Aspect based Sentiment and Emotion Analysis with ROBERTa, LSTM

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***Abstract*—Internet usage has increased social media over the past few years, significantly impacting public opinion on online social networks. Nowadays, these websites are considered the most appropriate place to express feelings and opinions. The popular social media site Twitter offers valuable insight into people's thoughts. Throughout the conflict between Russia and Ukraine, people from all over the world have expressed their opinions. In this study, "machine–learning" and "deep–learning" techniques are used to understand people's emotions and their views about this war are revealed. This study unveils a novel deep-learning approach that merges the best features of the sequence and transformer models while fixing their respective flaws. The model combines Roberta with ABSA (Aspect based sentiment analysis) and Long Short-Term Memory for sentiment analysis. A large dataset of geographically tagged tweets related to the Ukraine-Russia war was collected from Twitter. We analyzed this dataset using the Roberta-based sentiment model. In contrast, the Long Short-Term Memory model can effectively capture long-distance contextual semantics. The Robustly optimized BERT with ABSA approach maps words into a compact, meaningful word embedding space. The accuracy of the suggested hybrid model is 94.7%, which is higher than the accuracy of the state-of-the-art techniques.**

***Keywords*—Aspect based sentiment analysis, Twitter, LSTM, emotion analysis, Russia-Ukraine war, online social networks, Roberta model**

I. Introduction

People's voices are blaring out through social media in many communities. Modern society relies heavily on these platforms for sharing complete information and expressing opinions and feelings freely. Today, people spend a lot of time on social media websites [1] since the internet is so popular. Likewise, the popularity of social media platforms makes it very likely that people can positively or negatively impact society by sharing their opinions. Internet sources affect public opinion on politics, the economy, and social life. Most people are active on Twitter, sharing their views and feelings about a specific topic daily [2]. Millions of tweets are shared every day on Twitter. Sentiment analysis can mine vast amounts of text for information about people's views and responses [3,4]. People unable to express themselves in their daily lives for various reasons are more likely to express themselves on Twitter, a unique data source for sentiment analysis.

After annexing Crimea in 2014, Russia invaded Ukraine on February 24, 2022, turning the Ukraine-Russia crisis into war. Many deadly battles during the Russian invasion of Ukraine sparked global reactions, especially on Twitter. Many journalists cover wartime events fairly and impartially [5]. Such conflicts cause long-term economic, political, and psychological issues in society. Social media is used worldwide to express political opinions. Online users are constrained to their social surroundings when examining contentious opinions. Obviously, one person cannot read all tweets about a topic. NLP analysis of tweets regarding the Ukraine-Russia war on Twitter will give us an objective view of global tendencies, providing a unique data source for press member stories and articles. Thus, a literature analysis on a Twitter debate topic may help machine and deep learning-based opinion categorization. Deep-learning-based methods automatically pick and learn features from the textual information, unlike machine learning-based methods [6]. Many degrees of deep learning view data differently. NLP approaches allow sentiment analysis and word cloud for visualization of massive Twitter data.

Deep-learning is used in various aspects such as object-detection, image-captioning [39], image segmentation [40], etc. This study uses machine and deep learning approaches to assess how twitter discussions regarding the Ukraine-Russia war affect public sentiment. Twitter API was used to evaluate the suggested approach on a large geographically tagged tweet dataset containing Ukraine-Russia war themes. Now sentiment analysis and word clouds help to discover general themes in the study. Sentiments about the Ukraine-Russia war and classify and display them into subgroups categories.

This study continues as follows: Section 2 offers a survey of relevant research. Section 3 describes the model's dataset, pre-processing, and ABSA-based Roberta-LSTM architecture for sentiment analysis. Section 4 compares the experimental results of the suggested model for the dataset with the sentiment visualisation data analysis. Finally, Section 5 concludes the study.

II. Related Work

Sentiment analysis uses data and text mining to identify textual sentiments [7]. Complex AI challenges let us determine whether a text has a favourable or bad subjective attitude. "Opinion mining" has three levels: "document", "sentence", and "aspect-based" [8–13]. Document-level sentiment analysis determines text polarity. It focuses on single-topic or entity papers. Sentence-level sentiment analysis examines positive, negative, and neutral sentences and their subjective or objective sentiment. Aspect-based sentiment analysis emphasizes "entity/object-identification", "feature-extraction", and "feature-polarity". Dictionary-based sentiment analysis models are common. A sentiment dictionary lists words having good or negative subjective orientations. In semantic orientation labelling, word types can be classed as positive or negative or given a numerical value depending on pre-established parameters. LIWC and HULIUO use common, context-free terms, while ANEW SenticNet and SentiWordNet [14] use sentiment strength and quantitative scores. Sentiment dictionaries are problematic because any human language has grammatical variances, idioms, slang, and spelling errors, which make automatic language analysis harder.

