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SENTIMENT ANALYSIS OF WEB 3.0 ENABLED TWITTER DATASET

Nitin Kumar
Dept. of CSE
Sharda University
Greater Noida, India
nitinpro2000@gmail.com

Dheerendra Chaudhary
Dept. of CSE
Sharda University
Greater Noida, India
dheerendrasangwan@gmail.com

Himanshu Pal
Dept. of CSE
Sharda University
Greater Noida, India
himansh99singh@gmail.com

Abstract – In this paper, the focus is on sentiment analysis of web 3.0 enabled twitter dataset. The objective of the project is to explore various methods for performing sentiment analysis on Twitter datasets and implementing these methods on the web3.0 Twitter platform. The project involves collecting Twitter data through blockchain-based applications, preprocessing the data to remove noise, and applying machine learning models for sentiment analysis. Sentiment analysis is simply the extraction of thoughts, ideas, opinions, and emotions from sources such as text, speech, tweets, and databases using natural language processing (NLP) This process involves text segmentation mentally makes it "good," "bad," and "neutral" groups. In addition, it is known by other terms such as objective evaluation, mindfulness mining, and rating extraction. Web 3.0, also known as Web3, represents the third contemplated iteration of the World Wide Web, which aspires to establish a connected, transparent and intelligent online environment Based on the concept of decentralization, blockchain technology and the implementation of token-based economies. The main outcome of the project is to gain insights into the sentiment of users by analyzing WEB3.0 enabled Twitter data. By implementing sentiment analysis techniques on a WEB3.0 enabled Twitter dataset, the project aims to contribute to the field of sentiment analysis and showcase the effectiveness of using WEB3.0 enabled for data collection and analysis. The project aims to provide valuable insights for various methods of sentiment analysis for researchers.

Keywords – Sentiment Analysis, Blockchain-Enabled, Twitter data, WEB 3.0, Machine Learning Models, User Sentiment, Research Contribution

1. INTRODUCTION

Web 3.0, also known as the Semantic Web, signifies the next stage of internet evolution. This progression empowers machines to grasp and interpret data, facilitating intelligent and personalized user experiences. Significantly, Web 3.0 is propelling a transformation in social media platforms, making them more decentralized, secure, and compatible. Within this framework, sentiment analysis emerges as a crucial process for identifying and extracting subjective insights from text data. This entails a thorough examination of text content to determine its emotional undertones and polarity, providing a nuanced grasp of public sentiment on a range of subjects, items, and services.

Retrieval techniques focus primarily on the specific information that is analyzed, or evaluated in a text. While facts are inherently objective in nature, other are textual elements. there are reflections of subjective qualities. These elements are basically attitudes, emotions, evaluations. attitudes and emotions, form the core of affective assessment [29].

With the rapid expansion of the global internet, individuals are increasingly turning to social platforms such as Twitter, resulting in more opinion-related information in the form of tweets, ripe for sentimental analysis. This results in human-made information." making themselves. tweets." Challenges in extracting, reading, and analyzing speech based on rate tweets. To summarize and organize this much data in a meaningful way in a short period of time is a challenging task [28].

The characteristics of Web3, as gleaned from existing literature, identify it as a developing Web 2.0 characterized by the use of blockchain technology and decentralized architecture for convenient and user-friendly interactions is characterized by individuality and privacy [27].

The knowledge obtained through sentiment analysis is of immense value, offering insights into customer opinions, brand reputation, and prevailing market trends, especially in the era of data abundance produced by social media platforms. With these platforms continuously amassing substantial data volumes, sentiment analysis serves as a pivotal tool for comprehending and effectively dissecting this information landscape.

2. LITERATURE REVIEW

Catelli et al. [1] used techniques like Lexion-based sentiment analysis, emotion lexicon, temporal analysis, and emotion assessment, that research utilizes NLP and sentiment analysis to evaluate Italian COVID-19 vaccination sentiment, uncovering prevalent negativity and shifting perspectives.

Sunitha et al. [2] used techniques like BiLSTM, and CNN using phishing URL data and concludes the sentiment analysis model effectively assessed COVID-19 sentiments in Indian and European populations with high accuracy.

Chinnas et al. [3] used a Hybrid approach contains SVM with word embeddings, n-grams, hashtags, emojis using twitter tweets and concludes valuable data for sentiment analysis on diverse topics, including COVID-19 vaccinations, using Tweepy and donut graphs.

