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SENTITRUST: A NEW TRUST MODEL FOR DECENTRALIZED ONLINE SOCIAL MEDIA

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ABSTRACT Energy prices have gone up gradually since last year, but a drastic hike has been observed recently in the past couple of months, affecting people's thrift. This, coupled with the load shedding and energy shortages in some parts of the world, led many to show anger and bitterness on the streets and on social media. Despite subsidies offered by many Governments to their citizens to compensate for high energy bills, the energy price hike is a trending topic on Twitter. However, not much attention is paid to opinion mining on social media posts on this topic. Therefore, in this study, we propose a solution that takes advantage of both a transformer-based sentiment analysis method and topic modeling to explore public engagement on Twitter regarding energy prices rising. The former method is employed to annotate the valence of the collected tweets as positive, neutral and negative, whereas the latter is used to discover hidden topics/themes related to energy prices for which people have expressed positive or negative sentiments. The proposed solution is tested on a dataset composed of 366,031 tweets collected from 01 January 2021 to 18 June 2022. The findings show that people have discussed a variety of topics which directly or indirectly affect energy prices. Moreover, the findings reveal that the public sentiment towards these topics has changed over time, in particular, in 2022 when negative sentiment was dominant.

1.INTRODUCTION

Energy is at the core of modern life - 21*st* century humans heavily rely on energy to carry out basic life essential tasks including medical assistance, lighting, heating, cooling, transportation, home appliances, and much more. Due to the enormous reliance of humans on energy, it has also become an emotional issue. Any policy or price change related to energy by the government or corporate bodies, results in huge outrage from the public. In present times, probably the most convenient way of expressing such hue and cry is on social media where one can express all negative or positive views about any topic including energy. Indeed, the world has witnessed the change in governments due to the mismanagement of energy affairs and corresponding opinion expression on social media.

Twitter with 336 million active users monthly and around500 million tweets per day become the main source of feedback for government, private organizations, and other service providers [1]. Obviously, processing such a huge number of tweets manually is impossible, therefore a sub-field of natural language processing, namely Sentiment Analysis (SA) has emerged as a solution to computationally process text for extracting people's opinions about the topic of interest. Sentiment Analysis is a research field that extracts users' opinions from target text and points out its related polarity (positive, negative or neutral). In recent years, SA has become a strong tool for tracking and understating users' opinions. In 2020, with the start of the pandemic, social media platforms, particularly Twitter played an essential role as communication channels to share people's reactions to corona virus(covid-19) lockdown [2], [3], healthcare services [4], vaccination [5], [6], etc. From January 2022 as the price of energy is dramatically increased, Twitter became a platform for people to react to such a rise. The spike in energy prices affected living costs for people all around the world. Due to rising energy prices, two-thirds (66%) of adults in Britain reported their cost of living increased during April 2022.1 Moreover, according to Eurostat,2 the Euro zone annual inflation rate is risen to 8.6% in June 2022, the highest since the creation of the Euro, mainly due to the soaring energy prices. In the last two years with the huge oscillation in energy prices, makes it crucial to study and analyze public engagement on social media platforms. In this paper, we aim to investigate people's reactions to increases in energy bills that were expressed on Twitter from January 01, 2021 to June 18, 2022, and how the sentiment is developed over time. Additionally, the study aims to present experimental evaluation of various classifiers on sentiment analysis task. To that end, the collected tweets are initially annotated with sentiment labels using a transformer-based sentiment analysis approach and then a topic modeling based on BER Topic and LDA model is employed to identify other relevant hidden topics associated with energy prices for which people have shown positive and negative attitudes. The following are major contributions of this paper:

- Creation of a dataset composed of 366,031 tweets related to energy prices collected between 01 January 2021 and 18 June 2022.
- A solution leveraging sentiment analysis and topic modeling to explore public engagement with soaring energy prices on social media, i.e. Twitter.
- Using a machine learning model based on transformers and lexicon based-approaches for the prediction of sentiment labels as well as continuous and discrete topic modeling.
- Benchmarking evaluation of various conventional machine learning and deep learning models on the collected Twitter dataset.
- Analysis of people’s sentiment over time regarding energy issues world-wide.

