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Summarization of Unstructured Text Reviews for Opinion Analysis in Blockchain Secure Framework

Pratik K Agrawal[1]

[1] *Department of Computer Science & Engineering, Symbiosis Institute of Technology, Nagpur Campus, Symbiosis International (Deemed University), Maharashtra, Pune, India*

E-mail address: pratik.agrawaal@gmail.com

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Abstract: The E-commerce platform has provided the user and the organization with a new avenue for product distribution and selling. Product distribution is greatly hampered by the opinions provided by the end user, and if tampering and fake reviews are generated, it affects the product badly. The natural language processing domain deals with the analysis of this review and provides the user with recommendations for decision-making. The NLP domain deals with issues like fake reviews, tampering with the reviews, security for transferring thoughts, etc. This paper proposes a blockchain-based sentimental analysis module framework that provides the user with a secure and trustful environment for opinion reviews and a hybrid sentimental module that uses the algorithms from machine learning and deep learning for sentiment score generation. The Proposed Model was evaluated on different datasets of the varied domains. The proposed model performs a substantial improvement in providing accurate results.

Keywords: *Blockchain, Deep Learning, Opinion Analysis, Machine Learning, Opinion Language Processing, Sentiment Entity Analysis*

1. Introduction

Opinions and sentiments expressed in unstructured text data, such as online reviews, social media posts, and customer feedback, provide valuable insights for businesses and researchers. Analyzing and understanding these opinions can help organizations make informed decisions, enhance customer satisfaction, and gain competitive advantages. However, due to the sheer volume and complexity of unstructured text, manually processing and analyzing opinions becomes daunting [1]. This is where Natural Language Processing (NLP) techniques come into play.

Artificial intelligence consists of a subfield of natural language processing that focuses on facilitating computers to comprehend, recognize, and produce humanoid language. It has been widely adopted to automatically extract, classify, and analyze opinions from unstructured text data. In the context of opinion analysis, NLP facilitates the extraction of sentiment, identifying the emotions and attitudes expressed by individuals towards a particular subject. The process of NLP for opinion analysis involves several vital steps [2][3][4]. First, the unstructured text data needs to be pre-processed, which includes tasks like tokenization (breaking text into smaller units), stop word removal, and stemming/lemmatization (reducing words to their base form). This pre-processing step helps to standardize the text and remove irrelevant noise. After pre-processing, the next step is to apply sentiment analysis techniques.

Sentiment analysis aims to categorize the human language words in various categories, from positive to negative, based on the scaling level. Multiple approaches can be employed for sentiment analysis, extending from convention rule-based paradigms to supervised and unsupervised machine learning and recent deep learning algorithms. These methods consider linguistic patterns, word frequencies, context, and sometimes domain-specific knowledge. Once sentiment analysis is performed, additional NLP techniques can be utilized to extract other relevant information. Named Entity Recognition (NER) can recognize and classify mentioned entities such as products, individuals, groups, or places mentioned in the text. Entity-based opinion analysis drives out their total sentiment and determines sentiments towards specific entities or features of a product or service.

Several things could be improved by analyzing the opinions reviewed in the NLP. The NLP faces many issues, like

E-mail:pratik.agrawaal@gmail.com

• Data Integrity and Manipulation: One major challenge in opinion analysis is ensuring data integrity. Unstructured text data, such as online reviews, can be easily manipulated or tampered with, leading to biased or misleading results.
• Trust and Authenticity: Online reviews and opinions often suffer from trust issues, as it is difficult to authenticate the truthfulness and credibility of the sources.
• Data Privacy and Consent: Privacy is a significant concern when dealing with opinion data, as it often involves personal information and user-generated content.
• Data Ownership and Sharing: Ownership and sharing of opinions data can be complex, especially when multiple parties are involved, such as review platforms, businesses, and users.
• Data Access and Collaboration: Accessing and collaborating on opinions data can be challenging due to data silos, legal restrictions, and trust barriers

• Data Auditing and Traceability: In opinions analysis, it is crucial to trace the origin and processing of data to ensure its reliability and quality.

