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Sentiment Analysis of the Russia-Ukraine War Using Twitter Data based on Hybrid Deep Learning Models

[1]*Snehal Sarangi, [2]Jitendra Kumar Rout , [3]Subhasis Dash
[1*,3] Kalinga Institute of Industrial Technology, Bhubaneswar
[2] National Institute of Technology Raipur
[1]snehal.sarangi@gmail.com, [2]jitu2rout@gmail.com, [3]sdasfcs@kiit.ac.in

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Abstract:

The Russia-Ukrainian War denotes an ongoing conflict between Russia and Ukraine. When Russia initiated it in February 2014, the primary focus was on whether or not Crimea and the Donbass were officially regarded as parts of Ukraine. After a military build-up on the Russian–Ukrainian border that began in late 2021, the conflict escalated dramatically when Russia initiated its assault of Ukraine on February 24, 2022. The objective of this piece is to investigate how the general population views the situation between Russia and Ukraine. Social media has become a major communication tool these days, and as a result, opinions can be found on sites like Facebook, Instagram, and Twitter. The study uses 11,250 of his tweets from his Twitter account on the conflict between Russia and Ukraine. Machine learning has demonstrated the applicability, strength, and potential of techniques such as object recognition, natural language processing, and image processing. Three feature extraction techniques, TF-IDF (term frequency-inverse document frequency), BoW (bag of words), and N-gram, have been used in the development and testing of our models. The Twitter API is used to build and test hybrid deep sentiment analysis learning models, which integrate support vector machines (SVM), recurrent neural networks (RNN), convolutional neural networks (CNN), and long short-term memory (LSTM) networks. When compared to single models on the Twitter API dataset, the hybrid models particularly the combination of deep learning models and SVM—improved sentiment analysis accuracy.

Keywords: Sentiment Analysis, Hybrid Deep Learning Models.

1. Introduction

The International Monetary Fund (IMF) has previously stated that the unrest in two important commodity-supplying nations, Russia and Ukraine, is driving up global prices, particularly for natural gas and oil. Since up to 30% of the world's wheat is sent from Russia and Ukraine, food prices are rising. The IMF also anticipated reduced growth and increasing inflation, which will have an impact on all countries worldwide.

The conflict between Russia and Ukraine has resulted in a humanitarian crisis and the world economy's second significant shock in the past two years. Global recovery was already in trouble prior to the war due to escalating geopolitical tensions, a continuous COVID-19 flare-up, a decline in financial backing, and continued supply shortages.

Natural gas is one of the "main spillover channels" for Europe, and Russia is a significant supplier. The World Bank has emphasised that the necessity to transport natural gas as liquefied natural gas and the region's diminishing reserve capacity, particularly at import and export terminals, are the main causes of the increase in gas prices in Europe.

According to IMF predictions, nations that rely heavily on oil imports would see greater trade and budget deficits as well as higher rates of inflation. Nonetheless, exporters from Africa and the Middle East can benefit from increased pricing. The long-term impacts of conflict would seriously affect the global economic and geopolitical fabric if supply lines were reorganized, payment networks divided, energy exchanges were changed, and countries' reserve currency holdings were reevaluated.

The IMF states that significant supply chain disruptions may be one of the additional consequences of rising petrol prices. Global value chains may face challenges from disruptions, penalties, and growing commodity prices. As a result, companies everywhere may expect their existing issues to worsen, which will raise manufacturing costs and cause additional delivery delays.

International services Travel restrictions, rising fuel prices, and airspace limitations that deter foreign travel have all had an impact on trade. The disruption caused by COVID-19 has already made international tourism slow, and violence might make matters worse. Among the top ten nations with the greatest international tourist departures are Russia and Ukraine. It is a significant source of revenue for nations that mostly rely on tourism, such as those in Europe, East Asia and the Pacific, the Middle East, North Africa, and South Asia.

This study analyses the views expressed by people all around the world that are found on Twitter. The majority of the issues surrounding the conflict between Russia and Ukraine will be covered by tweets from people all over the world.

