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Hybrid Deep Learning Approach for Classification and Analysis of X Posts on Russia Ukraine War

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Abstract: X (formerly Twitter) has become a vital source of information on various variety of social, political, and economic concerns, as a consequence of its growth and popularity which has resulted in an enormous number of people sharing their opinions on a wide range of areas. To determine people's emotions about the Russia-Ukraine war (RUW), this study examines trends in English-language tweets. In this work, we have engaged 34 countries to tweet opinions that produce a strong perception of the people about the war and message to the world what people famine from the countries and that affects their lives. To analyze positive and negative emotions in tweets, which are represented by hope and fear, the LSTM-CNN model is based on deep learning. A time series is calculated that correlates with the rate of recurrence of negative and positive tweets in different nations. Additionally, an approach based on the average of the neighborhood has been used for modelling and grouping the time series of various countries. The clustering method gives results as significant information, how people feel about this dispute and share their opinions about RUW is approached. When compare on different models on overall data that the 96% accuracy is Achieved by the LSTM-CNN model. 97.09% accuracy, is achieved when the comparing the tweets from the cluster 1 countries. When comparing the tweets from the cluster 2 countries the 99% accuracy, is achieved. 97% accuracy is achieved by comparing the tweets from cluster 3 countries. 97% accuracy, is achieved when the comparing the tweets from cluster 4 countries. 96% accuracy is achieved by the LSTM-CNN model when the comparing the tweets from cluster 5 countries by the different models. This research study helps the uninfluenced press members to have an impartial source of information for their reports and articles.

Keywords: Clustering, CNN, LSTM, RUW, Social Network Mining, TSA, World Economy.

1. Introduction

The past 20 years have seen a significant impact on people's daily lives through social media. It is a platform for communication where thoughts and ideas are exchanged and influences the next generation as a tool to place user's opinions about any event or incident. Social networks give the ability to connect with one another and change the world, and by doing so, they have the potential to bring about immediate change with the help of tweets or text messages, images, audio, and videos. Both business and academia are interested in learning how and why people act, as well as how much they act collectively. Social media is a seamless platform to learn these aspects as much data is available on this platform to connect and communicate with the whole world to keep their sentiments and analyze to know people's opinions by collecting information as datasets. Cambridge Analytica is a distinguished and highly provocative instance, as it used data from social media, particularly Facebook, to conduct data analysis for political advertising [1]. Similar techniques can be used with X, which allows users to post brief messages known as tweets to analyze the user's attitude towards a particular subject through aggregation and determine the broad-spectrum compromise on the particular substance. User's sentiments and spirits are articulated through the information, which is primarily based on a shared object of concentration. These fragments of information have grown into informational treasure troves, providing numerous opportunities for analyzing consumer behavior, which is particularly useful in predicting product sales [2], stock market trends [3], and election results [4]. More than 300 million active users use X, which is one of the most widely used microblogging services [5],[6]. Due to its importance in understanding user's feelings and insolences, X Sentiment Analysis has received a lot of attention [7-9]. Furthermore, it is essential to get organized information from the abundance of

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chaotic data accessible on social media to use essential information. Enhance the ability of the social network to precisely visualize dispersed structured data. Natural Language Processing (NLP) can be utilized to determine and gather the sentiment of a specific tweet, which can be utilized to determine the general consensus on a subject. The compactness of the written verbal makes this task a challenging one, and a lot of exertion has been put into resolving it [10]. Sentiment analysis involves analyzing text and images to gather people's opinions and emotions, which can be used to identify information as positive, negative, or neutral [11]. In recent times, RUW has drawn attention to the world on its side. The entire world has been shocked by this war in many different ways. The inflation rate in the world has increased by 3%, while its GDP growth has slowed by 1.4%. Since the beginning of the war, the USA's GDP has decreased by 1.28% [12]. This research work analyzes the tweets regarding the RUW, in which tweets are quoted by 34 countries and categorized in two manners i.e., hope and fear. For this study, tweets in the English language have been considered only. The network has been trained and tested using two machine learning algorithms, Convolution Neural Networks (CNN) and Long Short-Term Memory (LSTM) [13-14]. LSTM has an advantage over CNN and Recurrent Neural Networks (RNN) in numerous ways due to its ability to selectively remember patterns for extended periods of time. The parameters taken up for the study are F1, precision, and recall.