Antypas et al. [4] used Large-scale multilingual analysis, BERT fine-tuning, unsupervised lexicon-based sentiment intensity computation techniques with 18.5 million tweets and concludes Negative sentiment in politicians' tweets, especially recently, appears to drive higher virality, revealing party and individual variances.

Xu et al. [5] used (RNN with LSTM and attention) for sentiment, and LDA with 1.6 million tweets and this study analyzes COVID-19 vaccine sentiment, revealing variations across countries, news, and key topics, offering trust insights.

Neethu et al. [6] used CNN, word embeddings, dropout layers on Twitter data using 40,000 tweets and concludes the electronics domain offers insights into users' opinions using machine learning.

Habiman et al. [7] used NLP, Logistic Regression, Multinomial NB, LSTM, GRUs, Bi- LSTM, Bi-GRU with SSTb dataset and concludes Web 2.0 data surge,and focuses on deep learning advancements and evaluate model performance, identify current issues, and suggest enhancements like BERT, word embeddings, attention models, and GANs.

Abraham et al. [8] used Cryptocurrency price prediction using Twitter and Google Trends data with dataset of Bitcoin or Ethereum, Google Trends, and tweet volume. It concludes Tweet volume, not sentiment, predicts Bitcoin and Ethereum price changes, offering valuable insights for users and traders.

Aslam et al. [9] used LSTM-GRU model, TF-IDF, Word2Vec, and BoW features, emotion analysis tools using tweet data of AIT-2018, Facebook tweets. It concludes Cryptocurrency sentiment analysis indicates a predominance of positive emotions, with LSTM-GRU ensemble model achieving high accuracy.

Furkan et al. [10] used LSTM architecture, combined with blockchain layer for metadata transfer with dataset of apple event tweets and concludes Integrating blockchain with LSTM enhances sentiment analysis accuracy, achieving significant improvement to 92.85%.

Zhao et al. [11] used deep learning feature extraction, LSTM emotional tendency mining using 1,79,396 tweets and concludes Blockchain enhances e-commerce regulation with reliable sentiment analysis, aiding regulators in making informed decisions.

Muhammad et al. [12] used TextBlob, VADER, SentiWordNet gauge sentiments. random forest, SVM and BoW features with More than 900,000 COVID-19 tweets and concludes E-learning sentiment analysis suggests high effectiveness, with top-performing models and key concerns identified.

Sureshbhai et al. [13] used decentralized framework, Blockchain for trust, transparency. LSTM 98.99% accuracy with dataset of bulk transaction on bitcoin addresses and concludes ABCDM, an attention-based CNN-RNN model, excels in sentiment analysis, outperforming recent DNNs in various datasets.

Umar et al. [14] used machine learning, lexicon, and hybrid techniques. Python, R, SentimentAnalyzer, and SentiWordnet with Novice researchers, social media data and concludes Sentiment analysis in Web 2.0 offers insights across various domains, with machine learning techniques proving effective.

Chakraborty et al. [15] used LSTM technique with dataset of 160,000 tweets and concludes the model (LSTM) has an accuracy of 91.67% with validation accuracy of 84.46%

3. ISSUES AND CHALLENGES IN WEB 2.0 FOR SENTIMENT ANALYSIS

In this section we are discuss about the issues and challenges in web 2.0 that are occur during sentiment analysis which are mentioned below:

3.1 Opinion spam detection

Detecting spam has become a challenge in sentiment analysis due to the increasing popularity of e commerce and review platforms. Opinion spams, also known as fake reviews are well crafted comments that either praise or criticize a product, for their own benefit. The goal of opinion spam detection is to identify three aspects of a phone review; the content of the review the metadata associated with it and the level of real world product expertise demonstrated wankhede et al. [25].

3.2 Aspect Based sentiment Analysis

Sentiment analysis at the aspect level presents challenges in identifying individual aspects, whether implicit or explicit and classifying them based on their meaning. Mining aspects in this context has been found to be particularly challenging Wankhede et al. [25]. To address this task algorithms such as LSTM, Bi LSTM or pre trained models like BERT and GPT 2 can be utilized. Researchers tend to steer of vanilla RNN due to issues, like vanishing and exploding gradient descent. It has been observed that attention based models are increasingly employed in aspect detection.