2.LITERATURE REVIEW

- **R. Ahuja et al. (2019) The Impact of Features Extraction on the Sentiment Analysis** R. Ahuja et al. conducted a study to investigate the significance of feature extraction techniques in enhancing the performance of sentiment analysis models. The objective was to understand how different methods of feature extraction impact the accuracy of sentiment classification. The authors performed experiments using various feature extraction methods, including Bag of Words (BoW), Term Frequency-Inverse Document Frequency (TF-IDF), and word embeddings like Word2Vec. They applied these techniques to a dataset of social media comments to analyze sentiments. Different machine learning algorithms, such as Support Vector Machines (SVM) and Naive Bayes, were employed to classify sentiments based on the extracted features. The findings revealed that feature extraction plays a crucial role in the accuracy of sentiment analysis. Specifically, word embeddings outperformed traditional methods like BoW and TF-IDF in capturing semantic meanings and contextual relationships between words. The choice of features significantly influenced the model's ability to generalize across different datasets, indicating that effective feature extraction is essential for robust sentiment analysis. The implications of this study suggest that researchers and practitioners should prioritize effective feature extraction methods to improve sentiment analysis outcomes. The authors also noted that future work could explore advanced deep learning techniques for feature extraction, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), to further enhance sentiment analysis performance.
- **A. S. Imran et al. (2020) Cross-Cultural Polarity and Emotion Detection Using Sentiment Analysis and Deep Learning on COVID-19 Related Tweets** A. S. Imran et al. focused on cross-cultural polarity and emotion detection using sentiment analysis and deep learning techniques on COVID-19 related tweets. The study aimed to analyze public sentiment and emotional responses to the pandemic across different cultures. The authors collected a large dataset of tweets related to COVID-19 from various countries and employed natural language processing (NLP) techniques to preprocess the data. They utilized deep learning models, including Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), to classify sentiments and detect emotions such as joy, anger, and fear. The findings indicated significant variations in sentiment polarity and emotional responses across different cultural contexts. The study highlighted that while some cultures exhibited resilience and positivity, others showed higher levels of anxiety and negativity regarding the pandemic. The implications of this research are critical for understanding how cultural factors influence public sentiment during global crises. The authors suggested that policymakers and health organizations could leverage these insights to tailor communication strategies and interventions that resonate with specific cultural groups. Future research could

expand on this work by exploring sentiment trends over time and their correlation with public health measures and media coverage.

- **Z. Kastrati et al. (2021) A Deep Learning Sentiment Analyser for Social Media Comments in Low-Resource Languages** Z. Kastrati et al. developed a deep learning sentiment analyzer for social media comments in low-resource languages. The objective of the study was to address the challenges of sentiment analysis in languages that lack extensive linguistic resources and annotated datasets. The authors proposed a novel approach that combines transfer learning with data augmentation techniques to enhance the performance of sentiment analysis models in low-resource settings. They collected a dataset of social media comments in a low-resource language and applied pre-trained language models to extract features. The study utilized various deep learning architectures, including Bidirectional Encoder Representations from Transformers (BERT) and LSTM networks, to classify sentiments. The findings demonstrated that the proposed approach significantly improved sentiment classification accuracy compared to traditional methods. The authors emphasized the importance of leveraging transfer learning to overcome the limitations of low-resource languages, enabling more inclusive sentiment analysis applications. The implications of this research extend to various fields, including social media monitoring, market research, and public opinion analysis in underrepresented languages. The authors recommended further exploration of multilingual models and cross-lingual transfer learning to enhance sentiment analysis capabilities across diverse languages.
- **E. Ainley et al. (2021) Using Twitter Comments to Understand People's Experiences of UK Health Care During the COVID-19 Pandemic: Thematic and Sentiment Analysis** E. Ainley et al. utilized Twitter comments to understand people's experiences of UK healthcare during the COVID-19 pandemic through thematic and sentiment analysis. The study aimed to capture public sentiment and identify key themes related to healthcare experiences during the crisis. The authors collected a dataset of tweets mentioning UK healthcare services and employed NLP techniques to preprocess the data. They conducted sentiment analysis to classify tweets as positive, negative, or neutral and performed thematic analysis to identify recurring themes in the comments. The findings revealed a mix of sentiments, with many users expressing gratitude for healthcare workers while also voicing concerns about service disruptions and access to care. The study highlighted the importance of understanding public sentiment to inform healthcare policy and communication strategies during crises. The implications of this research suggest that healthcare providers should actively engage with the public on social media to address concerns and provide timely information. The authors recommended further research to explore sentiment trends over time and their relationship with healthcare policies and public health messaging.
- **R. Marcec and R. Likic (2022) Using Twitter for Sentiment Analysis Towards AstraZeneca/Oxford, Pfizer/BioNTech and Moderna COVID-19 Vaccines**R. Marcec and R. Likic investigated the use of Twitter for sentiment analysis towards COVID-19 vaccines, specifically focusing on AstraZeneca/Oxford, Pfizer/BioNTech, and Moderna vaccines. The objective of the study was to analyze public sentiment regarding different vaccines and identify factors influencing vaccine acceptance. The authors collected a dataset of tweets related to the three vaccines and employed sentiment analysis techniques to classify the tweets as positive, negative, or neutral. They utilized machine learning algorithms, including logistic regression and support vector machines, to analyze the sentiment and gauge public opinion. The findings indicated varying levels of acceptance and concern associated with each vaccine, with notable differences in sentiment based on geographical location and demographic factors. The study underscored the importance of social media as a tool for monitoring public sentiment and understanding vaccine hesitancy. The implications of this research are significant for public health campaigns, as they can inform strategies to address misinformation and enhance vaccine uptake. The authors suggested that future research could explore the impact of media