A. *Motivation*

The existing literature in section 2 has concentrated on various areas to examine the influence of RUW on higher education, gas, energy, healthcare, and the stock market. In contrast, this paper concentrates on comprehensive social feelings and opinions of the RUW of various countries. In addition, we selected X data for this study to offer a framework for classifying sentiments by combining CNN and LSTM. According to the research CNN model is best for the purpose of feature extraction of the tweets and LSTM is used for the classification of the tweets based on those features. By the use of LSTM network internal memory, LSTM is capable to learn from past experience with long term state.

B. *Contribution of the Research.*

The research suggested consists of the following primary contributions. (i) Sentiment score creation for the RUW dataset using a lexicon-based method. (ii) If the resulting sentiment score is 1, then classify the tweets and messages as "fear". (iii) Consolidating all sentiments into one data frame to gather more closely linked opinions. (iv) By combining CNN and LSTM models, a hybrid deep learning model for sentiment categorization can increase accuracy. (v) Comparing the LSTM-CNN and LSTM models classification performance. (vi) Suggests a novel approach to clustering and modelling the time series of country opinion.

The remaining document is systematized as follows: Section 2 provides a literature review of the study. In section 3, there is a description of the proposed approach and methodology. The analysis and findings from this study are presented in section 4. The research work is concluded by section 5 which outlines future research directions to guide future work.