The problems mentioned above in the Natural language domain can be solved with a blockchain-based framework.

A. Blockchain

Blockchain skills have added noteworthy courtesy in recent years due to their potential to provide secure, decentralized, and transparent systems for various applications. Blockchain is a disseminated ledger expertise that allows for safe, translucent, and tamper-proof communications. It is a shared database retained by a network of PCs, and each chunk in the chain holds a record of communications. This makes it very tough to change or remove data on the Blockchain, as any changes would need to be approved by all network nodes.

Blockchain and NLP can be used to create several new and innovative applications. It can be applied in NLP to build decentralized marketplaces for NLP services [7] [8]. With the increasing demand for NLP services, creating a decentralized marketplace can provide a platform where buyers and sellers can interact and exchange NLP services using cryptocurrencies. This can provide a more secure and transparent platform for buying and selling NLP services, eradicating the need for mediators and reducing business costs. Blockchain can also store and secure NLP data, such as training datasets and models. This can help to protect NLP data from unauthorized access and tampering. Additionally, Blockchain can create decentralized NLP applications that do not rely on a central server. This can make NLP applications more secure, reliable, and scalable.

The article's remaining portion, Section 2, examines and lists the work of the researchers who have used a blockchain-based framework with different domains to achieve accuracy and efficiency. Section 3 presents the proposed blockchain-based framework for opinion analysis. Section 4 demonstrates the dataset's simulation outcomes. Section 5 summarizes the research.

2. Literature Review

Many researchers have explored and contributed to the development of blockchain concepts, as it has demonstrated its efficiency in financial security management and many more. The researchers examined that the blockchain can also provide the same level of security management for the domains dealing with these problems.

Zhen et al. (2023) [1] evaluate blockchain implementation obstacles in medical source chain management. The authors assess the proposed paradigm using a case study of the medical supply chain in China. The authors conclude that the proposed model combined with an opinion paradigm is a valuable tool for assessing blockchain implementation obstacles and promoting the adoption of blockchain technology.

Elen et al. (2023) [2] investigate the public's attitude towards cryptocurrency and blockchain technology by experimenting with the outcomes on Twitter datasets and lexicon-based opinion analysis. The authors collected a dataset of tweets that mention cryptocurrency or blockchain technology. They then used a lexicon-based sentiment analysis tool to classify each tweet as positive, negative, or neutral. The authors found positive overall sentiment towards cryptocurrency and blockchain technology. However, there is a significant difference in opinion between different countries. The authors conclude that their findings suggest that the public is generally optimistic about cryptocurrency and blockchain technology.

Wang et al. (2023) [3] discuss the use of blockchain technology to improve risk forecast and authority discovery of network public opinion. The Suggested approach carried out the risk forecast and credibility discovery framework that consists of a blockchain data storage system to store and share information about public opinion, a blockchain-based consensus mechanism to guarantee the accuracy and consistency of information and a blockchain workflow-based management system to automate the process of risk forecast and reliability detection. The authors evaluate the proposed framework using a case study of a public opinion risk forecast and reliability detection project in China.

Hassani et al. (2023) [4] discuss using blockchain technology to improve trust-building and consensus management in linguistic opinion dynamics. The authors propose a blockchain-based trust-building and consensus management framework that includes a blockchain-based trust network to store and share information about agents and a blockchain-based consensus algorithm to reach agreements between agents. The authors evaluate the proposed framework using a case study of a linguistic opinion dynamics application.

Luo et al. (2023) [5] discuss using blockchain technology to improve risk management in a big data situation. They propose a blockchain-based system for threat management that includes the following components: a) A blockchain data storage method to stock public opinion data in a protected manner. b) A blockchain-based consensus mechanism to safeguard the accuracy and reliability of public opinion datasets. c) A blockchain workflow management system to automate managing public opinion risk. The authors evaluate the proposed system using a case study of a public opinion risk management project in China. The authors conclude that blockchain technology can be a valuable tool for improving risk management systems in a big data environment.