Machine learning, dictionary-based, and deep learning-based sentiment analysis are utilized nowadays [15,16]. A bag of words helps machine-learning-based approaches interpret texts into features. After that, "Naive-Bayes", "Decision-Trees", and "Support-vector-machine" classifiers are fed complex machine learning features [17]. Dictionary-based methods calculate text polarity by summing positive and negative emotion terms [18]. Machine learning-based systems may use sentiment dictionaries with positive and negative scores for words, unlike dictionary-based approaches. Thus, machine learning-based methods outperform dictionary-based ones. Hybrid machine and dictionary-based techniques coexist in the literature [19]. Deep learning-based approaches have replaced machine learning approaches, and experimental results are more promising [20, 21,37,38].

Researchers are impressed by deep-learning-based sentiment analysis. To enhance document-level sentiment analysis, the authors of this research [22] suggested a one-dimensional convolutional neural network model that incorporates temporal relations into user and product representations. The authors of [23] presented an artificial neural network-based system that suggests idioms for essay writing by analyzing similar contexts and potential phrases. In [24], the authors use feedback to improve the RNN architecture and create the LTSM model. Schuster and Paliwal utilized the "Bi-LSTM" model [25]. Deep learning methods automatically identify text emotion features. Deep learning predicts sentiment on a large Twitter dataset.

Internet use has made social media platforms popular in the past decade. Microblogs allow social media users to quickly share their daily experiences. Professionals share news and information on microblogs. Microblogs are the fastest way to report global news. As of 2021, Twitter has 330 million active users [26]. Thus, Twitter is vital for social media news dissemination. Sentiment analysis on Twitter can unlock a lot of unstructured data for researchers.

The authors of [27] sentiment analyzed tweets on coronavirus outbreaks using deep-learning classifiers. They suggested that harmful tweet content created fear, horror, and despair and that detecting such tweets would reduce the negative consequences of a pandemic on society. The authors of [28] used the BERT model to analyze attitudes by single and plural tags. The proposed method relied on emojis to convey emotions. The authors of [29] analyzed Twitter sentiment during and after the Syrian chemical attacks. The writers of [30] used the LDA algorithm to identify common debate themes from 4 million tweets regarding Covid-19 under 25 tags between "1 March 2020 and 21 April 2020". The writers of [31] employed VADER natural language processing methods to assess coronavirus vaccine attitudes and behaviours using LSTM and Bi-LSTM-based and RNN-focused architectures. The authors of [32] employed topic modelling and sentiment analysis on tweets regarding global climate change to reveal public opinion. The authors of [36] used "IMDB", "Twitter-US-Airline-Sentiment", and "Sentiment140" datasets, and "Roberta-LSTM" outperforms state-of-the-art sentiment analysis algorithms.

The paper's contributions are threefold:

1) A hybrid ABSA-Roberta-LSTM model for sentiment analysis is proposed. Initially, aspect terms are generated, and then the Roberta model is used to tokenize words or subwords and build word embeddings. Meanwhile, the "LSTM" model encodes long-distance temporal dependencies in the word embeddings.
2) Due to the amount of Twitter data on the Ukraine-Russia war, a large spatially tagged dataset was collected from Twitter user's tweets about the war. This tweet collection was sentiment-analyzed using NLP.Twitter users often misspell and use contractions. Tweets may change tone due to spelling errors. Thus, our work performed powerful data cleansing, lemmatization, and noise removal.
3) Adjusting hyperparameters improves sentiment analysis outcomes. The empirical results reveal that ABSA-based Roberta-LSTM outperforms state-of-the-art approaches.

III. Proposed Methodology

This section describes the "ABSA-based-Roberta-LSTM" model for analysis. Pre-processing removes redundant tokens and symbols from the corpus. Our proposed model is then used to train and classify the dataset. The proposed methodology is shown in Fig. 1.

The "ABSA-based-Roberta -LSTM model" combines the Robustly optimised BERT method (Roberta) [33, 34] with "Long-Short-Term-Memory (LSTM)". The model efficiently maps tokens into meaningful embedding space using pre-trained Roberta weights.