3.3 Informal style of writing

Informal writting style poses an obstacle for various natural language processing tasks such, as sentiment analysis. Individuals tend to adopt a relaxed approach when writing reviews or texts often incorporating acronyms, emojis and shortcuts that can be challenging to interpret accurately. While universal acronyms can be managed efficiently the constant evolution and regional variations of acronyms present difficulties wankhede et al. [25].

3.4 Computational cost

To achieve accuracy it is necessary to expand the training data set and make the model more complex. However this will result in an increase in the computational resources needed for training. In fact training a model with a corpus may even require a high end GPU. Models are not expensive (by analyzing its computational cost) but the cost increases for attention models and neural networks wankhede et al. [25].

3.5 Intentional spelling error

In our dataset, we noticed instances where writers intentionally make spelling mistakes. One common intentional mistake is repeating letters, such as "I looooove it!" becoming "I love it!". Writers often use this repetition to highlight or convey strong emotions about a particular topic or event. One way to address this type of error is by removing the repeated letters until the correct word is formed. To identify these words, we simply look for instances where the same characters are repeated more than once in non-standard words Srivastava et al. [26].

3.6 Lingoes and Slang

In modern times, it is fascinating to see the use of slang and abbreviations (e.g. "gr8" for "great", "bcos" for "because", "gud" for "good") intentionally utilized by writers. However, this type of writing poses challenges in text processing. To address this, the Letter-to-Phoneme (L2P) approach is often recommended in literature as a solution for tackling slang and lingo. The CMU Pronouncing Dictionary (CMUDict) is a machine-readable dictionary that provides transcriptions for over 125,000 words and can be used in this context Srivastava et al. [26].

4. WEB 3.0 TECHNOLOGIES

4.1.1 BLOCKCHAIN

Blockchain is recognized as a decentralized ledger that does not rely on a central repository or authority. It can be replicated and distributed across network nodes. A blockchain is formed by a series of blocks, where each block stores and maintains transaction data over a specific period of time. Each block, except the initial block, contains the hash value of the preceding block. Combining these hash values creates a chain of blocks, known as a blockchain [16]. Blockchain technology is employed to ensure security when storing documents, as it is a reliable method. Regulatory authorities have the ability to leverage blockchain technology to generate a shared flow of de-identified patient data [17]. The comparison of blockchain types is shown below table 1 [16,17]:

Characteristic	**Public Blockchain**	**Private Blockchain**	**Consortium Blockchain**
Accessibility	Open to anyone	Permissioned (only authorized nodes can participate)	Permissioned (only a limited number of nodes have the authority to establish consensus)
Decentralization	High	Low	Medium
Security	High (due to the large number of nodes participating in consensus)	Medium (due to the smaller number of nodes participating in consensus	Medium (due to the medium number of nodes participating in consensus)
Suitability	Cryptocurrency transactions, decentralized applications (DApps), supply chain management, etc.	Enterprise applications, financial transactions, healthcare data sharing, etc.	Supply chain management, financial transactions, healthcare data sharing, etc.
Examples	Bitcoin, Ethereum, Solana, etc.	Hyperledger Fabric, Corda, Quorum, etc.	Hyperledger Fabric, Corda, R3 Corda, etc.

Table 1: Comparison of types of Blockchain

4.1.4 How Blockchain used in Sentiment Analysis

Web 3.0 integrates blockchain and decentralized technology with the internet to improve several applications, such sentiment analysis on Twitter datasets. Here, the results of sentiment analysis are stored in an immutable blockchain ledger, protecting the data's accuracy. Smart contracts are used to automate the process of gathering data and paying sentiment contributors. Tokenization is used to reward users that take part in sentiment analysis with cryptocurrency tokens. Decentralized applications (DApps) allow users to securely analyze Twitter data while keeping ownership over their data and receiving transparent compensation by promoting the development of sentiment-analysing tools. Web 3.0's decentralized architecture enhances privacy, openness, and user incentives, making it a strong basis for sentiment research on Twitter [18].