By gathering and examining people's opinions, a subfield of text analysis and sentiment analysis can call attention to the positive aspects of a subject, concept, person, or organization while highlighting its negative aspects. Numerous domains have advanced in the past 20 years, including text analysis, machine learning, deep learning, object recognition and localization, image processing, natural language processing (NLP) jobs, and text analysis [1, 2]. Furthermore, non-English literature in the following languages has been assessed using machine learning models: B. Turkish, Lithuanian, and French [5-7].

To classify and analyze user sentiment, this work makes use of deep learning and machine learning techniques.

2. Literature Review

Sentiment analysis examines the feelings and viewpoints of the general public towards a concept, idea, or subject using freely accessible unstructured data. Many studies have been conducted recently on the creation of technologies to analyze and describe the process in many languages.

Between January 2022 and the first week of March 2022, 1.2 million distinct English-language tweets were used in this study [8] to classify the tweets. In total, there were 31.83% positive tweets, 54.29%

negative tweets, and 13.88% neutral messages. Using a bag of words and sum vector, the most often used terms were discovered. Word clusters that were close together in tweets were identified by the Bigram and Trigram. In this research, daily findings are mapped to analyze public reactions to significant news events.

The scale and intensity of the cyberspace arguments surrounding the Russia-Ukraine War (RUW) have given rise to a new chapter in the annals of conflict [9]. It is a remarkable illustration of a public intellectual fight against cyber-physical-social systems (CPSS), and it will have a significant impact on mankind going forward, influencing not just how we see conflict but also how we conduct our daily lives.

Researching the opinion dynamics of the online RUW is therefore worthwhile. Chinese Weibo text is the only case study used in this article's research of the evolutionary dynamics of the public opinion battle. We categorize Weibo texts into four groups using latent Dirichlet allocation, an unsupervised learning technique, after which we extract keywords and gather feedback. Techniques for opposing evolution are offered in order to dynamically imitate opinion dominance during the evolutionary process. The proposed method of modelling and assessing data-driven public opinion dynamics opens up a whole new way of addressing opinion warfare in CPSS.

This study [10] employed machine learning to provide fresh data on public sentiment towards economic sanctions based on roughly a million social media posts from 109 different countries during the Russian-Ukrainian conflict. It illustrates how government positions and popular opinion differ geographically. Finally, political instability, business linkages, and political regimes might all have an impact on how people perceived this terrible war.

This study [11] looks at the impact of the escalating crisis in Ukraine on several economic indices. Through sentiment analysis of a significant 42 million tweet sample, we were able to determine the public's perceptions regarding the escalation of the armed conflict. Next, a Vector Autoregressive model is applied to 15 economic variables (stock markets, commodities, interest rates, currencies, and cryptocurrency) using emotion indicators and 5-min data. The examination of impulse response functions shows that the effects vary between sectors and geographical areas, with crude oil showing a strong and long-lasting response. Within 10 to 20 minutes of "shocks" about how the conflict is going, most countries adopt a negative response. Both the US dollar and the Chinese yuan have been shown to react positively to the war's negative results. Using the orientations of the different impulse reactions, long-term changes in the variables under study can be predicted.

The movie reviews are evaluated by the writers of [12] using KNN, NB, and LR (logistic regression). The dataset is assembled for analysis from multiple sources, with LR providing the highest level of accuracy. A large number of classifiers are tested with both short and long text data. For brief texts, NB and LR produce average outcomes of 91 and 74%, respectively. Both models perform poorly with long texts [13]. Machine learning algorithms are effective in classifying product reviews. For camera reviews, the accuracy rates for the Support Vector Machine (SVM) and NB were 93.54% and 98.17%, respectively [14]. Moreover, [15] states that sentiment analysis is a study of viewpoints from NLP, computer science, computational philosophy, and artificial intelligence. Subjectivity and polarity are words used in sentiment analysis. Polarities reflect positive or negative emotions, whereas subjectivity describes attitudes, feelings, and thoughts [16].