coverage and public health messaging on sentiment trends over time.

3.SYSTEM ANALYSIS

3.1. EXISTING SYSTEM

Although social media sentiment mining has been well investigated over different topics and events, energy-related topics have not received much attention. In the past couple of years, there is a handful of papers concerned with examining public reactions on social media about various aspects related to energy such as clean energy, energy supply & services, nuclear energy, among others. For instance, the authors in [7] used a lexicon-based sentiment analysis to analyze sentiments expressed on Twitter by the UK energy company consumers. They optimised the accuracy of the sentiment analysis results by combining functions from two sentiment lexicons. They used two lexicons where the first one extracted the sentiment and the second lexicon to classify the rest of the data. According to their experimental results, this method improved the accuracy compared to the common practice of using only one lexicon. The research work conducted in [8] used geo-tagged Twitter data collected from Alaska between 2014 and 2016 to investigate Alaskans' perceptions and opinions on clean energy sources. A lexicon-based sentiment analysis and fuzzy-based theory were employed to analyse the sentiment of each tweet. Their result shows thewords ''tidal'' and ''solar panel'' have the highest rank among 20 other words. They also found that Alaskans' attitudes toward energy and renewable energy changed positively during the period of study.

A similar study focusing on examining people's attitudes towards clean energy is conducted in [9]. In this study, the authors used Twitter data to do a comparative sentiment analysis on various renewable energy sources. Their results also confirmed that people are more positive towards renewable energy sources for a better environment. Similar results have been reported in [10], which shows that there exists a positive perception among people from the UK and Spain regarding renewable energy sources and a negative sentiment towards coal energy. Some research efforts [11], [12], [13], [14] have been put into the investigation of public opinion on social media regarding nuclear energy. For instance, researchers in [12] analyzed Twitter discussions regarding nuclear disaster and energy. For this purpose, they collected a dataset of 2 million tweets concerning the Fukushima Nuclear Disaster in 2011 and the Nobel Peace Prize announcement in 2017. Three various deep neural networks including CNN, LSTM, and Bi-LSTM were used to analyze the attitude of users if they were supportive or cynical towards nuclear energy. The findings showed that the dominant aspects discussed by supportive users are more about concepts such as clean energy, lower CO2 emission, and a sustainable future, whereas cynical users viewed nuclear energy as unsafe for human life and threatening to the environment. Public opinion expressed on social media about nuclear energy is also investigated by the researchers in [15]. Specifically, the study focuses on examining the sentiment of people from German-speaking countries toward nuclear energy. Three machine learning algorithms, namely decision tree, random forest and LSTM are used for sentiment analysis. The study found that majority of the comments (71%) were neutral, followed by positive and negative comments that accounted for 23% and 6%, respectively. Opposite results have been reported in the research work conducted in [13] where the authors found that negative comments expressed by Korean people toward nuclear energy were larger than positive ones. Additionally, the study found that positive-tone articles were more present than negative ones. A model for extracting people's opinions on several energy-related aspects is presented in [16]. The authors leveraged Twitter data using several word-embedding and deep neural models. More concretely, word embeddings are used for converting tweets to numerical representation, whereas BERT is employed for extracting people's sentiment from tweets. This approach is conceptually similar to ours but its focus and the approach used for the sentiment classification task are different. Specifically, we are focusing on exploring public engagement with energy prices on social media using transformer-based sentiment approaches as well as topic modeling for extracting various sub-themes. There is another strand of research [17], [18], [19], [20] which focuses on exploring people's sentiment about renewable energy. For instance, researchers in [17] applied social media analytics to determine the emotional discourse on social media towards renewable energy. Analysis of 6528 Twitter messages about 27 electricity utilities in the US showed that sentiment varied based on utility with joy and sadness being the dominant emotions.