2. Literature Survey

In [15] author focuses on the analysis of users' sentiments and feelings about the RUW that uses English tweets along with the bidirectional LSTM (Bi-LSTM) network to classify a multi-class classification approach. This work has achieved 91.79% accuracy with the Max pooling ID mechanism and Bi-LSTM layer which enhanced accuracy in terms of measured performance over previous studies. This work concentrates on an architectural model to solve any similar type of problem without entering into a complex architecture neural network model. The author proposed a framework in [16] to categorize several collective sentiments communicated on social media with the use of combined reaction optimization based on a bidirectional encoder to demonstrate a modifier pre-training methodology using machine learning to frame a combinational sentiment from the RUW. This study has 27 distinct extraction framework of X users which is classified by machine learning with 95% accuracy and visualized to have sentiment task for multilayer perceptron and logistic regression. According to the survey, 81% of X users hold a neutral attitude towards RUW that displays collective sentiments without any defense. Researchers have used text to form attitudinal perceptions by presenting social sentiments [17]. The war exertion has been strongly shared on social media by several nations regarding regions and their information. Civilians and politicians from countries that are involved in the war are confronted with an information conflict. The data collection process and data statistics process provide a comparison between state-affiliated and independent Russian media platforms. This study facilitates information warfare and reduces the prevention of disinformation and opinion manipulation campaigns for upcoming research. An approach to categorize the tweets based on their consequence on user's sentiments has been proposed in [18]. The author used the approach to locate the dataset by penetrating for the appropriate hashtags related to the war, and another objective is to organize tweets in groups to provide a higher level of precision with a moderate dataset using various ML models. To categorize a more comprehensive assortment of use cases, it's important to associate and differentiate the data-pairing approaches involved in sentiment analysis. The author identified in [19] a validation of RUW exertions as the worldwide communication to empower user sentiments and worldwide associations that consider the emotions of the universal community to examine the RUW. The conflicts raise the involvement of other countries' power that becomes more extensive to identify ratification of RUW efforts. The objective of this literature is to investigate the opinions and reactions of the universal platform on the Russian offensive on Ukraine. The first day of the UkraineRussia hashtag saw the analysis of 27,894 tweets that represented 'war', 'people', 'world', 'Putin', and 'peace'. Compared to positive sentiments with salient emotions of sadness, negative sentiments were the most frequently searched texts in the tweets database. A discussion is on [20] over the cyberspace adjacent to RUW with cyber-physical-social systems. This study demonstrates the topographical discrepancy between authorized situations and widespread sentiments using ML methodology. The new data on public sentiment in the RUW using ML for trade approvals is derived from around one million social media posts in 108 countries. These data predict ecological heterogeneity between the attitude and RUW towards public sentiment and observe their opinion about political organizations, trade-off relationships, and political variability. In [21] author examines the conflict between Russia and Ukraine and shows an extravagant number of fiscal indicators are able to evaluate the user's feelings about the progress of the fortified war. This work examines RUW as a case study that can be used as a supervisory tool to gather social media information for a few significant global war events, that acknowledge public perception through the analysis of feelings on 42 million tweets. Using different data, the author calculates instinct reactions for 15 economic and financial indicators that experience an immediate negative response. US stock markets became modest to respond while the United States Dollar ($) proceeded from positive to negative during the war and clarified that tweet basis content is useful and significant as a decision-making tool for imminent event prediction. In [22] author presented a vibrant study of the user sentiment aggressiveness, due to time constraints using Chinese Weibo texts with an unsupervised learning technique with distribution and accumulating sentiments by eliminating keywords. This work also proposed a dynamic model of the dominant gradation of user sentiments in the evolutionary methods to analyze data-driven public opinions. A new technique for admittance sentiment conflict in cyber-physical-social systems is developed by analyzing the data-driven user's sentiment from a Chinese Weibo dataset linked with the RUW approach. Author [23] introduced that nearly 6 million Ukrainians did not have access to drinking water at the end of March. Nearly 12 million people were evacuated in the middle of April and needed altruistic help. In order to improve the damaged economy of Ukraine, they released pressure on FX capitals and banks, Ukraine executed crisis financial measures, such as investment controls and limitations on the banking sector. Various provinces of the country are now unrealizable economically as a consequence of the war's ruin of a substantial percentage of Ukraine's construction infrastructure and the enforced closing of the trade. The estimated prediction of the war amended as a consequence in an approximately 45 percent dropout of the GDP in half of the year 2022. The OECD's [24] report shows in the latest Economic Outlook, that the world economy is expected to indenture in the imminent years as enormous consequences and remarkable shocking dynamism carried out by RUW are lashing inflationary stresses, corroding user self-reliance and domiciliary acquiring influence, and rising hazards around the world. OECD allures attention to the unstable and perilous attitude of the global economy is projected to increase at approx. 3.1% this current year and then quietly fail to 2.2% in 2023, and then raise up to an average of 2.7% pace in 2024, need to notice that these data as results are estimated before the war. In [25] author presented sentiment analysis using a lexicon-based approach where lexicons of words are pre-defined using polarity, which can be computed by comparing the number of positively and negatively annotated words in the text. It also formulates the task as a statistical classification problem and uses documents with pre-defined polarity as training data. SA is a calculative action against a tweet's opinions as sentiments. Various sentiment analysis techniques contributed to several parameters of data analysis as transfer learning, emotion detection, and building resources. Author presented in [26] that sentiment analysis is an automated mathematical computational technique to evaluate sentiments, feelings, and emotions expressed as comments, and feedback. Supervised machine learning techniques use faster text templates to analyze data for the analysis of feelings using a variety of machine learning algorithms. Precision, recall, F1-score, RoC-Curve, accuracy, running time, and k-fold cross-validation are determined by sentiment analysis to analyze the performance of various classifiers. The experimented results help to enhance the uniqueness of different deep learning techniques, resulting in a precise feature for the application. In [27] author presented a word embedding process to associate various vector features for bigrams and unigrams. By concerning the X-specific characteristics vector and word sentiment polarization structures, a division of sentiment features is created. Sentiment classification labels are trained and estimated in a deep CNN. TSA