IGSentiment Analysis of Russia and Ukraine War on Twitter Data: Using Azure Machin Learning and Deep Learning

Bhagirathi Nayak[1](✉), Pritidhara Hota[2], and Sunil Kumar Mishra[3]

[1] Sri Sri University, Cuttack, Odisha, India
bhagirathi.n@srisriuniversity.edu.in
[2] GITA Autonomous College, Bhubaneswar, Odisha, India
[3] Global Institute of Management, Bhubaneswar, Odisha, India

Abstract. Facebook, Twitter, and other social media sites have become popular places for people to connect and air their views on many topics. The importance of employing machine learning methods for sentiment analysis or opinion mining of these posts cannot be overstated. Russia-Ukraine conflict, users from all around the world descended upon the site to share their thoughts. By analyzing these comments, we may get a sense of how the general population felt about various events leading up to and during the conflict. This paper is mostly focused on tweet data in two steps on the Russia-Ukraine conflict. First, we collected 47885 tweet data to retrieve and analyze the tweets that reflected the proportion of positive, neutral, and negative categories-based sentiments using Azure Machine Learning, after that, we used Deep Learning for the segmentation of sentiments with scores. Finally, we got positive: 18846, negative: 12751, neutral: 16288.

Keywords: Twitter · Machine Learning · Deep Learning · Azure · Sentiments

1 Introduction

Twitter is a social media platform where users may connect, engage, and contribute to conversations about many topics through the sharing of short, 140-character entries or “tweets”. This can be accomplished through the use of various media types (text, images, emoji, and video) and user-generated feedback. As of the year 2023, Twitter is used by around 450 million people per month. By 2028, it is predicted that more than 652 million of them. Twitter has approximately 237 million people using it daily (Qi and Shabrina, 2023). The growing amount of data available online allows researchers to examine how people’s thoughts, actions, and mental states have evolved in response to widespread participation in social media (Alamoodi et al., 2021). As a result, there has been a rise in the popularity of conducting sentiment analysis with Twitter data. Natural Language Processing (NLP), Text Analysis (TA), Computational Linguistics (CLT), Machine Learning (ML), and Artificial Intelligence (AI) technologies for text analysis have gained traction as social media analysis has gained popularity. Text analysis can be

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used to learn about the perspectives of specific demographics. Although the majority of published works have been written in English, there is an increasing interest in analyzing texts in more than one language (Arun and Srinagesh, 2020). Extracting subjective comments about a topic utilizing distinct feelings like Positive, Negative, and Neutral can be used in text analysis. In this paper, we used the Twitter data set of the Russia and Ukraine war to find the people's sentiments through sentiment analysis, using Azure Machine Learning and Deep Learning because it allows for a more nuanced expression of the feelings Twitter's character count restriction, users are forced to condense their thoughts into succinct messages.

2 Review of Literature

The conflict between Russia and Ukraine is not the first to attract attention from around the world. One of the earliest global concerns involving widespread usage of social media was the local upheavals during the Arab Spring of 2010, especially in Egypt and Tunisia. After that, in 2022, the war between Russia and Ukraine is the most pressing international issue. The primary function of social media is to encourage relevant authorities to take immediate action in defence of human rights. Finding the truth is made more difficult by the Internet's abundance of information, which makes it hard to tell fiction from reality. Anomaly detection strategies in social networks are the subject of research by Sheth et al. (2022), and Venkatesan and Prabhavathy (2019). Tsugawa and Ohsaki (2015) and Salehi et al. (2018) outline many techniques for conducting sentiment analysis. Self-reported attitude scores are used by Featherstone et al. (2020) to verify sentiment scores from a large-scale investigation of public opinion towards genome editing. Although the strength of the correlation between attitude score and emotion differed between sample subgroups, the findings are encouraging overall.