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Sentiment analysis of Twitter messages related to renewable energy companies is also examined in [20]. The study used a lexicon-based technique to extract investor sentiment from tweets during both trading and non-trading hours whereas stock forecast is carried out using a hybrid deep learning model (CNN-LSTM). The study found that sentiment variables play an import roleon forecasting the stocks as they hold important information that can not be captured by standard financial market variables. Zhang et al. [21] proposed a study to assess user perception of renewable energy and GHG (greenhouse gas) emissions by analyzing Twitter mentions and Google search trends in the USA, Australia, and Europe. Public sentiment expressed on Twitter regarding energy crisis has attracted the attention of researchers. For example, Vasiliki Vrana et al. [22] recently conducted a study to determine the sentiment of EU citizens on Twitter regarding energy crises. Using a multilingual sentiment analysis approach that considers five major European languages and English, the authors found that fear and sadness are the predominant emotions expressed by citizens in relation to energy crises. In another study, Zeitun et al. [23] analyzed sentiment expressed on Twitter and its impact on sectoral returns in the US. They found that opinion swings on Twitter not only affect the energy sector, but also impact other sectors such as healthcare, information technology, materials, and communication.

Disadvantages

- The complexity of data: Most of the existing machine learning models must be able to accurately interpret large and complex datasets to detect Sentiment Analysis.
- Data availability: Most machine learning models require large amounts of data to create accurate predictions. If data is unavailable in sufficient quantities, then model accuracy may suffer.
- Incorrect labeling: The existing machine learning models are only as accurate as the data trained using the input dataset. If the data has been incorrectly labeled, the model cannot make accurate predictions.

3.2. PROPOSEDSYSTEM

VADER that stands for Valence Aware Dictionary for Sentiment Reasoning is a text sentiment analysis that takes a human-centered approach, integrating qualitative analysis with empirical validation utilizing human raters and the wisdom of the public. It primarily uses a lexicon that converts lexical characteristics into sentiment scores, a representation of the intensity of an emotion. By adding the intensity of each word in a text, one may get the sentiment score of that text. The VADER sentiment analysis produces a sentiment score that ranges from -1 to 1, with 1 being the highest positive sentiment. The sentiment score of a sentence is determined by adding the sentiment ratings of all the words in the sentence that are included in the VADER lexicon.

TextBlob is a python library for Natural Language Processing that determines the sentiment of a tweet by calculating the semantic direction and the intensity of each word in that tweet. This necessitates the use of a pre-defined vocabulary that categorises negative and positive terms. TextBlob returns a sentence’s polarity and subjectivity. Polarity is defined within the range of -1 and 1, where -1 represents
a negative sentiment and 1 represents a positive sentiment. Subjectivity is a measure of the quantity of personal opinion and factual information in a writing and its values are between 0 and 1.

Flair is a framework for natural language processing built on PyTorch. It uses a pre-trained deep neural network to analyze the text and determine the sentiment expressed in that text. Contrary to VADER and TextBlob that generate a sentiment score in rage of -1 and 1, Flair produces a sentiment output with a confidence score between 0 and 1, with 1 indicating maximum confidence.

Stanza is a natural language processing framework that uses deep learning techniques to identify the sentiment expressed in a text. It uses annotator class named *SentimentProcessor* to add a sentiment label to each sentence in the text. Stanza supports negative, neutral and positive sentiment denoted by 0, 1, and 2, respectively.

Advantages

- A solution leveraging sentiment analysis and topic modeling to explore public engagement with soaring energy prices on social media, i.e. Twitter.
- Using a machine learning model based on transformers and lexicon based-approaches for the prediction of sentiment labels as well as continuous and discrete topic modeling.