4.2.1 UBIQUITOUS IOT

The Ubiquitous Internet of Things (IoT) represents a future where every device and living being can be connected through the internet. it enables the seamless communication and interaction.. it extends to devices that can communicate and interact with humans or other devices autonomously. The advancement of 5G technology has brought us closer to ubiquitous iot with its high speed and low-latency communication capabilities. However, the coverage of the 5G networks is limited, specially in remote and harsh environments. This is where the integration of satellite and terrestrial networks comes into play [19]. Satellites can extend the coverage of terrestrial networks to areas that are unreachable. However, integrating these two distinct types of networks - each with its own set of characteristics and challenges - is no easy task. Research in this area has led to the development of hybrid satellite-terrestrial networks (HSTNs) which combine the strengths of both satellite communications (SatComs) and terrestrial communications (TerComs) [19]. Looking ahead, the vision for 6G is to create a ubiquitous IoT environment supported by an agile, smart, and secure HSTN. This would involve a cell-free, hierarchical, decoupled network that can support the massive connectivity requirements of the IoT [19]. Ubiquitous IoT represents a future where connectivity is not just universal but also uniformly strong , a world where every corner of the globe can be reached by the internet [19]. The comparison of ubiquitous IoT types is shown in below table 2 [20,21,22]:

Characteristic	Consumer IoT	Commercial IoT	Industrial IoT
Focus	End-user applications	Business processes and operations	Industrial automation and optimization
Devices	Smartphones, smartwatches, wearables, thermostats, cameras, smart lamps, appliances, etc.,	Sensors, actuators, controllers, industrial assets, remote telemetry, monitoring and management systems, etc.	Sensors, Actuators, Controllers, Remote telemetry units (RTUs), and Monitoring and management systems
Applications	Smart home, healthcare, wearable gadgets, smart production, farming, etc.,	Smart cities, transportation, electric vehicle monitoring, communication, and control, etc.,	Manufacturing, energy, utilities, transportation, healthcare, etc.,
Security	Security threats are often overlooked or not fully understood by consumers.	Comprehensive security measures are essential to protect commercial systems.	Cybersecurity risks are a major concern due to the critical nature of industrial processes and assets.
Data	Data is typically collected and used for convenience and entertainment purposes.	Data is collected and used to improve operational efficiency, reduce costs, and make better business decisions.	Data is collected and used to optimize industrial processes, improve productivity, and enhance safety.

Table 2: comparison of types of ubiquitous IoT

4.2.5 How Ubiquitous IoT is used in Sentiment Analysis

The utilization of ubiquitous IoT in the Web 3.0 era can significantly improve sentiment analysis for Twitter datasets by providing valuable contextual data. IoT devices like sentiment-tracking wearables, weather stations, and location-aware sensors can gather real-world data. By monitoring events and environmental conditions, IoT sensors can offer insights into the influence of real-world happenings on online sentiment. Through the integration of IoT data with Twitter sentiment analysis, and the implementation of technologies like blockchain for data security and privacy, a more comprehensive understanding of sentiment can be achieved. This integration, taking into account the physical context, ultimately leads to more accurate and valuable sentiment analysis results [23].

4.3 Advanced AI

Artificial Intelligence that aims to create intelligent machines is a fast-evolving field which is capable of executing and performing tasks that is usually require intelligence of human. Autonomous intelligent agents are fully produced by AI that interact with its environment, over time to improve its optimal behaviour through error and trial just like humans [24]. In general these tasks includes problem-solving, reasoning, learning and language Understanding. Deep neural network, complex machine learning algorithms, and cognitive computing system are all include in the field of artificial Intelligence which makes it “Advanced AI”. Modern AI can process enormous variety of data, judgement making, pattern identification, and speaking. These machines can find trends and hidden patterns or features in the dataset that might be missed by human, AI is not limited to computer science, it is ubiquitous and includes many areas like business, security, education, music, health, and art application [24]. The comparison of Advanced AI types is shown in below table 3 [24]:

Characteristics	**Machine Learning**	**Deep Learning**	**Natural Language Processing**	**Transfer Learning**	**Reinforcement Learning**
Definition	A field of computer science that gives computers the ability to learn without being explicitly programmed	A subset of machine learning that uses artificial neural networks to learn from data	A field of computer science that deals with the interaction between computers and human (natural) languages	A machine learning method where a model developed for one task is reused as the starting point for a model on a second task	A machine learning method where an agent learns to behave in an environment by trial and error
Focus	Developing algorithms that can learn from data and make predictions	Using artificial neural networks to learn from data	Developing algorithms that can understand and generate human language	Using pre-trained models to solve new tasks	Developing algorithms that can learn to behave in an environment by trial and error
Techniques	Support vector machines, naive Bayes, linear regression, etc.	RNN, CNN, transformer-based architectures, etc.	Tokenization, stemming, lemmatization, etc.	Fine-tuning, feature extraction, etc.	Q-learning, policy gradients, actor-critic methods, etc.
Applications	Image classification, speech recognition, natural language processing, etc.	Image classification, speech recognition, natural language processing, etc.	Sentiment analysis, machine translation, question answering, etc.	Natural language processing, computer vision, medical imaging, etc.	Robotics, self-driving cars, game playing, etc.
Role in sentiment analysis	Used to develop algorithms that can identify and classify the sentiment of text	Used to develop algorithms that can more accurately identify and classify the sentiment of text	Used to preprocess and understand the text	Used to transfer knowledge from pre-trained models to improve the performance of sentiment analysis models	Used to tune and improve the performance of sentiment analysis models

Table 3: Comparison of types of Advanced AI

4.4.6 Use of Advance AI in Sentiment Analysis

Advanced AI has made inclusive and more scalable sentiment analysis that can achieve up to 94.5% accuracy and it coverages over 100 languages. Advanced sentiment analysis has shifted from NLP to NLU(Natural Language Understanding) used recurrent neural network, BERT, neural network and Long-Short Term Memory. These AI technologies the sources that you choose to feed into machine and analyse the subjective context of any content or resource.

5. WHY WEB 3.0 IS SUGGESTED FOR SENTIMENT ANALYSIS

Over ten years have passed since Web 2.0 revolutionized lives worldwide, particularly in the global north. However, the global south is still striving to establish digital infrastructure to access the benefits of Web 2.0, including computer/laptop/smartphone facilities, internet connectivity, information and social media access, and learning opportunities. Despite its advantages, Web 2.0 also presents limitations for internet users, such as centralized control over information dissemination and access, inadequate security measures, and challenges related to personalization and privacy Hizam et al. [27]. Web 3.0 is viewed as the upcoming era of the internet, focusing on decentralization, user personalization, and privacy safeguards as its key elements Hizam et al. [27]. To address the drawbacks of existing web technologies, the idea of Web 3.0 is seen as a promising solution. The emergence of Web 3.0 also incorporates the "Metaverse" initiative, a groundbreaking concept introduced by Facebook, which envisions a future network centered around social connections in a 3D virtual world Hizam et al. [27]. This could be the first stage of Web 3.0's inception. Though Web 3.0 is the way of the future for the Internet, there is a dearth of research that can explain how people engage with it and adopt it, helping to comprehend end users' behavioral patterns and usability mechanisms. Web 3.0 adoption mechanism using sentiment analysis and PLS-SEM multi-analytical procedure. For this reason, sentiment analysis using Web 3.0 tweets and causal analysis of technology adoption determinants by hypothesis testing were carried out using PLS-SEM. Web 3.0 adoption behavior could be inferred by incorporating these elements into a theoretical framework and speculating on how they relate to Web 3.0 usability. Hizam et al. [27].

6. CONCLUSIONS

The purpose of this study is to understand the methods and approaches used in sentiment analysis of web 2.0 twitter is also suitable for the sentiment analysis of web 3.0 enabled Twitter. This article describes the valuable insights of various methods of sentiment analysis to perform and achieve better accuracy and provide the issues and challenges faced in sentiment analysis approaches. In this study the paper discusses and elaborate the elements and importance of web3.0 and it can be helpful in sentiment analysis, and the recent advances of web3.0. It provides the valuable insights for future research in Web3.0 twitter for sentiment analysis. Sentiment analysis of twitter helps to analyze and determine the emotional tone behind the tweets for positive , negative and neutral emotions and also helps for brand and companies to get the overview of , what customers are thinking about their company and their products and monitor the products for issues and bugs. It can be used for political analysis to understand public opinions and monitor political campaigns impact. It is also helpful for investors for making investment decisions by analyzing the public perceptions related to trending stocks, cryptocurrencies etc. It can be used by governments to manage crisis like covid-19 , corruption ,rumors etc.

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