Another study [17] analyses sentiment on COVID-19 tweets using lexicon-based approaches and machine learning. Text Blob is used to extract and annotate Twitter data, and TF-IDF and BoW features are used to build ML models. The outcomes demonstrate that the best combinations for the ETC models to function are the BoW features and Text blob. Due of their increased performance, deep learning models are used for sentiment categorization in several research. For example, deep learning and natural language processing (NLP) technology were used to assess public attitudes over the COVID-19 vaccination in the US and the UK [18]. We collected data from social media networks by employing pandemic-related keywords. Research indicates that people do not anticipate the knowledge process; instead, they view it as a last-minute learning strategy [19].

Ref. [20] examines the social and justice issues raised by artificial intelligence and offers recommendations for how to address them.

Quantitative, realistic, and even predictive models are being used more and more in scenarios involving crime, terrorism, pandemics, crowd disasters, and other events that involve real-life scenarios, statistical data analysis, analytical methods, and laboratory experiments. This opens up the possibility of using scientific knowledge to save lives [21]. Social difficulties can also be studied using physics methodologies [22].

3. Proposed Methodology

a. Dataset

The 25,000 records that make up the study's dataset were obtained via Twitter. There are no labels in the primary dataset, Russia-Ukraine-War-2022. Many relevant keywords are used to collect the necessary tweets, including "RussiaUkraineWar," "Ukraine," "StandWithUkraine," "Russia," and "ArmUkraine," among others. Table 1 shows a sample dataset along with the pertinent date, username, and user-generated tweet.

	Date	User	Tweet
0	2022-06-19 14:39:17+00:00	SuganthanRamak1	'For God's sake, it's their choice' - #Putin o...
1	2022-06-19 14:38:45+00:00	WilsonShilo	The EU warns that #Russian actions in #RussiaU...
2	2022-06-19 14:37:50+00:00	kiselliuda	#Ukraine #RussiaUkraineWar #war #culture #thef...
3	2022-06-19 14:37:19+00:00	NasticInc	A Russian Plane Crashes near Chernihiv!!!!!!...
4	2022-06-19 14:37:01+00:00	NasticInc	Russian Military Fleeing an area near Kherso...
...	...	...	...
24995	2022-05-27 00:04:53+00:00	RusskieUkraine	Insane footage from #Ukraine US and UK foreign...
24996	2022-05-27 00:03:51+00:00	Globalipolitics	Obesity is the second leading cause of death i...
24997	2022-05-27 00:01:02+00:00	Globalipolitics	List of 6 anti aging-food. \n#USA #China #Food...
24998	2022-05-27 00:00:41+00:00	Hashmat_M	The #West is supplying #Ukraine with weapons i...
24999	2022-05-26 23:59:43+00:00	knossavage	#ArmUkraine #StandWithUkraine #Ukraine #Russi...

25000 rows × 3 columns

Table 1: Typical tweets

Following data collection, the Text Blob Python module of the natural language processing toolkit is used to calculate the polarity score of tweets. Information is transformed via pre-processing into a standardized format that can be input into a model for analysis. After cleaning, 11,250 records were left, and they are used for further study. The sentiment score is divided into three categories: neutral, positive, and negative. Table 2 contains example tweets as well as the criteria for determining a tweet's emotion based on its polarity score. Subjectivity is used to define the opinion or judgement, while polarity is used to classify the tweet as positive or negative.