Lade et al. (2023) [6] propose a system for Bitcoin value forecast and NFT generation built on sentiment opinion analysis. The system uses LSTM to analyze the collected sentiment data and identify the sentiment of each tweet. The outcomes of the sentiment opinion analysis are used to predict the price of Bitcoin and generate NFTs. The system was evaluated using a dataset of sentiment data from Twitter. The outcomes showed that the projected model could precisely categorize the tweets' opinions. The plan was also able to forecast the value of Bitcoin with a high degree of accuracy.

Osman and Husien (2022) [7] compare the performance of different sentiment analysis techniques for classifying Twitter posts. The authors used a dataset of Twitter posts labeled as positive, negative, or neutral. They then used four different sentiment analysis techniques to classify the tweets: Lexicon-based sentiment analysis, Naive Bayes sentiment analysis, Support vector machine sentiment analysis, and Deep learning sentiment analysis. This technique uses a deep learning model to classify tweets. The authors conclude that deep learning sentiment analysis is the most effective technique for organizing Twitter posts. They also suppose that lexicon-based sentiment analysis is a good alternative for deep learning sentiment analysis, especially when resources are limited.

Chen et al. (2022) [8] propose a novel method for understanding consumer sentiment direction in social systems. The process is based on the idea that users' sentiment orientation can be learned from their interactions with other users. The technique consists of Feature extraction that extracts features from the user-user interaction network. These features contain the number of links between users, the strength of the links, and the sentiment polarity of the connections, and the Sentiment orientation method learns the sentiment orientation of each user. This is done using a machine learning algorithm to train a model that predicts the sentiment polarity of the links between the user and other users. The method can be used to advance the accuracy of opinion sentiment analysis in social networks.

Zhao et al. (2021) [9] propose a system for sentiment investigation of review datasets by considering blockchain and LSTM to advance directives for a defensible market. The system consists of a Data collection module for collecting review data from online platforms. The author proposes using LSTM to analyze the managed review data and identify the sentiment of each review. The author also uses the regulation module for the outcomes of the sentiment opinion analysis to regulate the market and ensure that it is sustainable. The system was evaluated using a dataset of review data from Amazon. The fallouts showed that the method was intelligent enough to recognize the sentiment of the reviews accurately.

Verma et al. (2021) [10] propose a framework for sentiment analysis of feedback data using blockchain technology. The framework uses LSTM to analyze the collected feedback data and identify the sentiment of each feedback. The module uses blockchain to store the collected feedback data and the sentiment analysis results. The framework was evaluated using a dataset of feedback data from Amazon. The results showed that the framework could accurately identify the feedback's sentiment.

Ye Liang and Ying Qin (2020) [11] discuss using blockchain technology to trace public opinion across languages. The authors recommend a blockchain public opinion tracing system that includes a data storage scheme to store public opinion data in a protected manner, a blockchain consensus mechanism to safeguard the correctness and consistency of public opinion datasets, and a blockchain-based workflow management system to automate the process of public opinion tracing. The authors evaluate the proposed method using the example of a public opinion tracing project in China. The authors conclude that blockchain technology can be a valuable tool for improving cross-lingual public opinion tracing.

Q. Pan et al. (2018) [12] propose a deep learning model for text opinion sentiment analysis. The prototype contains a bidirectional long short-term memory (BLSTM) model: This prototype removes features from the text and supports the vector machine (SVM) classifier. This model categorizes the text into positive, negative, or neutral sentiment polarity. The BLSTM is a deep learning model that can learn long-range dependencies in text. The SVM classifier is a machine-learning prototype that can classify text into different categories. The authors evaluated the model on a text dataset labeled as positive, negative, or neutral. The outcomes displayed that the prototypical achieved correctness of 93.2%. The authors concluded that the model is a promising approach for text sentiment analysis.