Two studies that use sentiment analysis on Tweets about financial stock performance are explained by Hamraoui and Boubaker (2022). Directed social networks are a more accurate depiction of the asymmetric nature of many relationships and forms of communication. Both Malliaros and Vazirgiannis (2013), and Tsopze and Domgue (2021) acknowledge the difficulties in modeling and analyzing directed social networks, so they are not a modeling panacea. According to Scott and Carrington (2011), social network analysis is the study of the "detailed logic" behind the intentional formation and maintenance of social ties between individuals. This SNA method takes advantage of links between entities to draw a diagram of a network with nodes and arcs, where the length of the arcs represents the relative strength of the connections as calculated by mathematics (Legradi, 2009). By analyzing the resulting network, we can learn about the dynamics of different groups and the extent to which individuals are related to one another. The findings show that when analysts collect Tweets from various talks using more generic search queries, the development of a topically-focused social network to reflect dialogues generates more robust findings regarding influential users (Logan, et al. 2023).

3 Sentiment Analysis of Russia and Ukraine War

The essence of using sentiment analysis is sorting the gleaned information into positive, negative, and neutral categories. Affective computing and sentiment analysis are two new areas that take into account a wide variety of emotions (Cambria, 2016). Depending on the area of study, emotions can be broken down further into satisfaction and anger (D'Andrea et al., 2015), for example in political arguments. To account for more nuanced outcomes and identify emotions like worry, grief, rage, enthusiasm, and happiness, sentiment analysis with ambivalence handling might be added (Wang et al., 2015, 2020). The conflict between Russia and Ukraine is not the first to attract attention from around the world. One of the earliest global concerns involving widespread usage of social media was the local upheavals during the Arab Spring of 2010, especially in Egypt and Tunisia. After that, in 2022, the war between Russia and Ukraine is the most pressing international issue. Twitter has become a hotbed of debate about the escalating confrontation between Russia and Ukraine, reflecting the concerns and perspectives of people all around the world. In addition to disseminating news, the site's diverse user base also uses it to show support for the victims and discuss the geopolitical issues at play. The #RussiaUkraineWar hashtag is a popular online meeting place for people looking for updates and a platform to be heard. Some tweets call for diplomatic solutions and de-escalation, while others emphasize the human cost of the conflict and the necessity of international cooperation to maintain regional stability. Twitter's ongoing importance in impacting public conversation on this crucial subject as a medium for real-time reactions, information dissemination, and online activism is clear. Politicians, celebrities, and businesses have all taken to Twitter to condemn Russia, and users have pushed for Twitter to pull the plug on its presence there. Twitter users can openly share their opinions and encourage others to join the pro-Ukraine movement through the use of hashtags. Twitter facilitates the rapid dissemination of information.

4 Methodology

There are two main methods by which emotions represented in the text can be detected and categorized. Azure Machine Learning approach analyses texts as a classification of positive, neutral, and negative categories. Whereas the Deep Learning technique makes use of the polarity of words and segments them into categories. The following Proposed Model (Fig. 1) displays various approaches that can be utilized for sentiment analysis in practice. We have collected the Tweet dataset from the website, which is freely available. After preparing it we analyze the sentimental analysis through Azure Machine Learning techniques and got the output of positive, neutral and negative sentiment with the score. These scores and sentiments are utilized for further analysis using Deep Learning techniques and segmented with a proper accuracy of 99.36%.