distributes the procedures to calculate user emotion and focuses on obtaining sentimentality features by evaluating lexical and syntactic structures through emotional words, sentiments, exclamation symbols, etc. This study introduced a X corpus-based word implantation technique to accomplish unsupervised learning by using suppressed circumstantial semantic interactions. To assess the appropriate performance on accuracy and F1-measure for X datasets using sentiment classification, the work compared the performance of the word n-grams model. In [28] author presented TSA to extract user's sentiments during the crisis and understand the circumstances as changing aspects and their sensitive influence on affected people. This study demonstrates user sentiment variation depending on position and vicinity to measure the situation and public opinion. Various problems of sentiment analysis such as natural calamities considering Bayesian network classifier on different dataset approach in Chilean earthquake and Catalan independence referendum in the year 2010 and 2017 respectively have been taken up for study. In this work, the Bayesian network classifier's purpose is to yield a more realistic network and show the effectiveness of measured competitive prediction to compare with SVM and random forest as training examples. Author proposed in [29] an approach for rating the inducement of events on the accessible user sentiment catastrophe using a multi-level catalogue system. The information ecosystem approach is used by the operational user sentiments to appraise documents using correlation study and principal component analysis (PCA). To precisely enumerate the expressive indices in the log system, a classification model of text sentiment is developed through deep learning training. In this literature, research uses an instantaneous evaluation of social media user's emotional inclinations and grades the emergency at various stages of social media user's emotions and propagation in order to comprehend the disaster threat. In [30] author proposed an opinion analysis of the tweets to utilize analogous words while tweets have identical positive and negative words to reflect the association of emotional oppressors paying little responsiveness to deliberate the different occasions in Afghanistan. Social media has acquired ubiquity for user communication and data inclination. X allows users to send a prompt tweet as responses of a maximum of 140 characters are used for opinion mining to check discrepancies to influence developments in Afghanistan. Author [31] presented the social media express, notions, and opinions to enhance the acceptance by a large number of users that produces enormous amounts of text comprising political insights to examine user's opinions and forecast imminent inclinations. X users' thoughts are used to extract tweets that impact the General Elections of India in 2019. Thus, the classification model that uses sentiments is capable of calculating the sentiment of tweets, unlike the conventional ML models that use LSTM. The author discussed the evolving understanding of using X to narrowcast situational awareness during the crisis [32]. Information is a major factor in reaching X distribution side during disasters by communicating instant and exclusive news, generating situational awareness, and connecting with digital viewers. X performances are a demonstrative outlet that enables the mining of summarized feedback toward incident-to-edge destruction response approaches. X is used for responsiveness and deeds as a sentiment and social sustenance classification by allocation of sentiments where tweets are associated with 35.71% of data are "distribute the broadcast and facts" and 2.12% of tweets belong to "supporting the government". Most of the users retweet just to censure the government, typical retweet calculation of 15.84%, trailed by "revealing sentiments". However, some of the tweets that "raise questions" just 3.32% and "provide suggestions" are just 2.51% and many of the users fail to gain attention, thus having less influence. Only tweets and tweets with images form have a greater number of tweets towards contributing with 8061 (61.27%) and 3137 (23.84%) of the entire number of tweets. The maximum level of text data as tweets are adorned with such text-video and text-image layouts that indicates 53.70% of the tweets (n=7065) reproduce undesirable sentiments as negative tweets, though 12.67% (n=1667) monitor optimistic sentiments such as positive tweets and 33.63% (n=4424) shows as unbiased as neutral sensitivity about the occurrence. The author proposed in [33] a significant role in communication with the consequences being controlled on various social media platforms. In this study, the applicability and effectiveness are examined with the help of ML and NLP toolkit models. The textual polarization and subjectivity notch of tweets have a great degree of classification accurateness to classify the sentiments. This study uses 11,250 tweets about the RUW from his X account dataset. The results of this work represent a tree classifier model (TCM) that achieves an accuracy of 0.84 in assortment to evaluate the efficacy of ML. The author in [34] presented a report that RUW is having an immense influence in the field of supply chain globally. It obstructs the pour of goods, fuel cost increases, deficiency of products, and shortage of disastrous food production. RUW may have contributing factor to the existing global supply chain crisis, and disruptions started fizzing up during 2018 and 2019 in the period of trade wars as well as over the sequence of the COVID-19 pandemic. The calamity of human loss was the main focus, which led to sanctions and other obstacles that made logistics and trade route operations vulnerable. In [35] author proposed to investigate the user's sentiments towards the Syrian migrant's crunch that are polarized in social media. In this work, Turkish sentiments were considered to have commended the uppermost Syrian migrants and Turkish tweets conceded data to replicate user awareness. The consequences indicated the sentiments are more constructive towards Syrians and migrants than impartial and undesirable sentiments. X is analyzing public sentiments and compiling an overall of 2381,297 relevant tweets in different languages, including Turkish and English, as part of this study. The results of the percentage of positive feelings in Turkish tweets remained at 35% of all Turkish tweets. The number of English tweets with negative sentiments towards Syrians and migrants was limited to only 12%. Author presented in [36] a report of Coronavirus related tweets that are measured using NLP and classification of the information retrieval systems. Consuming a language twisted by the Geo-Names topographical database, the tweet's positions are determined. Economic terms are used and compiled into enormous terminology, and associated tweets are impassive, and the feelings associated with tweets are analyzed with high accuracy and real performance. The initial-level reactions have shown in [37] conduct concurrent assessments of social media platforms such as X. They have also given some estimations on polarity kinds of tweet expansion to measure sentiment analysis on X data to appraise the evaluation of supervised ML classifiers. This study collected around 362,566 tweets by the United States from Afghanistan between 11 August and 27 August 2021 and was analyzed by using text mining analysis. TF-IDF and Word2vec techniques were used in the study to extract features for sentiment classification using machine learning classifiers and demonstrate negative reactions on social media. SVM classifier shows superior performance with 0.83 accuracy and significant precision, recall, and F1-score during crises and provides insights to stakeholders to prevent this situation in the future. Author [38] said that Ukraine demands compensation which seems to be not possible currently, instead of Russia performing to be adhesive for a lengthier and extensive conflict. The factions had apprehended $30 billion in properties governed by the