A. Dataset Description

Sentiment analysis relies on data. Since the Twitter API allows real-time tweet extraction and sentiment analysis, research has expanded. For example, Twitter sentiment analysis helps to explain the Russia-Ukraine war by monitoring public opinion.

The study draws on a dataset obtained from Kaggle(https://www.kaggle.com/code/ssaisuryateja/eda-and-sentiment-analysis#EDA). The dataset is named "Ukraine Conflict Twitter Dataset". We collected the tweets from April and May of about 484221 tweets. Tweets were retrieved using hashtags. Hashtags can help with sentiment analysis, named entity recognition, and information extraction. Twitter hashtags included #ukraine, #russia,#Putin, #standwithUkraine, #Kyiv, #mariupol, #russian, #Ukrainewar, #nato, #standtogether and shown in Fig. 2.

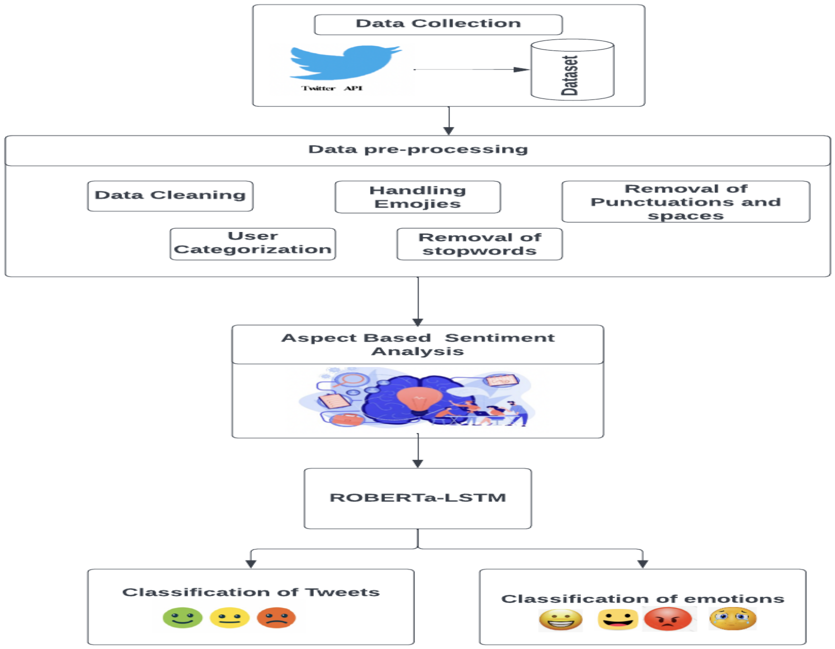

Fig. 1. Overview of Proposed Model.

	Hashtag	Tweets
0	ukraine	96959
1	russia	35708
2	putin	32641
3	standwithukraine	17762
4	kyiv	14581
5	mariupol	10585
6	russian	10326
7	ukrainewar	8477
8	nato	8399
9	russiaukrainewar	8058
10	ukrainerussiawar	6539
11	ukraineunderattack	5833
12	anonymous	4467
13	standtogether	4196
14	ukrainian	4162
15	kharkiv	4014
16	marinaovsyannikova	3901
17	china	3874
18	war	3771
19	saveukraine	3687
20	stopputinswar	3680
21	slavaukraini	3372
22	stoprussia	3034
23	ukrainerussianwar	3009
24	stopputin	2659

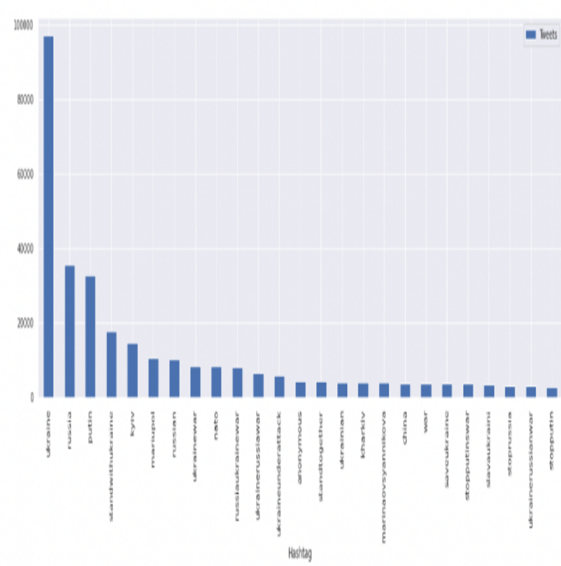

Fig. 2. Hashtag Analysis.