Kuo et al. (2017) [13] provide an overview of the potential applications of blockchain scattered ledger technologies (DLTs) in biomedical and health care (BMH). The authors discuss the benefits of DLTs for BMH, such as their decentralized, secure, and transparent nature. They also discuss the challenges to address before DLTs can be widely adopted in BMH, such as security and privacy concerns. The authors conclude that DLTs can transform BMH by improving the efficiency, safety, and privacy of data sharing and collaboration. DLTs could also advance the excellence of care, reduce healthcare costs, and accelerate the development of new treatments.

Yue et al. (2016) [14] propose a blockchain-based architecture for healthcare data gateways. The proposed architecture addresses healthcare data sharing challenges, such as data fragmentation, security, and privacy. The proposed architecture has several advantages over traditional healthcare data-sharing approaches. First, the blockchain-based data storage system provides a secure and tamper-proof way to store healthcare data. Second, the PAAC system ensures that only authorized users can access healthcare data and that data is only used for the intended purpose. Third, the healthcare data gateway provides a secure interface for organizations to access and share healthcare data.

The literature review analysis provided the information that the blockchain approach has dramatically improved the performance of the area in which it has been deployed for security management, efficient distribution of the datasets, and providing integrity and security to the domain.

3. Methodology

The Proposed Mechanism uses Blockchain algorithms, also known as consensus algorithms, which are fundamental components of blockchain technology. They play a critical role in enabling participants in a blockchain network to approve the validity of communications and reach a consensus on the state of the blockchain. These algorithms ensure the blockchain's integrity, security, and decentralization by providing mechanisms for achieving agreement among participants without the need for a central authority.

By leveraging these consensus algorithms, blockchain technology enables decentralized and trustless networks where participants can reach agreements and maintain the integrity of the shared ledger. The selection and implementation of a suitable consensus algorithm are crucial in designing a blockchain system that meets the specific needs and objectives of the intended application.

The proposed work focuses on Proof of Work consensus algorithms that help develop the Blockchain-based framework for the opinions reviews analysis. Figure 1 depicts the proposed architecture containing four entities: user, processor, manager, and organization. The four entities involve four modules: the opinion data module, the sentiment analysis module, the trust management module, and the review analysis module for organizations.

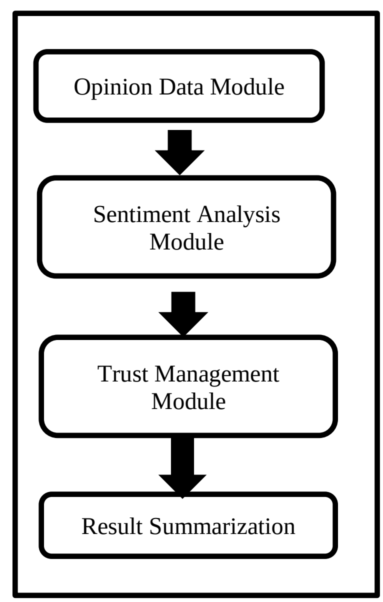


Figure 1. Proposed Blockchain Framework for Opinion Analysis

A. *OPINION DATA MODULE*

The opinion data module hosts the user on the blockchain network with the help of the Ethereum blockchain framework. It registers the user, e-commerce, and the organization on the web. The account is created for every user, the organization of which the products are mentioned, and the user has provided a review of the products. The study will be linked to the product ID and collected in the secure blockchain in the form of a distributed peer-to-peer model. The Block related to the particular product will store all users' reviews around the network. This will provide substantial security and validation to the user reviews generated and stored on a secure blockchain network for access.