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- Benchmarking evaluation of various conventional machine learning and deep learning models on the collected Twitter dataset.
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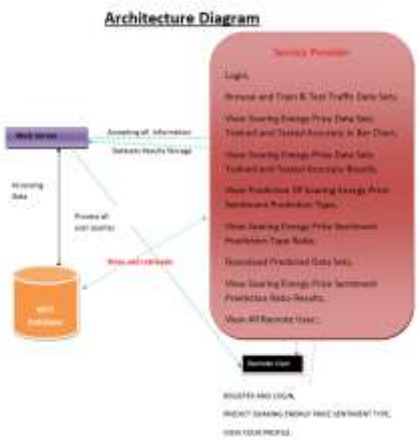
4.IMPLEMENTATION

4.1. ARCHITECTURE



4.2. MODULE'S

- Service Provider

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operation's such as Browse Datasets and Train & Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Prediction Of DDOS Attack Found Status, View DDOS Attack Found Status Ratio, Download Predicted Data Sets View DDOS Attack Found Ratio Results, View All Remote Users.

- View and Authorize Users

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

- Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, PREDICT DDOS ATTACK FOUND STATUS, VIEW YOUR PROFILE.

5.ALGORITHMS

5.1. DECISIONTREE CLASSIFIERS

Decision tree classifiers are used successfully in many diverse areas. Their most important feature is the capability of capturing descriptive decision making knowledge from the supplied data. Decision tree can be generated from training sets. The procedure for such generation based on the set of objects (S), each belonging to one of the classes C1, C2, …, Ck is as follows:

Step 1. If all the objects in S belong to the same class, for example Ci, the decision tree for S consists of a leaf labeled with this class

Step 2. Otherwise, let T be some test with possible outcomes O1, O2,…, On. Each object in S has one outcome for T so the test partitions S into subsets S1, S2,… Sn where each object in Si has outcome Oi for T. T becomes the root of the decision tree and for each outcome Oi we build a subsidiary decision tree by invoking the same procedure recursively on the set Si.

5.2. GRADIENT BOOSTING

Gradient boosting is a machine learning technique used in regression and classification tasks, among others. It gives a prediction model in the form of an ensemble of weak prediction models, which are typically decision trees.[1][2] When a decision tree is the weak learner, the resulting algorithm is called gradient-boosted trees; it usually outperforms random forest.A gradient-boosted trees model is built in a stage-wise fashion as in other boosting methods, but it generalizes the other methods by allowing optimization of an arbitrary differentiable loss function.

5.3. LOGISTIC REGRESSION CLASSIFIERS

Logistic regression analysis studies the association between a categorical dependent variable and a set of independent (explanatory) variables. The name *logistic regression* is used when the dependent

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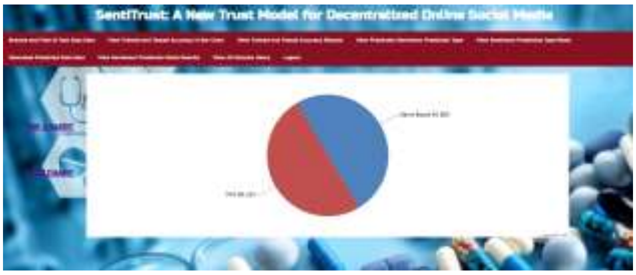
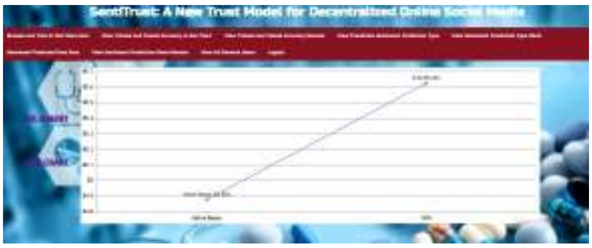
variable has only two values, such as 0 and 1 or Yes and No. The name *multinomial logistic regression* is usually reserved for the case when the dependent variable has three or more unique values, such as Married, Single, Divorced, or Widowed. Although the type of data used for the dependent variable is different from that of multiple regression, the practical use of the procedure is similar. Logistic regression competes with discriminant analysis as a method for analyzing categorical-response variables. Many statisticians feel that logistic regression is more versatile and better suited for modeling most situations than is discriminant analysis. This is because logistic regression does not assume that the independent variables are normally distributed, as discriminant analysis does. This program computes binary logistic regression and multinomial logistic regression on both numeric and categorical independent variables. It reports on the regression equation as well as the goodness of fit, odds ratios, confidence limits, likelihood, and deviance. It performs a comprehensive residual analysis including diagnostic residual reports and plots. It can perform an independent variable subset selection search, looking for the best regression model with the fewest independent variables. It provides confidence intervals on predicted values and provides ROC curves to help determine the best cutoff point for classification. It allows you to validate your results by automatically classifying rows that are not used during the analysis.