Overall, there were 17 distinct types of information included in the dataset, including Date, Hashtag, Followers, Friends, Location, Retweet, Username, Text, and Polarity.

B. Data Pre-processing

Data exploration helps uncover data patterns and trends. Check for missing or null values first. There are several steps involved in pre-processing data. Removal of Hashtags, removal of special symbols and punctuations, removal of stop words from data, removal of URL, stemming the words in the data, and deleting unwanted white space characters.

C. Aspect based Sentiment and Emotion Analysis

ABSA pinpoints the degree to which people's opinions differ about a specified topic.ABSA provides more detailed information than broad sentiment analysis. "Aspect Category Classification" determines an opinion text's subject and aspect pair. A dataset will receive a collection of present entities and one or more attributes based on the context of the text. Fig. 3 shows how ABSA Classification. In this example, general sentiment analysis yields "mixed" because there is one negative and one positive sentiment.

Fig. 3. ABSA based Sentiment and Emotion Analysis.

The ABSA aspect phrase "Zelensky" is positively received, whereas "Putin" is not. General sentiment analysis identifies only a tweet's predominant sentiment [34]. ABSA enables a more in-depth, sophisticated analysis by extracting sentiments from a single tweet. Since we wanted to examine how people felt about various topics across the time frame, we decided to use ABSA to glean further insight from each tweet. Using ABSA, a piece of more detailed information about the emotions in tweets is also analyzed. So in Fig. 3, the aspect term is "Woman", and the emotion of that woman illustrates "angry."

D. ROBERTa

Roberta extends Bidirectional Encoder Representation from Transformers (BERT). The Transformers [35] family developed BERT and Roberta for sequence-to-sequence modelling to address long-range dependencies. The Transformer module implements the NLP model Twitter Roberta base-sentiment in Python. This "Roberta" based model has been pre-trained on 58M tweets and is optimised for sentiment analysis using the "TweetEval benchmark".

ABSA on pre-trained models functions extremely similarly to Roberta. The exception is that these models additionally get as input the aspect words of the sentences. Roberta tokenizes input sequences and sequence aspect terms. The suggested ABSA-based Roberta-LSTM model (Fig. 4) tokenizes the cleaned text into words or sub-words to simplify encoding word embeddings. For example, ¡s¿ is appended to the beginning and end of the text to indicate a sentence and vector length. To tokenize text at the byte level, the Roberta model uses the Byte-Pair Encoding tokenizer. The tokenizer doesn't split common words. Unusual terms are broken out.

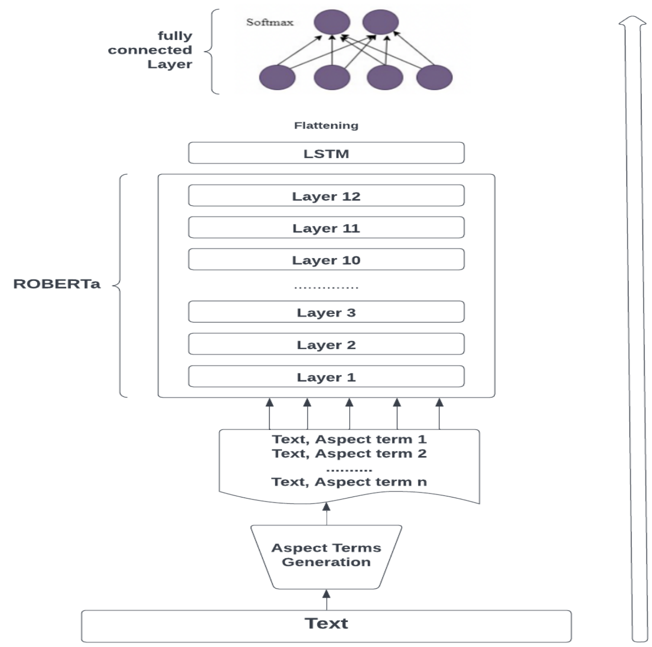

Fig. 4. ABSA based Roberta LSTM Model.