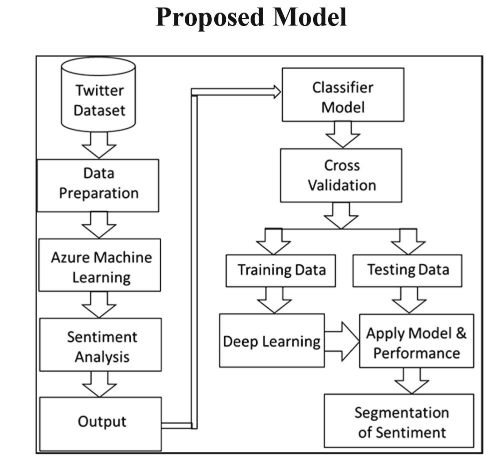

Fig. 1. Proposed Model of Sentiment Analysis

5 Azure Machine Learning Method

Data scientists, machine learning engineers, and AI developers can now construct, deploy, and manage machine learning models at scale with Azure Machine Learning, a robust and feature-rich cloud-based platform. Azure Machine Learning simplifies the entire machine-learning process with its intuitive UI and extensive range of capabilities. Users may easily do data preprocessing and analysis, model selection and tuning, and model deployment as either web services or containerized apps. Azure services tools and AI capabilities may be easily incorporated into preexisting processes. It's a flexible option for businesses that want to include AI and machine learning in their work. The cutting-edge Deep Learning for Segmentation method uses neural networks to accurately detect and separate target regions or objects from larger datasets. This method has been game-changing in many applications that rely on precise outlining of complex structures, including image processing and medical imaging. Pixel-level segmentation is made possible by the deep learning model's ability to understand complex patterns and features in data with the use of architectures like convolutional neural networks (CNNs) and feed-forward convolutional networks (FCNs). As a result of its superiority in capturing complex visual correlations, this approach excels in tasks such as semantic segmentation, instance segmentation, and even video segmentation. Boosting automation and comprehension of visual data, Deep Learning for Segmentation has promising uses in fields as diverse as autonomous vehicles, satellite imagery analysis, medical diagnostics, and augmented reality.

6 Data Analysis and Findings

In this paper, we used Azure machine learning methods to analyze the tone of text messages. As per our proposed model (Fig. 1) sentiment analysis is performed by applying distinct machine-learning methods to the pre-processed messages and getting the output. We collected 47885 tweet data from the website regarding the Russia and Ukraine wars and analysed the sentiment with a score (Fig. 2).

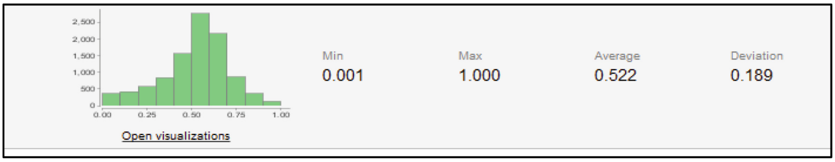

Fig. 2. Statistics

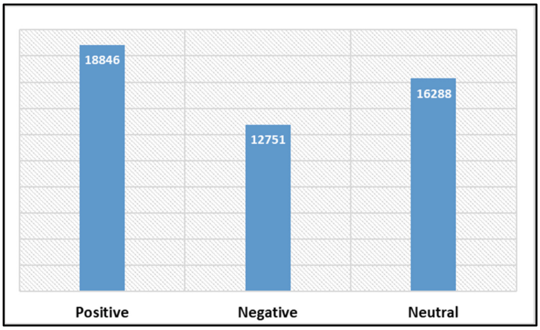

Fig. 3. Categories of Sentiment

After analysis we can observe the sentiment categories in above Fig. 3, the number of positives is 188846, negatives are 12751, and Neutrals are 1628 tweets. After that, we used the following Deep Learning model to segment the categories accurately (Fig. 4).