Table 2: Screenshot of the assigned emotion score

	Date	User	Tweet	Subjectivity	Polarity	Analysis	Label
0	2022-06-19 14:39:17+00:00	SuganthanRamak1	for gods sake its their choice putin on ukrain...	0.000000	0.000000	Neutral	2
1	2022-06-19 14:38:45+00:00	WilsonShilo	the eu warn that russian action in russiaukrai...	0.050000	0.050000	Positive	1
3	2022-06-19 14:37:19+00:00	NasticInc	a russian plane crash near chernihiv ukraine r...	0.133333	0.033333	Positive	1
6	2022-06-19 14:35:51+00:00	NasticInc	terror attack catch on cctv footage standwithu...	0.000000	0.000000	Neutral	2
7	2022-06-19 14:35:23+00:00	NasticInc	a russian ship burn at port of berdyansk ukrai...	0.000000	0.000000	Neutral	2
...	...	...	...	...	...	...	...
24994	2022-05-27 00:11:50+00:00	ichbin_ironhill	russia doesnt kill the 5000 ukrainian pows ukr...	0.333333	0.200000	Positive	1
24995	2022-05-27 00:04:53+00:00	RusskieUkraine	insane footage from ukraine us and uk foreign ...	0.545000	-0.265000	Negative	0
24996	2022-05-27 00:03:51+00:00	Globalpolitics	obesity be the second lead cause of death in t...	0.000000	0.000000	Neutral	2
24997	2022-05-27 00:01:02+00:00	Globalpolitics	list of 6 anti agingfood usa china food antiag...	0.000000	0.000000	Neutral	2
24998	2022-05-27 00:00:41+00:00	Hashmat_M	the west be supply ukraine with weapons in a t...	0.341667	0.075000	Positive	1

11250 rows × 7 columns

b. Methodology

The sequential process of the methodology is depicted in Figure 1, along with the methods, algorithms, and state of the data for each stage. First, the Twitter dataset is extracted and added to the "Russia–Ukraine War dataset." Using the SNSCRAPE API, the tweets are extracted to create this. The method used to collect tweets from Twitter is SNSCRAPE. The largest benefit is that there is no restriction on the quantity of tweets retrieved or the range of dates, making it easier to retrieve older tweets.

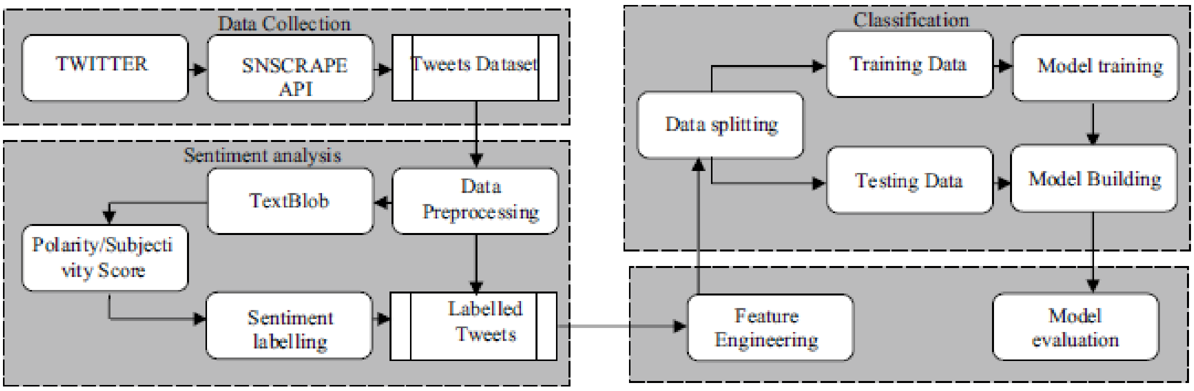

Figure 1: Proposed System Architecture

A lexicon-based method will be utilized to gloss the data with the proper label after a series of preparatory actions to clean the dataset. The training and testing sets are then created from the labelled dataset. In this case, BoW, TF-IDF, and N-gram features are used. Each of these phases is briefly described in the section that follows.

c. Pre-processing

Data analysis applications need to preprocess the data in order to remove unnecessary information and hasten the classification models' learning process. Any input that broadens the feature vector and raises computation costs without significantly improving the target class prediction is considered superfluous information. Therefore, when pre-processing is skipped or done improperly, classification models perform worse. As a result, data cleaning, or pre-treatment, is done before encoding [23]. Python's NLP toolbox was used to pre-process the tweet data for this investigation. Links, HyperTextMarkup Language (HTML) elements, and punctuation are removed once the text is converted to lower case. After then, stopwords are removed and the text is cleaned up using lemmatization and stemming procedures.