The model learns better when words are converted into numbers. Roberta uses input ids and an attention mask to tokenize text. Token indices and their numeric representations are input ids. The attention mask is not required if the sequence is to be batch processed. Tokens requiring attention are highlighted by the attention mask. The attention mask and ids are sent to the "ABSA based Roberta -LSTM" model. The "Roberta base model" consists of "12 base layers" and "125 million" parameters. The Roberta base layers aim to generate a meaningful word embedding as the feature representation, from which the more advanced layers can easily extract the required information.

E. LSTM

The results of the dropout layer are then fed into a model called "Long Short-Term Memory". Long short-term memory (LSTM) models retain data for the purpose of identifying input dependencies that are far away in the future. LSTM has shown effective in a variety of sequence modelling applications, including text classification, sentiment analysis, time series prediction, and others.

Flatten Layer This layer flattens the input from 3D to 2D to fit inside the dense layer.
Dense Layer Dense layers are fully connected. Information is supplied to the dense layer's activation units from below. Roberta-LSTM has two layers. First dense layer hidden neurons capture the input-class relationship. Then, classification layer neurons match dataset classes. SoftMax activation function produces sentiment analysis dataset's probabilistic class distributions dataset's probabilistic class distribution in the classification layer.

F. Training Parameters

Huggingface transformer provides both Pytorch and TensorFlow implementation of the Roberta models. The "Adaptive Moment Estimation" optimizer optimizes gradient descent in "ABSA based Roberta-LSTM" model training. The "Adam optimizer" avoids local minima by using the gradient moving average, enhancing gradient descent. The Adam optimizer can deal with sparse gradients even when applied to noisy problems. The optimization approach uses the loss function to estimate the model loss in each training period. Since sentiment analysis involves multi-class, the loss function is categorical cross-entropy.

IV. Evaluation Metrics and Experimental Results

A. Evaluation Metrics

Accuracy, Precision, Recall, and F1-score were used to evaluate the classification and comparison of models. In addition, train and test validation accuracy confirmed model performance. "Accuracy" refers to how well the forecast was made, and its calculation looks like this:

$$Accuracy = \left(\frac{\text{“}Correctpredictions\text{”}}{\text{“}Totalpredictions\text{”}}\right) \quad (1)$$

The positive and negative accuracy of the binary classification can be determined using the following formulas:

$$Accuracy = \left(\frac{\text{”}TP\text{”} + \text{”}TN\text{”}}{\text{”}TP\text{”} + \text{”}FN\text{”} + \text{”}FP\text{”} + \text{”}TN\text{”}}\right) \quad (2)$$

"True positive", "true negative", "false positive", and "false negative" are denoted by the letters TP, TN, FP, and FN.

Precision is the percentage of clusters labelled positive that are positive. It's computed as

$$Precision = \left(\frac{\text{”}TP\text{”}}{\text{”}TP\text{”} + \text{”}FP\text{”}}\right) \quad (3)$$

Recall, a measure of integrity, is the percentage of genuine positive predictions properly classified and calculated as

$$Recall = \left(\frac{\text{”}TP\text{”}}{\text{”}TP\text{”} + \text{”}FN\text{”}}\right) \quad (4)$$

The lack of a balanced dataset may make the accuracy evaluation measure unreliable. The F1-score is employed. The F1-score gives target class outcomes. It considers classifier precision and recall in statistical classification study and is calculated as

$$F1 - score = (2 * Precision + Recall) \quad (5)$$

B. Experimental Results

This section explains the experimental settings and compares the "ABSA-based Roberta-LSTM" model with other state-of-the-art approaches. The training session is limited to 100 iterations and terminated early to prevent overfitting.

According to this study, people's emotions toward the Ukraine-Russia war were mostly unfavourable. After pre-processing tweets, the tweets are passed to the "ABSA-based-Roberta-LSTM model", classified into three sentiment polarities: negative, positive, and neutral. Fig. 5 exhibits tweet sentiment polarity. Word Cloud, a sentiment analysis visualisation tool, was used to discover and show words and concepts for three sentiment studies to understand the psychological underpinnings for these reactions. Fig. 6 shows twitter dataset terms for "positive", "negative", and "neutral" attitudes.