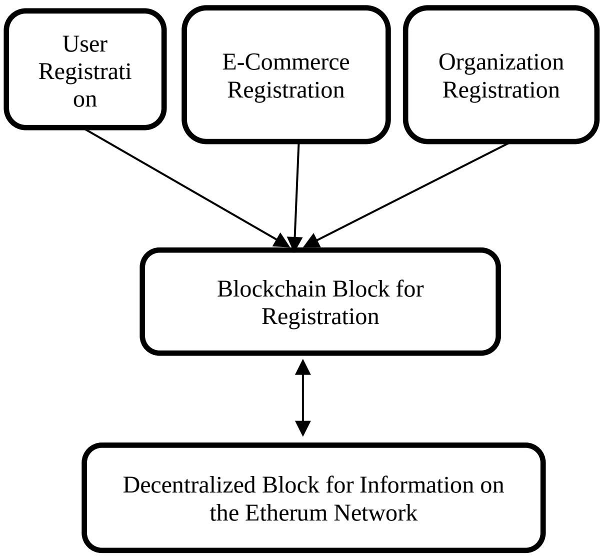


Figure 2. Opinion Data Module

B. *SENTIMENT ANALYSIS MODULE*

The opinion reviews generated and shared by the opinion data module are used to classify the reviews and extract the sentiment from the unstructured text. The unstructured text deals with many issues for sentiment extraction. Machine learning and deep learning approach systems generate the investigation from the text reviews.
The proposed architecture of the sentiment analysis uses machine learning, the Naive Bayes Model, and the LSTM Deep learning model for computing the polarity of the input unstructured text reviews.

Naïve Bayes Classifier Algorithm
It is a graphical model most widely used in Bayesian networks because it can handle uncertain information.
The steps for the Naïve Bayes classifier Algorithm are as follows:
Step 1: The Naïve Bayes classifier algorithm assumes the dataset (D) with words; all the words from the dataset (D) belong to the specified class (Cj) and presumes that there are no missing values.
Step 2: The Previous Probability P (Cj) is calculated for all classes (Cj) in the dataset.

$$D: P(C\mathrm{j}) = \frac{\sum t_i \to C_j}{\sum_{i=1}^{n} t_i} \quad (1)$$

Where t represents the occurrence from 1 to n
Cj represents the class in the Datasets.
Step 3: For all attribute value (Aij) the class provisional probabilities $\mathrm{P}\left(\mathrm{Aij}/_{\mathrm{Cj}}\right)$ for each characteristic values are calculated in the D.
Step 4: The previous probability of the class is multiplied by the class conditional Probability.
Step 5: The Class with the uppermost classifier probability is considered by comparing the output probability of each class from 1 to N
LSTM (Long Short-Term Memory) classifier
It belongs to the recurrent neural network (RNN) category that is frequently used for text investigation and natural language processing tasks. LSTM networks are real in capturing long-range dependencies in successive data, making them well-suited for tasks involving text classification, sentiment analysis, named entity recognition, and more.
The architecture of an LSTM opinion analysis review model is typically composed of the following layers:

- Embedding layer: This layer converts each word in the review into a fixed-length vector. This is done to represent the meaning of each word in a way that is understandable by the LSTM network.
- LSTM layer: This layer is responsible for learning long-term dependencies in the review text. It does this by maintaining an updated state as the network processes each word in the review.
- Dense layer: This layer categorizes the review as positive, negative, or neutral. It does this by taking the output of the LSTM layer and passing it through a series of linear operations that produce a probability distribution over the three classes.

The Naïve Bayes Classification Algorithm and the LSTM classifier provide a fast and scalable search for the various domain mapping applications of information retrieval. The approaches deal with some challenges that need to be addressed to refine the system's correctness. The efficient solution is used in the hybrid approach that will associate the output score of both algorithms for searching and forecasting the domain as both imply different approaches. This can result in improved performance for the mapping. The performance of the mapping can be further improved by working on the input sets used at the time of comparison.
The suggested deliberate hybrid approach will associate the output score of both algorithms for searching and predicting the domain as both imply different approaches.

The architecture for the Hybrid approach is as follows.