Lowercase the text: When the text is lowercased, "go" and "Go" seem to be "gone" because machine learning models understand them differently. How models treat capital and lowercase words affects their performance in training and classification. Changing the instance would help with feature engineering, which improves the data that a machine learning model can comprehend and produces results that are passably decent.

Eliminating Links to URLs, tags, punctuation, and numerals simplifies the feature space but has no beneficial effect on classification performance since they don't give learning models any new meaning. However, the feature space shrinks as a result of eliminating them.

The goal of lemmatization and stemming is to reduce a word's derivationally related variations and inflectional forms to a basic form that all words share [24]. For example, this reduces the words "talks," "talking," and "talked" to the essential word "talk."

Stopwords ought to be removed since they are overused and offer no useful information for analysis. Stop phrases such least, let, just, and like have to be omitted [25]. Table 3 illustrates the pre-processing step by which stop words such as hash (#), full stop (.), comma (,) and exclamation mark (!) are eliminated.

d. TextBlob

Many NLP tasks, including part-of-speech tagging, sentiment analysis, noun phrase extraction, paraphrasing, and sorting, can be accomplished with the lexicon-based TextBlob approach [26]. Consequently, our proposed method extracts the feature automatically using ST3DCNN in the first and second streams, then manually extracts the feature from two motion templates (MHI and MEI) from RGB-D data in parallel for classification using 2DCNN in the other four streams. It was used for sentiment analysis in this inquiry. The sentiment function of TextBlob yields a polarity score ranging from -1 to 1. A bad tweet is denoted by less than zero, a neutral remark by zero, and a good statement by more than zero [27]. Table 2 presents TextBlob's results for a sample of tweets.

e. Data Splitting

Thirty percent of the data in this study are utilized for model testing, while the remaining seventy percent are used for model training. To lessen volatility and ensure the models' generalizability, the data are moved about before being split. Furthermore, rearranging the data helps prevent the overfitting of the model and makes the training set a better representation of the distribution of the data overall.

f. Feature Engineering

The three most popular feature extraction techniques, BoW, TF-IDF, and N-gram are utilized to extract features from tweets. BoW is a straightforward method that is frequently used in NLP and information retrieval to extract features from condensed text or data [28]. BoW creates a feature vector by figuring out how frequently appears in a text and using that information to categorize the texts. The main purpose of the BoW is to expand all of the learning models' unbeatable phrases' frequency-based vocabulary.

Text data can have weighted features extracted from it using the TF-IDF extraction of features technique. To help learning models perform better, it gives each term in the corpus its weight [29].

The aforementioned feature engineering techniques were employed, and the produced data was subjected to the following models to evaluate each model's effectiveness.

g. Hybrid Methods

There are several ways to include sentiment analysis into a hybrid model. The combination of multiple effective strategies was explored in this study. The CNN and LSTM models employed in the following stages are then switched around in order: Word2vec/BERT - > LSTM - > CNN or Word2vec/BERT - > LSTM - > CNN. Additionally, we change the model's last stage by either employing an SVM or a ReLU function.

In our experiments, we created feature vectors using two different methods. In order to discover the embedding for every word in our training datasets, the first method used Word2vec, which was started with random weights. Our second method was BERT since Word2vec lacks contextual analysis to address complex semantical or polymorphic instances in natural languages. In this work, a pretrained BERT model was employed. The BERT model was utilized as a feature extractor to produce input data for the hybrid model proposal once the parameters were adjusted. The BERT model was used to create the feature vectors, which are then fed into the hybrid models that carry out the classification, using the data from the tweets and reviews.