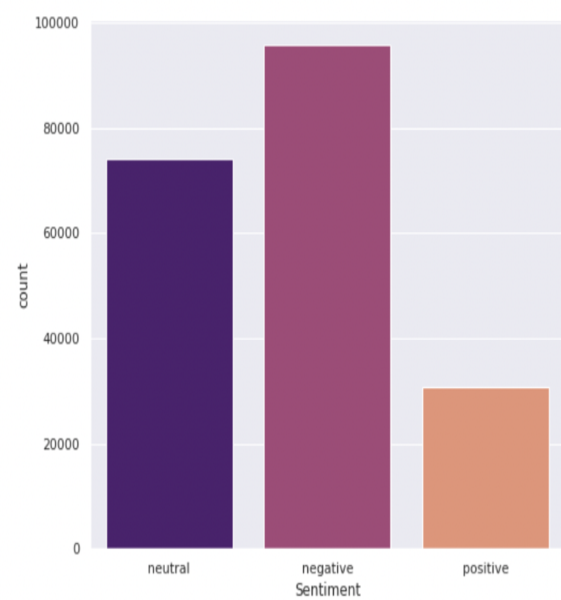

Fig. 5. The Percentages of Sentiment Polarities in the Ukraine-Russia Tweet Dataset.

Several "machine-learning" and "deep-learning" sentiment analysis approaches are tested for fairness (Table-I). The machine learning methods include "Bernoulli-distribution", "Logistic-Regression", "Decision-Tree", "K-nearest-neighbour", "Support-vector-classification" and "Random-Forest-Algorithm". The deep learning methods include "Long-Short-term-Memory" and "ABSA-based-Roberta-LSTM model". Machine learning algorithms and deep learning algorithms classify sentiments (positive, negative, neutral) w.r.t. to precision, recall, F1score in Table I and a bar plot is plotted in Fig. 7.

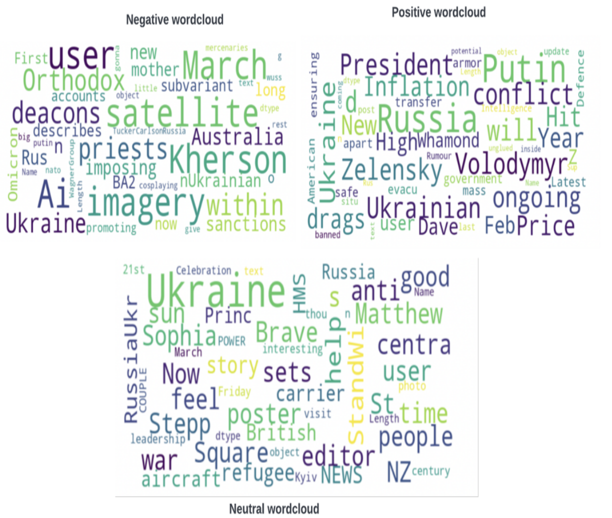

Fig. 6. Word Cloud Representation of Prevalent Words in each Sentiment Polarity.

TABLE I. EXPERIMENT RESULTS ON UKRAINE-RUSSIA TWEET DATASET(SENTIMENTS)

Classification Algorithms	Sentiment	Precision	Recall	F1:score
Bernoulli	NEGATIVE	0.94	0.92	0.93
	NEUTRAL	0.79	0.93	0.86
	POSITIVE	0.99	0.62	0.76
K Nearest Neighbours	NEGATIVE	1.00	0.71	0.83
	NEUTRAL	0.67	0.97	0.79
	POSITIVE	0.87	0.71	0.78
Decision Tree Classifier	NEGATIVE	0.92	0.90	0.91
	NEUTRAL	0.85	0.88	0.87
	POSITIVE	0.86	0.84	0.85
Random Forest Classifier	NEGATIVE	0.93	0.95	0.94
	NEUTRAL	0.88	0.91	0.90
	POSITIVE	0.96	0.83	0.89
Logistic Regression	NEGATIVE	0.95	0.96	0.95
	NEUTRAL	0.91	0.92	0.92
	POSITIVE	0.93	0.89	0.91
Support Vector Classification	NEGATIVE	0.95	0.96	0.96
	NEUTRAL	0.92	0.92	0.92
	POSITIVE	0.93	0.90	0.92
LSTM	NEGATIVE	0.94	0.95	0.95
	NEUTRAL	0.91	0.91	0.91
	POSITIVE	0.92	0.90	0.92
ABSA based Roberta+LSTM (Our model)	NEGATIVE	0.96	0.96	0.97
	NEUTRAL	0.93	0.93	0.93
	POSITIVE	0.94	0.92	0.94

Highly followed Twitter users can affect the audience with their emotions. The number of followers can be used to estimate outreach, but a user's interactions (mentions, responses, retweets, attributions) are a superior indicator of influence. Fig. 8 shows tweet count versus emotion analysis. According to Fig. 8, anger (1,00,445) is the biggest feeling on Twitter associated with the Ukraine-Russia war, followed by optimism (39,284), joy (25,091), and sadness (25,795). Fig. 9 shows Ukraine-Russia Tweet Dataset in terms of joy, optimism, sadness, and anger emotions.