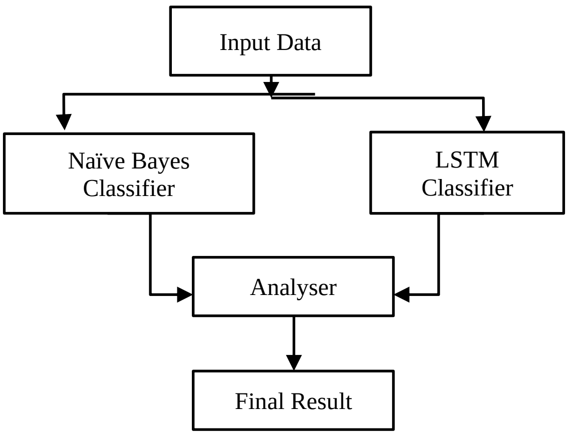


Figure 3. Architecture for Hybrid Sentiment Analysis Approach Module

The Suggested Hybrid Methodology for sentiment analysis is defined below:

Step 1: Take the Input from the opinion input data module.

Step 2: Compute the Naïve Bayes Supervised Classifier and LSTM unsupervised classifier for producing the Score value (SV) and weighted vector (Vi).

Step 3: The Naïve Bayes score value is combined with the scoring output (Sv) of the weighted vector (vi), and average grouping is considered for the matching. Cap$CapFinal\ Score\ Value = (Sv + Vi)/2$

Where Sv represents the Naïve Bayes score output

Vi represents weighted LSTM (V)

Step 4: The resulting Score output is the best sentiment analysis assessment.

The steps are consequently run repeatedly until the final output is reached.

C. Trust Management Module

This module deals with the security and service constraints of the proposed sentiment analysis module. It consists of four entities, user, processor, manager, and organization, representing the four nodes in the blockchain Ethereum network P1, P2, P3, and P4 for executing the smart contracts. The architectural flow diagram for the trust management module is depicted in Figure 4. The P1 represents the user who provides the opinion for the product, and the reviews are stored in the blockchain network for security. The P2 nodes represent the processor that includes the sentiment analysis module that takes the hybrid approach to make the sentiment analysis of the data coming from the P1 nodes.

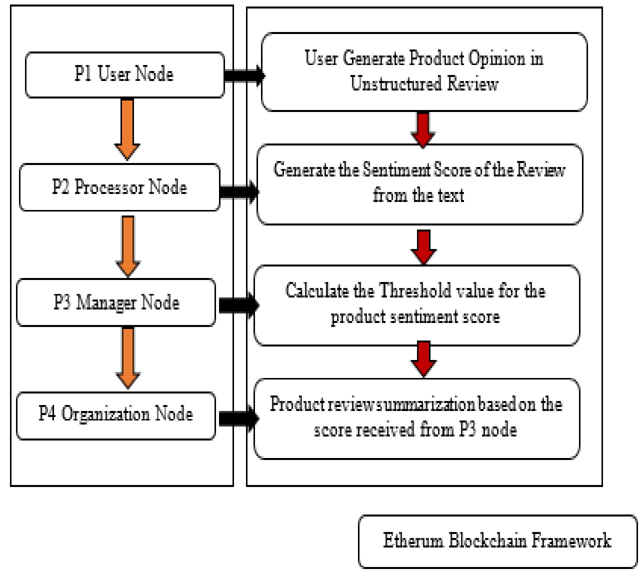


Figure 4. Architecture for Trust Management Module

The generated results for every product are stored in a distributed network of blockchains spread around the complete Ethereum, and subsequent smart contracts are generated for every couple of opinions and stored in the network. The P3 nodes in the network act as a manager that manages the complete information coming from the P2 nodes for efficient and proper management.