To use the two network architectures and perform sentiment analysis on data from multiple domains, the following phase combines LSTM and CNN deep learning models, which are employed due to their strong performance on sentiment analysis [30]. As a overall observation in current scenario, in the text as well as image pattern classification deep leaning based techniques has useful to find the hidden features from the input which is convenient to accurately detect the classes of the input data.[31][32][33]

One kind of neural network called a recurrent neural network (RNN) uses the output from the preceding stage as the input for the current step. Conventional neural networks have inputs and outputs that are independent of one another. However, there are situations where predicting a sentence's next word necessitates knowing the preceding words, which means that prior knowledge is necessary. Thus, RNN was created, and it used a hidden layer to tackle this problem.

The development of the Long Short-term Memory Network (LSTM) led to its higher performance. LSTM features feedback connections in contrast to conventional feedforward neural networks. It can handle complete data sequences (text, voice, and video) in addition to individual data points (images).

Three gates—the input, forget, and output gates—as well as a cell memory state are features of the LSTM design. The addition of data to the cell state is handled by the input gate. The process of deleting data from the cell state is carried out via forget gates. By multiplying a filter, the information that is no longer necessary for the LSTM to comprehend things or that is less significant is eliminated. This is necessary to maximise the LSTM network's performance. Utilizing the output gate, the output gate's function is to extract relevant data from the present cell state and display it.

4. Experimental Result and Discussion

Using the SNSCRAPE API, the tweets are extracted to create the "Russia–Ukraine War dataset".

Pre-processing of the data is done using the Python NLP tools. With TextBlob, lexical analysis is carried out. Following lexical analysis, the data were split into testing and training sets. The performance of each feature engineering methodology is assessed by using several machine learning models after the BoW, TF-IDF, and N-gram feature engineering methods have been applied. Below are the results of the analysis that was done. Table 3 presents the result analysis for F1-score, precision, recall, and accuracy. Figure 2 represents the ROC curves CNN-SVM and CNN-BiGRU. Figure 3 represents the ROC curves of CNN-biLSTM and LSTM. Figure 4 represents the ROC curves of LSTM_CNN and RNN.

Bag of Words Results

Utilizing the initial dataset, tests are conducted using BoW characteristics. The result achieved using CNN-SVM, CNN-BiGRU, CNN-BiLSTM, LSTM, LSTM-CNN and RNN are 0.772, 0.745, 0.755, 0.513, 0.747, and 0.513 which presents the system accuracy using BoW. The outcomes demonstrate that using BoW features enhances tree-based models' performance on the dataset. The main aspect that explains this is the size of the training feature set; a tree-based model performs best when a large feature set is available.

TF-IDF Results

Experiments are conducted on the dataset utilizing TF-IDF features. The result achieved using CNN-SVM, CNN-BiGRU, CNN-BiLSTM, LSTM, LSTM-CNN and RNN are 0.763, 0.517, 0.527, 0.513, 0.587, and 0.548 which presents the system accuracy using TF-IDF. Using TF-IDF features does not significantly alter the performance of tree-based models on the dataset, as the results show. The main reason is the large feature collection that is used for training.

N-Gram Results

Trials are performed using N = 2 N-gram features on the original dataset, and the result is computed using evaluation metrics. When comparing BoW, TF-IDF, and N-gram, it can be seen that for a dataset with a variable sample size, BoW or TF-IDF yields the same performance results. On the other hand, machine learning models perform far worse when N-gram is used. The result achieved using CNN-SVM, CNN-BiGRU, CNN-BiLSTM, LSTM, LSTM-CNN and RNN are 0.719, 0.708, 0.714, 0.513, 0.716, and 0.513 which presents the system accuracy using N-gram.

