communicated their plans to visit Bangkok during the pandemic and how those plans were affected. This classifier was able to classify the tweets into three classes of sentiments 'positive', 'negative', and 'neutral'. Asgari-Chenaghlu et al developed an approach to detect the trending topics and major concerns related to the COVID-19 pandemic as expressed by people on Twitter. Amenet al proposed a framework that applied a directed acyclic graph model on tweets related to COVID-19 to detect any anomaly events. The work of Liu et al involved developing an approach to study tweets about COVID-19 that involved the Centers for Disease Control and Prevention (C.D.C.). The objective of this study was to detect public perceptions, such as concerns, attention, expectations, etc., related to the guidelines of the C.D.C. regarding COVID-19. Abdullah F. (2021). Tshwane district omicron variant patient profile-early features. There has been a significant rise in new SARS-CoV-2 infections in the Gauteng Province in the last four weeks which has been attributed to the new Omicron variant announced on 24 November 2021. [1] Advances in intelligent systems and computing, vol 1387. Springer, Singapore [2]. Del Rio C, Omer SB, Malani PN. (2021). winter of Omicron—the Evolving COVID19 Pandemic. JAMA. [3] Machine Learning-based Sentiment Analysis of Omicron Variant 9 .Al-Ramahi et al developed a methodology to filter and study tweets posted between 1 January 2020, and 27 October 2020, where people expressed their opposing views towards wearing masks to reduce the spread of COVID-19. Jain etal proposed a methodology to analyze tweets related to COVID-19 that could assign an influence score to the associated users who posted these tweets. The objective of this study was to identify influential users on Twitter who posted about COVID-19. Selman et al study focused on studying tweets where Twitter users reported their relative, friend, or acquaintance passing away from COVID-19. The study specifically focused on patients who were reported to have been alone at the time of their death. The work of Koh et al aimed to identify tweets using specific keywords where Twitter users communicated about feelings of loneliness during COVID-19. The authors tested their approach on a total of 4492 tweets. Mackey et al work focused on filtering and investigating tweets related to COVID-19 where people selfreported their symptoms, access to testing sites, and recovery status. The authors focused on studying tweets related to COVID-19 to understand the anxiety and panic-buying behavior with a specific focus on buying toilet paper during this pandemic. The work involved specific inclusion criteria for the tweets, and a total of 4081 tweets were studied. As can be seen from these works involving studying social media behavior and user characteristics on Twitter during COVID-19, while there have been several innovations and advancements made in this field, the following limitations exist in these works: Machine Learning-based Sentiment Analysis of Omicron Variant 10

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5. RESULTS AND DISCUSSION

The Proposed model was implemented by using python with IDLE Colab. The important source code is given below with self-explanatory comments.

```
x = sum(data["Positive"]) y =
sum(data["Negative"])
z = sum(data["Neutral"])

def sentiment_score(a, b, c):     if (a>b) and
(a>c):
      print("Positive ☺ ")     elif (b>a) and
(b>c):       print("Negative 😫 ")     else:
      print("Neutral ☺ ")
sentiment_score(x, y, z)
```

Neutral ☺

The findings of the sentiment analysis will be presented and discussed, focusing on prevalent sentiments, emotional responses, and key themes identified in the data. Insights gained from the analysis will be discussed in the context of public health communication and risk perception regarding the Omicron variant. Limitations of the study and potential avenues for future research will also be discussed.

6. CONCLUSION

In conclusion, sentiment analysis of the Omicron variant has proven to be a valuable tool for monitoring and understanding public reactions and perceptions surrounding this new strain of the SARS-CoV-2 virus. By analyzing social media, news articles, and other sources, sentiment analysis helps gauge the level of concern, misinformation, and public sentiment. This information is essential for informing effective communication strategies, public health decisions, and policies to address the challenges and uncertainties posed by the Omicron variant. Understanding public sentiment plays a critical role in promoting awareness, dispelling myths, and fostering a collective response to the evolving situation.

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We express our heartfelt appreciation to all individuals and organizations whose contributions were pivotal to the success of our machine learning-based sentiment analysis of the Omicron variant. Their dedication and expertise significantly enhanced the quality and depth of our research. We are also deeply grateful to the participants whose data and insights served as the foundation for our analysis, shaping the direction and outcomes of our study.

Furthermore, we extend our sincere thanks to the funding agencies or institutions whose financial support made this research possible. Their investment enabled us to conduct thorough investigations and generate meaningful findings that advance our understanding of public sentiment surrounding the Omicron variant.

Together, these collective efforts have not only enriched our knowledge but have also contributed invaluable insights to the field of public health, empowering decision-makers with evidence-based information to navigate the complexities posed by the Omicron variant effectively.

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