Russian leading and freezing $300 billion preserved by the Russian central bank as of June 2022, whether it is possible to transfer some of this to Ukraine, and the involvement will be observed as a necessity. It will induce Russia to pay compensation to Ukraine depending on the consequences of the war. In [39] author presented a lexicon-based approach with the topographical catalogue to indicate each tweet with its position and analyze the tweet's sentiment analysis which shows the frequency and sentiments for each country that correlate with the authorized facts of COVID-19. The highest emphasis on the nations with Coronavirus shows the frequency of the tweets with a significant correlation and extracts knowledge that was inherent in the tweets. Author [40] presented a conditional instigation due to COVID-19 diseases, combining the intellectual and emotional health of people which is exploited by people to interconnect their emotions and beliefs. X text contents as datasets are fetched across the globe and categorized into uncomplicated sentiments such as annoyance, expectation, repulsion, anxiety, happiness, sorrow, wonder, and belief. The X outline exploits tweets posted by users during the crisis and ruptures the outlooks of people. It measures to adopt the strategies to fight against coronavirus which has affected socially and economically around the world. The author presented in [41] TSA to examine the data on social media that uses CNN enriched via an arithmetic optimization algorithm approach to extract the features that are applied to obtain the data from CNN for the selection process. In order to create a useable database utilizing FastText Skip-gram and the CNN model as a feature extractor, this work has built an API with 173,638 tweets concerning COVID-19 that were collected from X between July, 2020, and August, 2020. To measure TSA performance using different approaches, an arithmetic optimization algorithm was used to classify the tweets. This work classifies the results to achieve tweet classification performance at the highest level with 95.098% rate of accuracy as experimental research demonstrates much higher sentiment analysis performance in comparison to other comparable methods. The solution of the conflict between the Russia and Ukraine has not found until November 2022 [42]. And now this has raised an international concern because if the both the parties cannot control this, this war can take the form of war or open conflict. No one can predict the end of this conflict because it can only handle by the leader of both the countries and agreement between them otherwise this conflict can convert into a war. The war between the Russia and Ukraine is now converting into the world war [43]. So that all the countries try to update their foreign policy to defend any unwanted situations due to this conflict. As a member of international community Indonesia also has a concern that how to handle this kind of situations because Indonesia has its free and proactive foreign policy. From the study of the literature survey, it is evident that there is no specific model to analyze the tweet sentiment on RUW, and no researcher has discussed the area in which the classification and analysis have been done on various countries' tweets as data.