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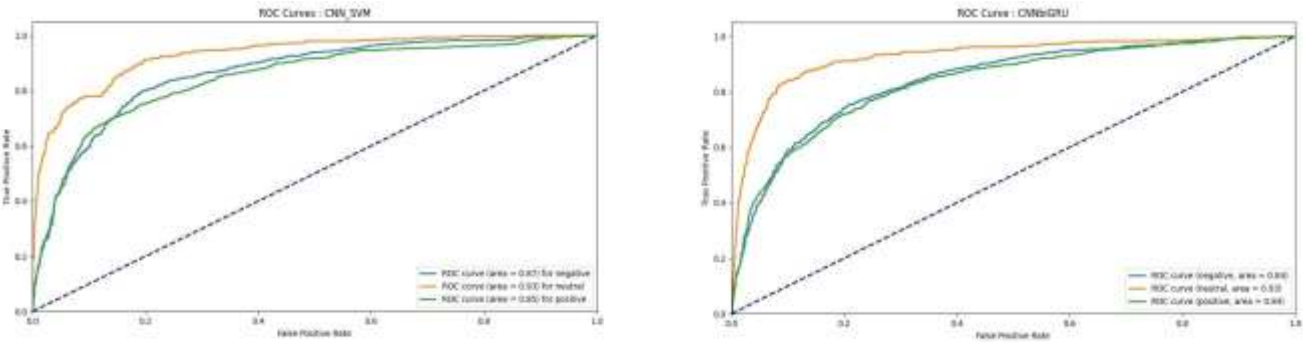
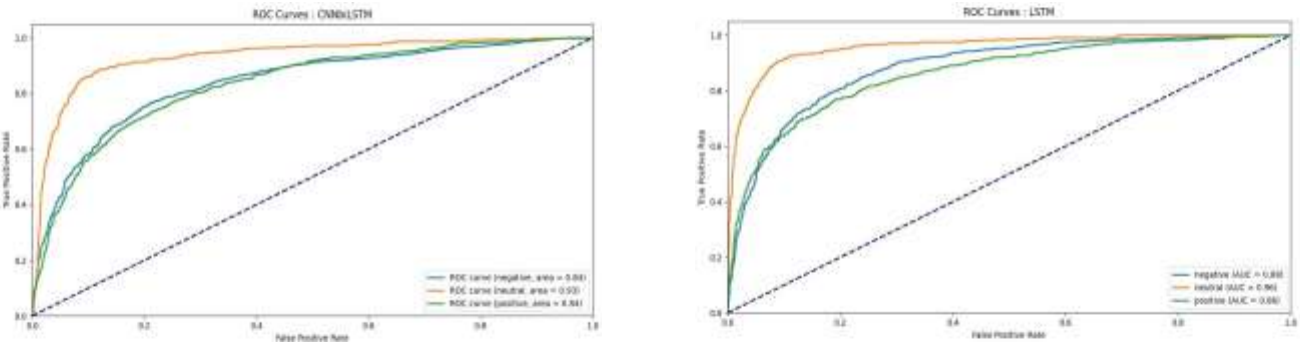
Table 3: Machine learning models' outcomes

Models	Accuracy	Precision	Recall	F1-score
CNN-SVM	0.7630	0.7617	0.7630	0.7609
CNN-BiGRU	0.7473	0.7466	0.7473	0.7466
LSTM-CNN	0.7126	0.7115	0.7126	0.7117
LSTM	0.7683	0.7692	0.7683	0.7684
RNN	0.7526	0.7639	0.7526	0.7544
CNN-BiLSTM	0.7303	0.7332	0.7303	0.7302



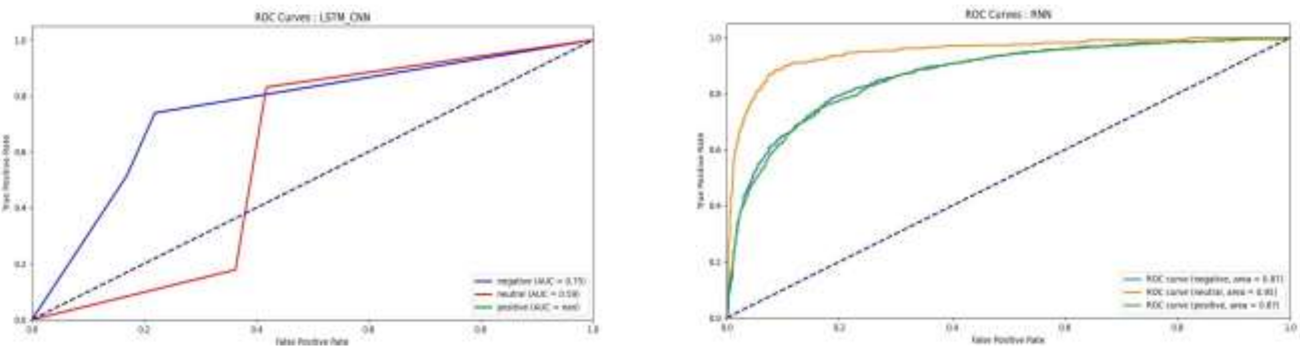
a) b)

