**Deep Learning-Based Sentiment Analysis of War in Ukraine from different parts of the World**

**Abstract**

*The war between Ukraine and Russia started on February 24th, 2022, and since then, it has escalated, resulting in the loss of lives of both civilians and soldiers across both countries. This became a trending news topic for discussion across various news outlets and all social media platforms, especially Twitter. Sentiment analysis is one method for discerning popular opinion and categorizing these opinions as either positive, negative, or neutral. This study employs three Natural Language Processing(NLP)/text classification models: Long Short-Term Memory(LSTM), Bi-directional LSTM, and Naïve Bayes, using Naïve Bayes as the baseline model, to analyse the sentiments from a Twitter dataset comprising a total of 300,361 tweets posted about the war between Ukraine and Russia by Twitter users. The results show that the LSTM and Bidirectional LSTM models achieved accuracies of 97.97% and 98.11% respectively, compared to an accuracy of 82.77% accuracy achieved by the Naïve Bayes model and thus highlighted the superiority of deep learning models in sentiment classification.*

**Keywords:** Sentiment Analysis, Long Short-Term Memory, Bi-directional LSTM, Russia, Ukraine, Ukraine War, Natural Language Processing.

**Introduction**

Conflict is a common occurrence in our daily lives, ranging from minor disagreements to major confrontations (Julianto et al., 2022). Various factors can lead to conflicts, but they often emerge from differences in interests and can also be fuelled by a desire for dominance or the need to assert control. The ongoing war between Ukraine and Russia is a most recent example. Ukraine was on the verge of joining NATO and Russia saw this as a threat to their nation because it would enhance the influence of the Western powers most especially, the United States, within the region.

In Russia’s aim to safeguard its borders and limit Ukraine’s closeness to the European Union and NATO, Russia invaded Ukraine in the early morning hours of February 24, 2022. Russia launched a military invasion of Ukraine, despite the efforts and intervention of international leaders to avoid war(JW.ORG, 2022 ; BBC News, 2022; Murphy, 2022). Friday, February 24, 2023, marks a grim anniversary—one year since the war in Ukraine began. According to some reports, estimates show that Russia had suffered 180,000 dead and wounded, while Ukraine had 100,000 killed or wounded in action along with 30,000 civilian deaths (Cooper, Schmitt, & Gibbons-Neff, 2023). However, the total may be higher. In the pursuit of a safe haven, millions have also been displaced, families broken apart while fleeing the country. Throughout the past year and continuing, these events have led to an enduring experience of distress and hardship for the residents of Ukraine. They have witnessed their previously tranquil and serene nation transformed into a desolate and conflict-ridden warzone.

This sparked worldwide reactions, a widespread condemnation from other governments, non-governmental organizations, and the public(Shevtsov et al., 2022). Most of these reactions were widely expressed on social media. A lot of people worldwide expressed their opinion about the war on one of the most significant social media platforms, Twitter. Ukraine gained a lot of support while Russia received a lot of disapproval, and this was expressed grandly on social media. Social media has become an environment for the expression of opinions and Twitter has become an active platform where its users share their thoughts, feelings, beliefs, and opinions about the ongoing conflicts and wars. This research aims to extract and analyse the opinions shared by people and the sentiments expressed in Twitter posts over the domino effect of all the chaos that resulted after the invasion. Sentiment analysis and deep learning will be used to investigate how public opinion has shifted over the course of the conflict. The goal will be to group all the tweets collected based on the emotions conveyed in the tweets. The sentiment could be positive, negative, or neutral.

In light of the background presented above in Section I, this report details a deep learning-based approach utilizing LSTM and Bidirectional LSTM models to proficiently classify sentiments in tweets worldwide regarding the Ukraine war using Naïve Bayes as a baseline. The subsequent sections of the report follow this structure: Section II introduces related sentiment analysis studies outlining what other researchers have done and how it is related to our study. In Section III, the dataset and preprocessing methods are outlined. Section IV delves into the architecture of the baseline model Naïve Bayes, as well as the proposed LSTM and Bidirectional LSTM models. Section V presents the experimental outcomes, compares them to the baseline, and discusses the findings. Section VI contains the discussion. In section VII we have the conclusions and future work for this study.

**II. Literature Review**

Several approaches have been explored by numerous researchers who conducted sentiment analysis. The two most widely used methodologies are the machine-learning method and the lexicon-based method. The machine-learning method involves training models on labeled datasets to recognize patterns and make predictions or classifications on new textual inputs. In contrast, the lexicon-based method relies on predefined word lists to determine sentiment in text. This method entails matching words in the text against entries in a sentiment lexicon to assign sentiment values and ultimately determine the overall sentiment conveyed in the text(Bhuta et al., 2014).