6.RESULT





CONCLUSION

In this paper, we examined people's reactions toward energy price hike expressed on social media. An unsupervised solution leveraging Twitter data was applied. We initially employed BERT to divide tweets into neutral, positive and negative, and then a topic modeling based on BER Topic and LDA is used to identify relevant sub-topics associated to energy prices from both positive and negative tweets subsets. To find a suitable number of topics/themes in the LDA, we tested various models using a grid search approach and the best performing model with five topics was selected. Findings showed that people discussed various topics that have direct effects on energy prices and this could help the decision-makers such as Government agencies and energy actors, to understand the public sentiment towards these topics and take the appropriate actions to deal with them. The decision-makers also should increase the public awareness on many of the identified topics like tree planting, solar energy, crypto mining, electric vehicles, as a measure to save energy and help consumers reduce energy bills. We also investigated people's reactions toward identified topics and how the sentiment has changed over time. At the beginning of the considered period, people seemed to pay not much attention to the situation, but the last quarter of 2021 and half of the first quarter of 2022 were characterized by positive sentiments due to various supporting schemes introduced by different governments to help people pay high energy bills. The last period, starting from the end of February 2022, was dominated by negative sentiments due to the unexpectedly raising prices of energy/oil/gas because of the Ukraine war. In this study, we leveraged Twitter data posted only this year and the previous one, therefore, future work will be focusing on collecting more tweets going back in years. Also, the dataset used in this article is highly imbalanced (positive tweets are underrepresented), so as a future work we plan to use sampling-based and text generation techniques, i.e GAN-based models [30] and GPT [31] for balancing the dataset and assess its impact on overall classification performance.

REFERENCES

1. R. Ahuja, A. Chug, S. Kohli, S. Gupta, and P. Ahuja, ''The impact of features extraction on the sentiment analysis,'' *Proc. Comput. Sci.*, vol. 152, pp. 341–348, Jan. 2019.
2. A. S. Imran, S. M. Daudpota, Z. Kastrati, and R. Batra, ''Cross-cultural polarity and emotion detection using sentiment analysis and deep learning on COVID-19 related tweets,'' *IEEE Access*, vol. 8, pp. 181074–181090, 2020.
3. Z. Kastrati, L. Ahmedi, A. Kurti, F. Kadriu, D. Murtezaj, and F. Gashi, ''A deep learning sentiment analyser for social media comments in lowresource languages,'' *Electronics*, vol. 10, no. 10, p. 1133, May 2021.
4. E. Ainley, C. Witwicki, A. Tallett, and C. Graham, ''Using Twitter comments to understand people's experiences of UK health care during the COVID-19 pandemic: Thematic and sentiment analysis,'' *J. Med. Internet Res.*, vol. 23, no. 10, 2021, Art. no. e31101.
5. R. Marcec and R. Likic, ''Using Twitter for sentiment analysis towards AstraZeneca/Oxford, Pfizer/BioNTech and Moderna COVID-19 vaccines,'' *Postgraduate Med. J.*, vol. 98, no. 1161, pp. 544–550, Jul. 2022.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 1, January : 2025
6. R. Batra, A. S. Imran, Z. Kastrati, A. Ghafoor, S. M. Daudpota, and S. Shaikh, ‘‘Evaluating polarity trend amidst the coronavirus crisis in Peoples’ attitudes toward the vaccination drive,’’ *Sustainability*, vol. 13, no. 10, p. 5344, May 2021.
7. V. Ikoro, M. Sharmina, K. Malik, and R. Batista-Navarro, ‘‘Analyzing sentiments expressed on Twitter by UK energy company consumers,’’ in *Proc. 5th Int. Conf. Social Netw. Anal., Manage. Secur. (SNAMS)*, Oct. 2018, pp. 95–98.
8. M. Abdar, M. E. Basiri, J. Yin, M. Habibnezhad, G. Chi, S. Nemati, and S. Asadi, ‘‘Energy choices in Alaska: Mining people’s perception and attitudes from geotagged tweets,’’ *Renew. Sustain. Energy Rev.*, vol. 124, May 2020, Art. no. 109781.
9. A. Jain and V. Jain, ‘‘Renewable energy sources for clean environment: Opinion mining,’’ *Asian J. Water, Environ. Pollut.*, vol. 16, no. 2, pp. 9–14, Apr. 2019.
10. M. L. Loureiro and M. Alló, ‘‘Sensing climate change and energy issues: Sentiment and emotion analysis with social media in the U.K. and Spain,’’ *Energy Policy*, vol. 143, Aug. 2020, Art. no. 111490.