The P3 nodes follow a stop-and-wait approach for processing and providing the information to the P4 nodes. The P3 nodes process the information stored in the Ethereum block; the P3 node calculates the threshold value of the analysis based on the review provided by the P1. If the value of the sentiment analysis information meets the given threshold, information is provided to the P4 node that acts as a manager of the product for the organization. The information contains the sentiment analysis score for the product. The P4 node makes an appropriate judgment based on the review policy. Still, if the threshold value is not met, the information will be stored in the blockchain through smart cards, so a collaborative and enough data is required for processing. Therefore, the threshold is used for the purpose. The Flow chart representing the process of sending the sentiment score by the P3 node to the P4 nodes is depicted in Figure 5.

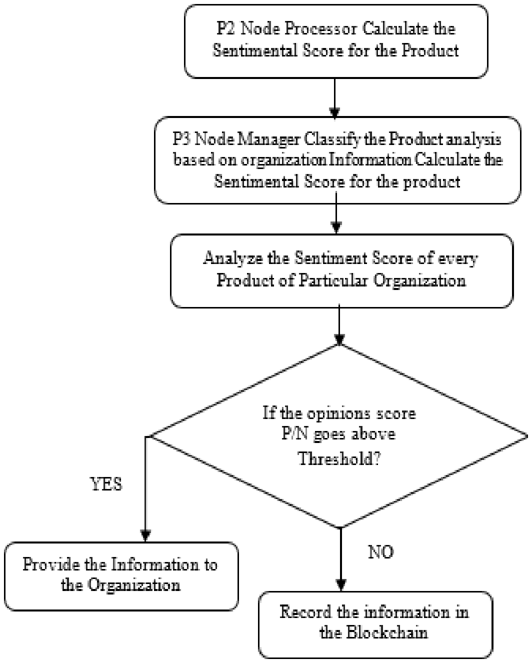


Figure 5. Flow chart representing the process of sending the sentiment score

4. Results and Discussion

A. Datasets

The experimental evaluation of the suggested blockchain approach for opinion sentiment analysis is carried out on the following datasets driven from the different domains and sources for effective consideration.

The five datasets from the various domains are taken into consideration. They are defined as follows:

E1: This set consists of the 40000 opinions of the students from an educational institute for the institute performance outcomes.

E2: This set consists of the textual unstructured 9000 customer opinions for the video camera. This dataset has been taken from Kaggle, a research platform for data science projects.

E3: This set consists of the 12000 Hotel Reviews given by the customer based on the amenities and services provided by the hotel authority. This dataset has been taken from the trivago portal.

E4: This set comprises 20000 reviews for the Cars from customers who have extensively used the product for a long time. The reviews are taken from the Edmunds website. It consists of about 140-250 car reviews for each year model.

The final dataset (D) is a combination of all the datasets combined to calculate the system's performance outcomes.

B. Evaluation of the Metrics for Comparison

It is imperative to calculate the performance of the sentiment analysis module; the proposed algorithm is trained with the training datasets and evaluated on the test datasets for comparison. Two metrics are used for the evaluation of the set, which are accuracy and F1-score, respectively.

Accurateness: The suggested approach's accuracy is calculated based on truthful sentiment prediction on the given sets.

$$Accuracy\ Percentage = \frac{TP+TN}{\mathrm{TP + FP + FN + TN}} \quad (2)$$

Sum of Delay: It is intended to be the time mentioned by the system for processing the correct outcomes.

Precision and recall are two usually used performance indicators for assessing the correctness of cataloging models. They provide an understanding of unalike aspects of model presentation and are mostly useful when allocating with excessive datasets.

Precision:

Precision is the relation of true positive forecasts (TPi) to the total number of positive forecasts made by the model. It tests the number of properly forecasted positive occurrences out of all instances predicted as positive and false positive (FPi).

Precision = TPi / (TP + FPi) (3)

Recall:

Recall, also known as understanding or correct positive rate, is the ratio of correct positive forecasts to the total number of positive occurrences in the dataset. It events the capability of the ideal to properly identify positive occurrences.