Deep Learning Model

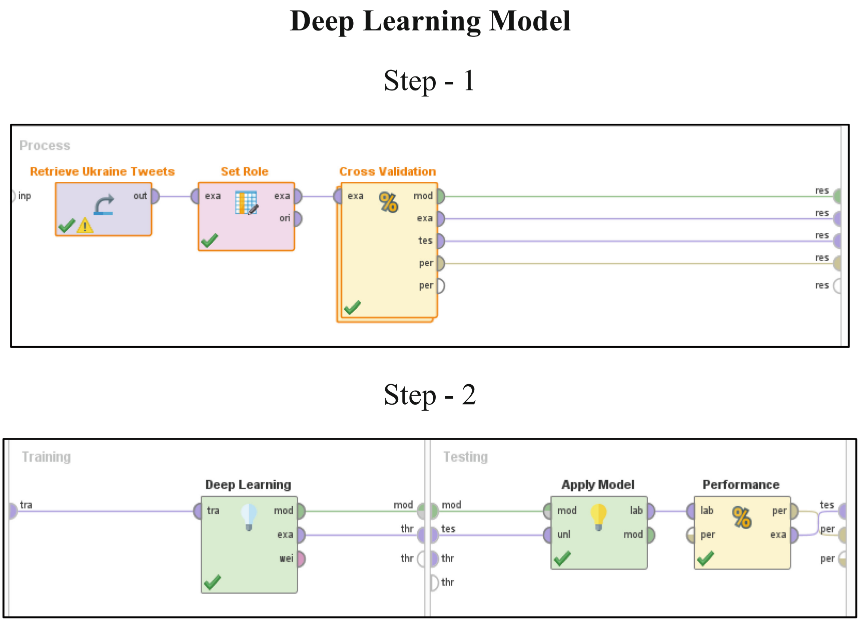

Fig. 4. Deep Learning Model

In this model (Step-1) we retrieve the tweet data and select the sentiment column as a label, then do cross-validation with 10 folds. In (Step 2) we selected the Deep Learning algorithm with a 50:50 hidden layer and 10 numbers epochs in the training set and applied the model with measure performances finally we got the following outputs.

Accuracy: 99.36% (±0.32%), Kappa: 0.990 (±0.0005), MSE: 0.004563168, RMSE: 0.067551225, R-Square: 0.99360317, Log loss: 0.016823301.

Output of Sentiment Categories

Table 1. Output of Sentiment Categories

	True Positive	True Negative	True Neutral	Class Precision
Positive	18829	0	17	99.91%
Negative	0	12566	185	98.55%
Neutral	111	24	16258	99.17%
Class Recall	99.32%	99.79%	98.84%	

As per above Table 1, we can observe the True positive: 18829 with 99.91% class precision, True negative: 12566 with 98.55%, and True neutral: 16258 with 99.17% (Fig. 5).

Scatter Plot of Sentiment Score

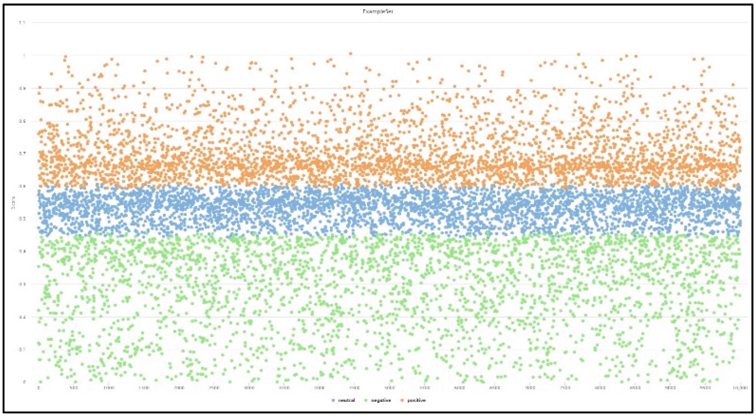

Fig. 5. Scatter plot of Sentiment Score.

The above figure derives the scatter plot of the sentiment categories score, the orange colour defines a positive score, the blue colour defines a neutral score, and the green colour defines a negative score. The following figures show the word cloud of positive, negative, and neutral sentiments (Figs. 6, 7, 8 and 9).