In a recent study by Simarmata et al. (2023), a unique approach was employed to conduct sentiment analysis on Twitter posts related to the Russia and Ukraine war. The study focused on utilizing the LSTM(Long Short-Term Memory) machine learning technique and focused on a dataset in the Indonesian language. This dataset was collected using a web scraper and processed using Sastrawi, a text-processing library (Siswanto & Dani, 2021). The outcome of the evaluation of this model using this Twitter dataset indicated that the distribution of sentiments was as follows: 54.7% positive, 35% neutral, and 10.2% negative.

Additionally, the study further highlighted the effectiveness of the LSTM model in sentiment analysis, achieving an accuracy rate of 82%. This finding suggests that the LSTM algorithm is a reliable tool for sentiment analysis and can effectively capture public sentiment concerning the ongoing war.

Elshakankery and Ahmed (2019) conducted a study where they applied a hybrid approach combining lexicon-based analysis and Support Vector Machine (SVM) classification on an Arabic language dataset. The results demonstrated the superiority of this hybrid model, achieving an improvement of up to 17.55% compared to other models that solely relied on either lexicon or SVM. This research highlights the effectiveness of integrating multiple techniques to enhance sentiment analysis performance, especially when working with Arabic language datasets.

Furthermore, in a study by Haddi et al.(2014), the authors explored the significance of text pre-processing in sentiment analysis, specifically in the context of analysing sentiment in movie reviews. The experimental findings reveal that the accuracy of sentiment classification may be significantly improved using appropriate feature selection and representation after pre-processing. The authors recommended that pre-processing techniques should be chosen based on the characteristics of the dataset under consideration and this was put to use in this research to elevate the accuracy of our results.

Another study by Kouloumpis et al. (2011) explored Twitter sentiment analysis and its inherent challenges. The authors highlighted the importance of understanding sentiment on Twitter and the difficulties or complexities involved in accurately gauging sentiment due to the informal nature of tweets. The study explored various approaches and techniques for sentiment analysis, highlighting the strengths and weaknesses of these different approaches to sentiment analysis. Overall, the study shed light on the complexity of analysing sentiment on social media platforms such as Twitter and determined that a combination of techniques and approaches including SVM and Naïve Bayes is necessary to achieve accurate sentiment analysis, leading to the use of Naïve Bayes as a baseline model in this research.

From the above reviews, sentiment analysis on tweets about the war in Ukraine is a tough task due to the informal nature of tweets, the use of slangs and abbreviations, and the complex and dynamic nature of the topic. This study proposes using LSTM and Bidirectional LSTM as the two models of choice. LSTM is better suited to capturing the temporal dynamics of language that are particularly relevant in social media data, such as tweets. Additionally, LSTM can handle variable-length inputs and learn to encode the context of the language in the hidden state, which could help in identifying the sentiment expressed in each tweet. Furthermore, the Bidirectional LSTM’s unique feature of processing inputs in both forward and backward directions enhances its ability to handle variable-length inputs and encode comprehensive language context within hidden states, thereby holding significant potential in accurately discerning the sentiment conveyed in each tweet.

**III. Methodology**

**Dataset**

The Twitter dataset collected from the Twitter platform using the Twitter API consisted of raw and unlabelled tweets. The dataset covers a time span of six months ranging from January to June 2023. The dataset was generated using a careful selection of 22 keywords relevant to the conflict between Ukraine and Russia. It was provided in an Excel format and contains 300,361 tweets. Among the massive collection of tweets, it was observed that 99.9% were written in English (300,076), and the remaining 285 tweets were written in nine other different languages. This diversity introduced linguistic complexities that warranted attention, but the 285 tweets were filtered out because the study focuses on English as the primary language of analysis due to its prevalence and scope (Crystal, 2003; Piller, 2016). Lastly, missing values or duplicates were not found in the dataset.

This dataset is particularly suitable for this research because it contains the needed tweets to conduct an analysis and achieve a good result. The objective of studying the sentiments expressed in these tweets about the Ukraine and Russia war is to gain valuable insights into the opinions and reactions of the world during this conflict and understand the impact of the war on people’s lives.