Recall outcomes = TPi / (TPi + FNi) (4)

F1-Score is a regular value of recall and precision as mentioned in eq 3, 4; It ranges its finest assessment at one and poorest value at 0. As given in Eq (5), it reflects false posives and negative outcomes.

$$F1 - score = 2 * precision * recall / (precision + recall) \quad (5)$$

TPi stands for True Positives outcomes and TNi for True Negatives outcomes signify the right training results. FPi stands for False Positives, and FNi stands for False Negatives, signifying the improper result.

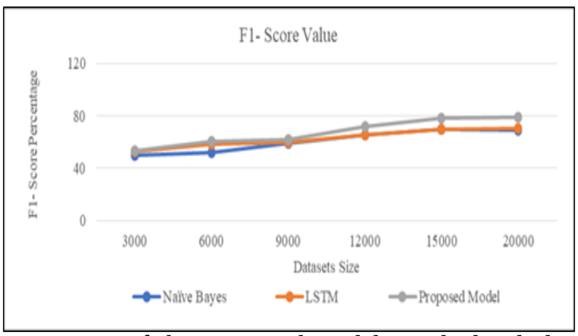
A. Performance Outcomes

Outcomes of the suggested model are carried out on the D data, including the different data sets for comparison ranging from E1 to E4. The opinions expressed in the datasets are combined to evaluate performance. The F1-score of the suggested model is calculated along with the other existing approach, and the result of the calculation is depicted in Table 1 and Figure 6.

TABLE I. F1-SCORE CALCULATION ON THE VARIED DATASETS

Sr.No	Data Scale Size	Naïve Bayes	LSTM	Proposed Model
1	3000	59.234	60.214	63.321
2	6000	52.432	56.321	61.342
3	9000	56.432	57.432	64.321
4	12000	63.432	67.345	67.432
5	15000	67.845	69.432	73.213
6	20000	68.321	70.895	74.543

Figure 6: F1-score Graphical representation



The accuracy of the suggested model is calculated along with another model, and the result of the calculation is depicted in Table 2 and Figure 7.

TABLE II. AVERAGE SCORE CALCULATION ON THE VARIED DATASETS

Sr.No	Data Scale Size	Naïve Bayes	LSTM	Proposed Model
1	3000	50.012	52.421	53.321
2	6000	52.222	58.121	60.122
3	9000	59.245	59.400	62.173
4	12000	65.132	65.532	71.642
5	15000	69.445	69.932	78.514
6	20000	69.111	70.342	78.543

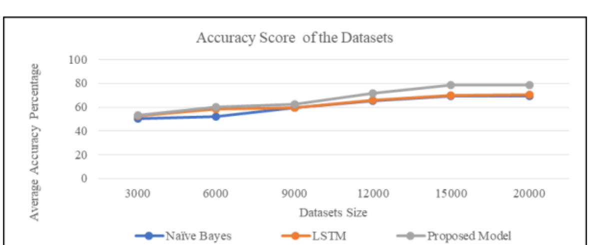


FIGURE 7: Average Accuracy Graphical representation of the results

5. CONCLUSION

The research paper presents an innovative approach to blockchain-based unstructured text analysis approach that provides the user and the organization with a level of security and trust related to the generation of opinions; the Natural language processing domain faces many drawbacks because of the authenticity of the reviews, the second part presents a combination of the machine learning supervised algorithm and LSTM deep learning algorithm for the calculation of the sentiment score of the reviews. The proposed model combines the two approaches, and the varied evaluation metrics justified the result. The training corpus increased the f1-score and the accuracy parameters to a good and better extent. The system provided a secure framework for the transaction of the reviews from the user to the analysis system and then to the particular organization for which it was expressed. The future scope of the work will be to test the datasets in different languages and to create the blockchain transaction extra secure by consensus algorithms.

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Pratik K Agrawal, Ph.D, received the Bachelor of Engineering from Sant Gadge Baba Amravati University and Master of Technology in Computer Science from Nagpur University. he recently completed her PhD studies from the Sant gadge Baba University India. His research interest includes Machine Learning, Deep Learning, Artificial Intelligence. He has published more than 20 papers in National and International Journals.