In order to provide a reliable basis for comparison, the experiments make use of a variety of "machine-learning" and "deep-learning" approaches for emotional analysis, i.e. shown in Table II and Fig. 10.

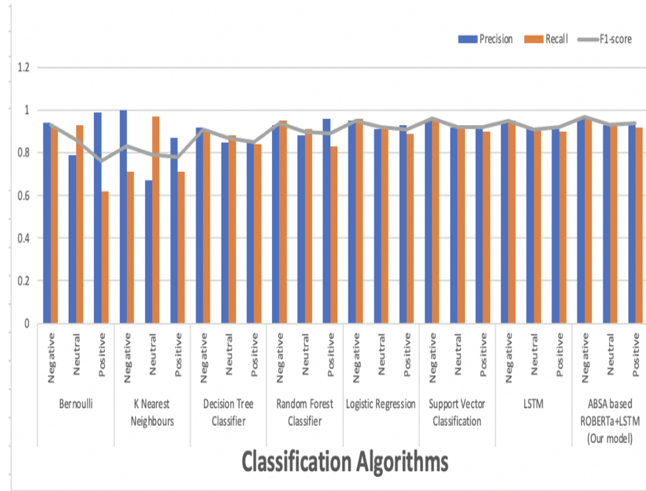

Fig. 7. Experiment Result Analysis on Ukraine-Russia Tweet Dataset (Sentiments).

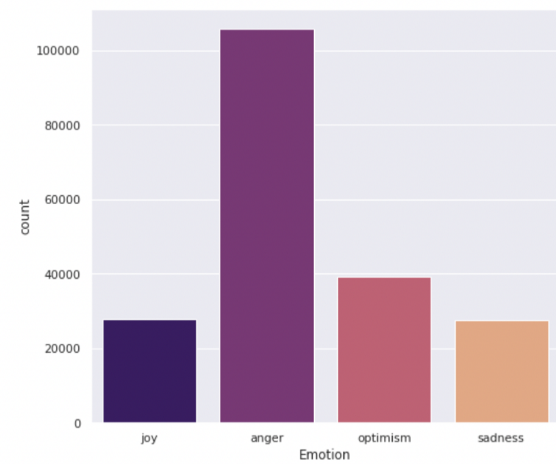

Fig. 8. The Percentages of Different Emotions in the Ukraine-Russia Tweet Dataset.

The Experiment results of the state-of-the-art approaches using the Ukraine-Russia Tweet Dataset in terms of accuracy (Sentiments) are illustrated in Table III, and a bar pot is plotted in Fig. 11.

V. CONCLUSION

Sentiment analysis plays a key role in various sectors, such as business and politics, to comprehend the public sentiments so that a strategic decision can be taken. Therefore, an effective algorithm is required to automatically determine the polarity (positive, negative or neutral) of the opinions. "Machine learning", "Deep learning", and "Recurrent neural networks" dominate sentiment analysis research. There are few works that employ transformers for sentiment analysis.

This paper provides an hybrid deep learning models for sentiment analysis i.e. "ABSA-based Roberta-LSTM" model.

Fig. 9. Word Cloud Representation of Prevalent Words in each Emotion.

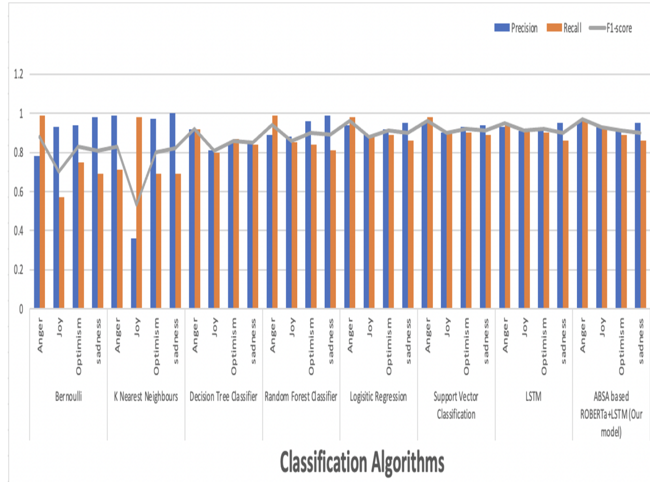

Fig. 10. Experiment Result Analysis on Ukraine-Russia Tweet Dataset (Emotions).