Fig 2: a) ROC curve of CNN-SVM b) ROC curve of CNN-biGRU



a) b)

Fig 3: a) ROC curve of CNN-biLSTM b) ROC curve of LSTM



a) b)

Fig 4: a) ROC curve of LSTM-CNN b) ROC curve of RNN

Comparative Analysis:

A comparative analysis is being carried out based on various algorithms used in the proposed work to evaluate the accuracy. The performance of algorithm are based on BoW, Ngram, and TF-IDF. Table 4 shows the comparative analysis of proposed algorithms. Figure 5 shows are graph of comparative analysis of proposed algorithms.

Table 4: Comparative analysis of proposed algorithms

Parameters	CNN-SVM	CNN-BiGRU	CNN-BiLSTM	LSTM	LSTM-CNN	RNN
TF-IDF	0.763000	0.513333	0.513333	0.513333	0.513333	0.513333
Ngram	0.719667	0.708667	0.714667	0.513333	0.716667	0.513333
BoW	0.772000	0.745667	0.755000	0.513333	0.747333	0.513333

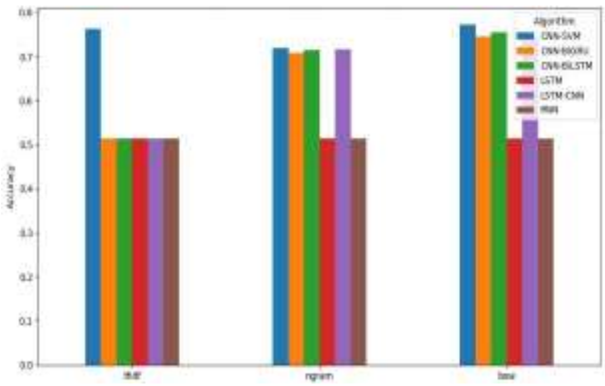


Fig 5: Comparative analysis of proposed algorithms with tfidf, ngram, bow.

5. CONCLUSION

Russia has begun publicly assaulting citizens and civilian infrastructure as part of an aggressive war against Ukraine that began on February 24, 2022. The Russian strategy's current shift towards a war of attrition has worrisome ramifications that affect everyday life, the existence of Ukraine as a nation-state, and the attention NATO countries have to pay to Russia's nuclear escalation threat. Russia's unprovoked invasion of Ukraine sparked this war, which has resulted in significant suffering and deaths among Ukrainian soldiers and civilians.

In this paper, we suggested using Twitter API sentiment analysis with hybrid deep learning models, and the appropriate keywords were utilized to create the dataset for this research. A range of text preparation methods, such as stop word removal, tokenization, stemming, and normalization, have been used to clean up the tweets. We evaluated the effectiveness of combining CNN, LSTM, RNN, and SVM using TF-IDF, N-Gram, and BoW.

Our experiments show that hybrid models performed better for sentiment polarity analysis than any other examined model in terms of reliability. For sentiment analysis, combining deep learning models with the SVM method produces superior results than utilising a single model. The hybrid models that use support vector machines (SVM) have higher dependability than those that do not in the majority of the investigated datasets. However, the hybrid models that use SVM need much more computing time. It has been noted that the quality and attributes of the datasets have a significant impact on the algorithms' efficiency.

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