**Data Cleaning and Preprocessing**

In order for the data to be usable for training and validating the proposed models, the tweets were cleaned and prepared by applying several pre-processing techniques. The following steps were applied to the tweets:

* **Removing Twitter Handles(@user):** A function was created to eliminate the undesirable pattern of text from the tweets. It takes two arguments and removes the text patterns. The method will give the desired string after removing unwanted text patterns in the output. In order to clean the tweets and remove unwanted patterns, including @usernames, we employed the function. (Shlkamy, Mahar, & Sedky, 2023)
* **Converting the text to lowercase**: The step ensures that text is converted to lowercase to ensure all words are normalized to ensure consistent word representation.
* Remove URLs, mentions, special characters, hashtags, digits, and tags, essentially cleaning the tweets from any irrelevant characters.
* Using the NLTK library used to remove stop words, add custom stop words, and apply the Lemmatizer (by using WordNet Lemmatizer).
* **Tokenization**: The tokenizer is another step that breaks up the input text into individual words known as tokens and makes it easy for the system to read it easily. For example, if elements of a word are more prevalent than the word itself, there can be more tokens than words.

**Sentiment**

In order to classify these cleaned tweets, TextBlob library was used to compute the polarity score of each tweet(Aljedaani et al., 2022). The polarity score indicates whether the sentiment expressed is positive, negative, or neutral. Based on these scores, the sentiment labels (positive, negative, or neutral) were assigned to each of the tweets. Understanding the sentiment distribution within the dataset holds significant value, as it provides insights into the responses of individuals towards the topic. The sentiment distribution within the dataset is as follows:

* Positive – 120,420 (40.7%)
* Neutral – 99,903 (33.8%)
* Negative – 75,481 (25.5%)

The bar chart below vividly illustrates the distribution of sentiments across the dataset:

Figure 1:The figure shows the sentiment distribution of the three classes of sentiment generated from the cleaned tweets

A graph of blue rectangular bars with white text

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**Word Clouds**

Word clouds are graphical representations of word frequency that give greater prominence to words that appear more frequently in a source text. The larger the word in the visual the more common the word was in the document(s). After pre-processing the data, generating word clouds can visually represent the most frequent words in the text. This could provide insights into the key themes and topics associated with different sentiments.

Figure 2. The figure shows the more frequent or common words found in the dataset. It provides insight into the key themes and topics.

A close up of words

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**IV. Classification Models**

In our study, we proposed two simple and efficient deep learning-based classification models for sentiment analysis namely, LSTM and Bidirectional LSTM network. However, we also explored the Naïve Bayes algorithm for sentiment analysis to compare with our two proposed deep learning models.

**Baseline Model - NAÏVE BAYES**

The Naive Bayes algorithm is a supervised machine learning algorithm based on Bayes’ theorem. It is a probabilistic classifier that is often used to identify an emotional or sentimental tone or opinion in a text (Dasgupta Chaudhri,2022; Leung, 2007). Bayes’ theorem is used to determine the probability of a hypothesis when prior knowledge is available. It depends on conditional probabilities and is efficient and easy to implement when carrying out sentiment analysis. The formula is given below :

where P(X|Y) is posterior probability i.e., the probability of a hypothesis X given the event Y occurs. P(Y|X) is likelihood probability i.e., the probability of the evidence given that hypothesis A is true. P(X) is prior probability i.e., the probability of the hypothesis before observing the evidence, and P(Y) is marginal probability i.e., the probability of the evidence.

Although Naïve Bayes does not consider the sequential nature of the text and the semantic meaning of words leading to a loss of context in the information related to the sentiment, it is a good starting point for sentiment analysis tasks and provides a benchmark against the performance of more complex models. Its simplicity makes it easier to interpret the model’s predictions and gain insights into the classes.

**Proposed Models – Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (BiLSTM)**

In order to address the shortcomings of the Naïve Bayes and better capture the contextual information in the dataset, we propose using the Long Short-Term Memory(LSTM) and Bidirectional Long Short-Term Memory (BiLSTM) as the deep learning models for the sentiment analysis of the war in Ukraine.

**Long Short-Term Memory (LSTM)**

LSTM is a type of recurrent neural network(RNN) that makes it easier to remember past data in memory. It is a network that deals with the vanishing gradient problem present in traditional RNNs. It is well suited to classify, process, and predict textual data when carrying out sentiment analysis because of its ability to consider the sequential order in sentences and can capture long-range dependencies between words.