TABLE II. EXPERIMENT RESULTS ON UKRAINE-RUSSIA TWEET DATASET (EMOTIONS)

Classification Algorithms	Emotion	Precision	Recall	F1:Score
Bernoulli	Anger	0.78	0.99	0.88
	Joy	0.93	0.57	0.70
	Optimism	0.94	0.75	0.83
	sadness	0.98	0.69	0.81
K Nearest Neighbours	Anger	0.99	0.71	0.83
	Joy	0.36	0.98	0.53
	Optimism	0.97	0.69	0.80
	sadness	1.00	0.69	0.82
Decision Tree Classifier	Anger	0.92	0.92	0.92
	Joy	0.81	0.80	0.81
	Optimism	0.85	0.87	0.86
	sadness	0.86	0.84	0.85
Random Forest Classifier	Anger	0.89	0.99	0.94
	Joy	0.88	0.85	0.86
	Optimism	0.96	0.84	0.90
	sadness	0.99	0.81	0.89
Logisitic Regression	Anger	0.94	0.98	0.96
	Joy	0.89	0.88	0.88
	Optimism	0.92	0.89	0.91
	sadness	0.95	0.86	0.90
Support Vector Classification	Anger	0.95	0.98	0.96
	Joy	0.90	0.90	0.90
	Optimism	0.93	0.90	0.92
	sadness	0.94	0.89	0.91
LSTM	Anger	0.93	0.94	0.95
	Joy	0.91	0.91	0.91
	Optimism	0.92	0.90	0.92
	sadness	0.95	0.86	0.90
ABSA based Roberta+LSTM (Our model)	Anger	0.96	0.96	0.97
	Joy	0.93	0.93	0.93
	Optimism	0.92	0.89	0.91
	sadness	0.95	0.86	0.90

TABLE III. COMPARISON ANALYSIS OF VARIOUS ALGORITHMS USING UKRAINE-RUSSIA TWEET DATASET

Classification Algorithm	Precision	Recall	F1:score	Accuracy
Bernoulli	0.91	0.82	0.85	0.88
K Nearest Neighbours	0.84	0.80	0.80	0.81
Decision Tree	0.88	0.88	0.88	0.89
Random Forest Classifier	0.93	0.9	0.91	0.916
Logistic Regression	0.93	0.92	0.93	0.933
Support Vector Classification	0.94	0.93	0.93	0.937
LSTM	0.91	0.91	0.91	0.92
ABSA+Roberta+LSTM(Our model)	**0.93**	**0.93**	**0.94**	**0.947**

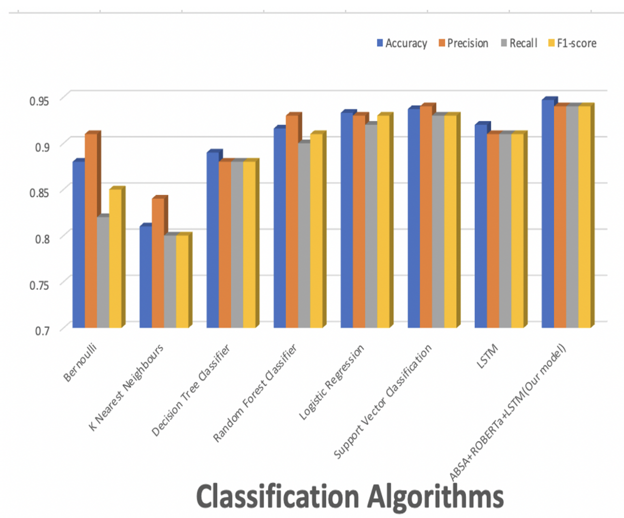

Fig. 11. Comparison Analysis of Various Algorithms w.r.t to Evaluation Metrics.

Text pre-processing normalizes and removes unimportant words. Our Proposed model is trained and analysed on the cleaned corpus. Our Proposed model uses aspect terms, Roberta, and LSTM to efficiently encode words into word embedding and capture long-distance dependencies. The "ABSA based Roberta-LSTM" model outperforms state-of-the-art sentiment analysis approaches on Ukraine-Russia twitter dataset with an accuracy of 94.7 when compared to the existing approaches.

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