Tweet_text	Sentiment	Score
Dear vaccine advocate Do take the COVID-19 mRNA shot and boosters, but do know that @OurWorldInData data shows it offers zero protection, and actually accelerates death of the vaccinated. Regards #Pfizer #AstraZeneca #Moderna #NWO #Agenda2030 #COP27 #Biden #Obama #Trudeau #Jacinda #life https://t.co/VTbfuqiDvu	positive	0.66691792
#Mundo Al menos 6 muertos y 16 heridos en bombardeo ruso en #Kharkiv https://t.co/AZzEgw2NLe	negative	0.32037485
Animal shelter Dogs and Cats, we need your help! Raising funds for food for animals. PayPal: dogandcat.helper@gmail.com https://t.co/Z3re0ItTfy https://t.co/I9dbwRrtg0 https://t.co/71pErM8xBZ #Ukraine #Patreon #dogsoftwitter #Shelter #Dogs #Cats #Cute #Pets #Funny #Dogsarefamily https://t.co/HLEnTp9yk7	neutral	0.56244934
Welcome to our shelter! Located in Ukraine, Kyiv Our shelter needs your help! Raising funds for food for animals. PayPal: dogandcat.helper@gmail.com https://t.co/RH0peqvaXT https://t.co/rTtTVpoCi1 #Ukraine #Kyiv #Shelter #Dogs #Cats #Pets #DogsofTwittter #patreoncreator #Patreon https://t.co/rRWH17R813	neutral	0.53714919

Fig. 6. Sample output of Tweet text, Sentiment, and Score

Fig. 7. Wordcloud of positive sentiment

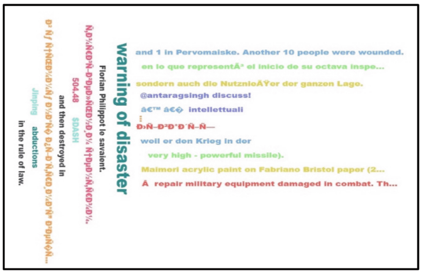

Fig. 8. Wordcloud of negative sentiment

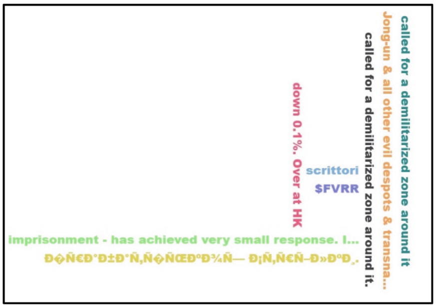

Fig. 9. Wordcloud of neutral sentiment

7 Conclusion

This article aggregates Twitter data from the most populous Russian and Ukraine wars. At the outset, we cleanse the data and classify the tweet's sentiment orientations using Azure Machine Learning-based techniques. Then, we use the annotated data sample to train the Deep Learning, techniques. Changes in public opinion about Russia and Ukraine conflict tweets can be tracked over three distinct phases. The 39.36% of scores who feel positively about the war tend to rise, then fall, whereas the 26.63% who feel negatively about the wars in the opposite manner, but 34.01% are neutral. The interaction of various elements is highlighted in the summary. Although there were alternate paths that could have been taken, the causes of the conflict ran much deeper, and the participants were subject to more external and internal constraints than is suggested by the blame-oriented literature. This suggests that waiting for Russia to leave or enacting plans to make Ukraine a neutral country are not viable options for ending the conflict.

Further research is needed to confirm this inference, but it is possible to draw a connection between the rising number of positive cases and the declining volume by analyzing the number of negative and neutral sentiments as well as tweet situations.

8 Future Work

The future of sentiment analysis holds exciting possibilities as technology continues to advance. Enhanced Natural Language Processing (NLP) algorithms, fueled by machine learning and deep learning techniques, will enable sentiment analysis systems to better understand the nuances of human emotions and expressions. As data sources become more diverse, incorporating not only text but also multimedia content such as images and videos, sentiment analysis will evolve to provide a more comprehensive understanding of sentiment. The integration of contextual information and the ability to recognize sarcasm, and cultural nuances will contribute to more accurate sentiment predictions. Additionally, the ethical considerations surrounding sentiment analysis, such as bias detection and fairness, will play a crucial role in shaping the future of this field. As sentiment analysis continues to mature, its applications will extend beyond social media monitoring and customer feedback analysis, finding utility in areas like healthcare, finance, and human-computer interaction, ultimately contributing to more empathetic and context-aware artificial intelligence systems.