LSTMs have three types of gates: input gates, forget gates, and output gates that regulate the flow of information (Bai, 2018). Input gates decide which new information to store in the current state. Forget gates determine the information to be discarded from the previous state, assigning a value between 0 and 1 to the previous state. Output gates control the information to be output from the current state, assigning a value between 0 and 1 to the information, taking both previous and current states into account. This allows the network to make predictions both in current and future time steps. The hidden layer output of LSTM includes the hidden state and the memory cell’s internal state (Siami-Namini et al., 2019). Only the hidden state is passed into the output layer while the memory cell’s internal state is entirely internal. The LSTM network structure is shown in the following figure below:

Figure 3. This figure shows the LSTM architecture

A diagram of a cell structure

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LSTM understands how the sentiment of a sentence might evolve as more information is presented and detect sentiment shifts that might occur during a narration. It leverages its word embeddings which enables it to understand the meanings and relationships between words beyond mere word frequency. Overall, using it as a proposed model addresses the limitations of the baseline model Naïve Bayes and offers a sophisticated approach to the analysis.

**Bidirectional Long Short-Term Memory (BiLSTM)**

A **Bidirectional LSTM**, or **BiLSTM**, is a sequence processing model that consists of two LSTMs: one taking the input in a forward direction, and the other in a backward direction(Alam et al., 2022). BiLSTMs effectively increase the amount of information available to the network, improving the context available to the algorithm (e.g., knowing what words immediately follow and precede a word in a sentence). The **BiLSTM** network structure is shown in the figure below:

Figure 4. This figure shows the BiLSTM architecture and the forward and backward direction of the two LSTMs

A diagram of a network

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In comparison to LSTM, Bidirectional LSTM can better capture the long-range dependencies in the text, and this is beneficial when analysing long and complex sentences (Mahar et al., 2023; Xu et al., 2019 ). By leveraging on both past and present context, BiLSTM excels at capturing subtle sentiment variations, enabling it to distinguish between different levels of emotions and sentiments expressed in the context of the ongoing war in Ukraine.

The Bidirectional LSTM is a more advanced and powerful model compared to both Naive Bayes and standard LSTM for sentiment analysis. It builds upon the strengths of LSTM and further improves the model's ability to comprehend the context and temporal dynamics of the text, making it a strong contender for accurately capturing the sentiments related to the war in Ukraine.

**V. Experiments and Results**

The goal of the experiment was to compare the performance of different sentiment analysis models on Twitter data discussing the war in Ukraine. The baseline model, Naïve Bayes, was contrasted with the two proposed models, namely, LSTM and Bidirectional LSTM, to evaluate their efficiency in sentiment classification.

**Experimental Setup**

The dataset was pre-processed and converted using a count vectorizer. The dataset was then split into testing and training sets, 20% and 80% respectively. The Naïve Bayes algorithm was then implemented. Once the Naïve Bayes model was trained, we proceeded to evaluate the data using the following metrics:

* **Accuracy**: Measures the proportion of correct predictions among all the total predictions in the testing data.
* **F1 Score**: Represents the harmonic mean of precision and recall, providing a balanced evaluation metric for imbalanced classes. (Wongvilaisakul et al., 2023)
* **Precision**: Measures the accuracy of true positive predictions for the sentiment classes. (Wongvilaisakul et al., 2023)
* **Recall**: This is the proportion of true positive predictions out of the total actual positive instances.
* **Confusion Matrix**: Provides a comprehensive summary of true positive, true negative, false positive, and false negative predictions for each sentiment class (Agrawal, S.K.,2021).

By analysing these metrics, we gained insights into the Naive Bayes model's ability to accurately classify people's emotions during the war based on tweets.

The Naive Bayes model achieved an overall accuracy of 82.77%, an F1 score of 82.39%, and a precision of 83.63% on the test dataset. The confusion matrix below summarizes the model’s predictions in comparison to the true labels.

Figure 5. Confusion matrix for Naïve Bayes

A graph of blue squares

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To compare, both the LSTM and Bidirectional LSTM models were introduced and then implemented using Keras with TensorFlow as the backend. The sentiment labels were encoded using a label encoder to convert the text into numerical sequences which were then padded to ensure uniformity.

The models were trained with an embedding layer to represent words in vector space, an LSTM layer of 64 units to capture sequential dependencies, and a dense layer with a softmax activation function. Additionally, hyperparameters including the embedding dimension (set at 100), dropout rate, and recurrent dropout rate (both set to 0.2) were monitored closely and tuned to avoid overfitting and achieve a high accuracy in the prediction. Categorical cross-entropy was also used as the loss function because it is a multiclass classification while Adam was used as the optimizer.

**Results and Performance Comparison**

The models gave a remarkable and improved result after training, the LSTM model achieved an accuracy level of 97.97% while the BiLSTM achieved an accuracy of 98.11%. The confusion matrix below summarizes both models’ predictions against the true labels for LSTM and Bidirectional LSTM.