References

Qi, Y., Shabrina, Z.: Sentiment analysis using Twitter data: a comparative application of lexicon and machine-learning-based approach. Soc. Netw. Anal. Min. **13**(31) (2023). https://doi.org/10.1007/s13278-023-01030-x

Alamoodi, A.H., et al.: Sentiment analysis and its applications in fighting COVID-19 and infectious diseases: a systematic review. Expert Syst. Appl. **167**, 114155 (2021). https://doi.org/10.1016/j.eswa.2020.114155

Arun, K., Srinagesh, A.: Multilingual Twitter sentiment analysis using machine learning. Int. J. Electr. Comput. Eng. (IJECE) **10**(6), 5992–6000 (2020). https://doi.org/10.11591/ijece.v10i6.pp5992-6000

Sheth, A., Shalin, V.L., Kursuncu, U.: Defining and detecting toxicity on social media: context and knowledge are key. Neurocomputing **490**, 312–318 (2022). https://doi.org/10.1016/j.neucom.2021.11.095

Venkatesan, M., Prabhavathy, P.: Graph-based unsupervised learning methods for edge and node anomaly detection in social network. In: IEEE 1st International Conference on Energy, Systems and Information Processing (ICESIP), pp. 1–5 (2019). https://doi.org/10.1109/ICESIP46348.2019.8938364

Tsugawa, S., Ohsaki, H.: Negative messages spread rapidly and widely on social media. In: Proceedings of the 2015 ACM Conference on Online Social Networks, pp. 151–160 (2015). https://doi.org/10.1016/j.osnem.2023.100242

Salehi, A., Ozer, M., Davulcu, H.: Sentiment-driven community profiling and detection on social media. In: Proceedings of the 29th ACM Conference on Hypertext and Social Media, pp. 229–237 (2018). https://doi.org/10.1145/3209542.3209565

Featherstone, J.D., George, A.B., Ruiz, J.B., Zhuang, Y., Millam, B.J.: Exploring childhood anti-vaccine and pro-vaccine communities on Twitter a perspective from influential users. Online Soc. Netw. Media **20**, 100105 (2020). https://doi.org/10.1016/j.osnem.2020.100105

Hamraoui, I., Boubaker, A.: Impact of Twitter sentiment on stock price returns. Soc. Netw. Anal. Min. **12**(1), 1–15 (2022). https://doi.org/10.1007/s13278-021-00856-7

Malliaros, F.D., Vazirgiannis, M.: Clustering and community detection in directed networks: a survey. Phys. Rep. **533**(4), 95–142 (2013). https://doi.org/10.1016/j.physrep.2013.08.002

Scott, J., Carrington, P.J.: The SAGE Handbook of Social Network Analysis. SAGE Publications Ltd. (2014). https://doi.org/10.4135/9781446294413

Legradi, J.: An exploratory social network analysis of military and civilian emergency operation centres focusing on organization structure. Master's thesis, Air Force Institute of Technology, Wright Patterson AFB, OH (2009)

Logan, A.P., LaCasse, P.M., Lunday, B.J.: Social network analysis of Twitter interactions: a directed multilayer network approach. Soc. Netw. Anal. Min.Netw. Anal. Min. **13**(1), 65 (2023). https://doi.org/10.1007/s13278-023-01063-2

Cambria, E.: Affective computing and sentiment analysis. IEEE Intell. Syst. **31**(2), 102–107 (2016). https://doi.org/10.1109/MIS.2016.31

D'Andrea, A., Ferri, F., Grifoni, P., Guzzo, T.: Approaches, tools and applications for sentiment analysis implementation. Int. J. Comput. Appl.Comput. Appl. **125**(3), 26–33 (2015). https://doi.org/10.5120/ijca2015905866