Figure 6. Confusion matrix for LSTM and BiLSTM

A green squares with white text

Description automatically generated A diagram of a model

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Comparing the performance of the models, we observed that the baseline model, Naïve Bayes, achieved an accuracy of 82.77%, whereas the proposed models LSTM and Bidirectional LSTM outperformed with accuracies of 97.97% and 98.11% respectively. This suggests that the proposed LSTM models performed better, and their results show how well they did in identifying the sentiments. The table below lists these accuracies:

**Table 1**: Comparison of the accuracies of the sentiment analysis models

|  |  |
| --- | --- |
| **Model** | **Accuracy (%)** |
| Naïve Bayes | 82.77 |
| LSTM | 97.97 |
| Bidirectional LSTM | 98.11 |

The accuracy curves below illustrate how the model’s performance evolves across epochs(20) and how they are learning from the training data (Maxwell et al., 2021). The training accuracy curve reveals how well the model is performing on the training data as training progresses. The validation accuracy curve, in contrast, shows the model's performance on a separate validation dataset that it has not seen during training. This curve allows us to observe how well the model generalizes to new, unseen data and whether it is overfitting or underfitting

Figure 7. Accuracy curves that display the Training and Validation Accuracy of LSTM and Bidirectional LSTM. It also shows no signs of overfitting or underfitting

A graph of a training and validation accuracy

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**VI. Discussion**

In this study, we presented the LSTM and bidirectional LSTM models to accurately predict the sentiments/opinions of people around the world regarding the Ukraine war. From the study, it is clear that the war involving Russia and Ukraine has hugely affected and had an impact on people’s lives. It elicited reactions and our research indicates that 40.7% of the analysed tweets conveyed positive sentiments, primarily in support of Ukraine against the unjustified invasion by Russia. These people who were vocal and stood up for Ukraine can be tagged as Humanitarians. Carrying out this research achieved this conclusion and demonstrated that it can be possible to analyse people’s opinions and extract the overall sentiment found in them.

A fundamental strength of our study lies in the achieved accuracy levels of 97.97% and 98.11% achieved by the two proposed models – results that show how well deep learning models work when text classification is conducted and also highlighted the superiority of the BiLSTM model’s performance. So, it can be inferred that 40.7% of the tweets were positive with 33.8% neutral and 25.5% negative.

Furthermore, comparisons against previous work serve to validate the significance of our study and benchmark our findings as this would help in assessing the contributions our research brings to the field. Siswanto and Dani(2021) conducted sentiment analysis on Twitter data related to Covid-19 detection tools utilizing the Text Blob library. While their research focused on a different topic, their use of Text Blob for sentiment analysis aligns with our methodology. Correspondingly, Aljedaani et al. (2022) also integrated TextBlob with deep learning models for its analysis underscoring the usability of Text Blob as a tool for sentiment Analysis.

As regards accuracy, Simarmata et al.(2023) conducted a study of the Russian and Ukraine war using the LSTM model on Indonesian-language tweets and achieved a prediction accuracy of 82%. In comparison, our work stands out here because we took good advantage of hyperparameter tuning and modified deep learning architectures to achieve an impressive prediction accuracy of 97.97% for LSTM and the highest accuracy of 98.11% for Bidirectional LSTM. This only showcases the potential of deep learning methods in elevating sentiment analysis performance.

**VII. Conclusion and Future Work**

In conclusion, this sentiment analysis project explored the effectiveness of Naive Bayes, LSTM, and BiLSTM models in understanding public sentiments regarding the war in Ukraine. Through extensive hyperparameter tuning, we optimized the performance of the LSTM and BiLSTM models, outperforming the Naive Bayes baseline.

Addressing numerous obstacles is essential to design an efficient sentiment analysis method. These challenges include handling noisy and informal language in tweets and also addressing expressions that impact sentiment interpretation. Despite these challenges, the study offered significant contributions by uncovering people's attitudes and sentiments toward the war in Ukraine. Through a detailed analysis of sentiments expressed during conflicts, the study provides valuable insights into the emotions and needs of individuals in the midst of such difficult circumstances.

Comprehending sentiment in opinions plays a vital role in mitigating misunderstandings, preventing missed opportunities, and averting potential violence. Our study's results show that approximately 40.7% of opinions expressed during the conflict are positive, underscoring the significance of solidarity and support for Ukraine.

There are also avenues for future work to be explored. These include:

* Incorporating a more extensive dataset that includes tweets from the onset of the war to the present situation in order to uncover evolving sentiments and shed light on the impact of the war.
* Exploring other languages raises interesting possibilities for future research
* Integrating Word embeddings such as GloVe and Word2Vec into the models to provide a richer and more meaningful representation of words and also contribute a more accurate classification of sentiments.

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