3. Proposed Algorithm

Deep learning is the basis of a LSTM-CNN model used in this work. The time series grouping technique is utilized to analyze the sentiment and feeling of the tweets. The most emphasized occurrence of 2022 worldwide is RUW, which has received a significant number of tweets on X as social media.

A. *Tweet Collection and Processing*

The conflict between Russia and Ukrain was the most dominating tweets in March 2022. Initially, the tweets from the world about the conflict in Ukraine are gathered and organized according to the tweet's location. Then, sentiment analysis is used to separate positive as hope and negative as fear from the tweets. Clustering the time series of tweet sentiments is the last step. During the month of March 2022, around 1.64 million English language tweets about the RUW using the phrase of Ukraine are collected. The geotag has been used to distinguish tweets from various nations, as a result, tweets having an ambiguous location are removed. TSA is the technique to identify whether a tweet is good, undesirable, or unbiased such as positive, negative, or neutral. On social media like X users can express their feelings and opinions so a large number of sentiment analyses perform on that kind of posts. To ascertain the changes in public opinion over time regarding this war, we use sentiment analysis.

B. *Sentiments Trends of Clustered Countries*

For modelling and clustering of user opinions in social networks, various techniques have been presented. The average of the method, neighborhood is used to create a zone cluster of the countries. The data for each country is normalized first on weekly basis because there are variances in the number of tweets among nations, the majority of which are significant. The frequency of tweets that are positive and negative on a weekly basis is then calculated for each nation. As a result, for the first four weeks after starting of the war, four positive and four negative frequencies are determined for each nation and modelled as an eight-featured vector. The coefficients generated from the suggested model for the countries are then clustered using the average of the neighborhood method. The Euclidean meter is used to compute the distance between nations, and the nations that have a smaller distance are grouped together. Below is more information on the suggested model, which employs the support vector machine (SVM).

For the time data the following model is consider first,

$$Z_t = \sum_{j=1} W_j Z_{t\ j} + W_0 = \mathbf{w}^T z_t + w_0 \quad where; \mathbf{z}_t = (z_{t\ 1}; :::; ::: z_{t\ p}) \tag{1}$$

SVM has been used to estimate the vector $\mathbf{w}$ and w_0 by the equations,

$$z_{t1} = \sum_{j=1}^{P} w_j z_{t\ j} + w_0 \quad e \tag{2}$$

Figure 1. SVM based Estimation

$$\text{Min}\ \ w; w_0; \sim; \sim\ J(w, w_0; \sim; \sim) = 1{=}2\ \ w^T w + c \sum_{t=P+1}^{T} (\ _t + \ _t) \tag{3}$$

$$z_t \quad w^T z_t \quad w_0 \quad e + \ _t \quad \text{where}, t = p+1; :::::::; T \tag{4}$$

$$w^T z_t \quad w_0 \quad z_t \quad e + \ _t \quad \text{where}, t = p+1; :::::::; T; \ \text{and};$$

$$_t;\ _t \quad 0 \tag{5}$$

For the above optimization, Lagrange's equation is as follows with coe cient $a_t\ ; a_t;\ _t;\ _t$:

$$L(w; w_0; \sim; \sim; a; a\ ;\ _1\sim) = J(w; w_0; \sim; \sim) \quad \sum_{t=p}^{T} a_t(e + \sim \quad z_t \quad w^T z_t \quad w_0)$$

$$\sum_{t=p}^{T} a_t (e + \sim \quad z_t \quad w^T z_t \quad w_0) \quad \sum_{t=p}^{T} (\ _t\ _t + \ _t^{0}\ _t) \tag{6}$$

To reach the optimal value J in equation (3) uses L in the above equation (6).

$$\max(a; a\ ; \sim; \sim) \tag{7}$$

$$\min(w; w_0; \sim; \sim^{0}) \tag{8}$$

$$L(w; w_0; \sim; \sim; a; a\ ;\ _1\sim) \tag{9}$$

We can get,

$$\frac{@}{@w} = 0 \ ! \quad w = \sum_{t=p+1}^{T} (a_t \quad a_t) z_t \tag{10}$$

$$\frac{@}{@w_0} = 0 \ ! \quad w = \sum_{t=p+1}^{T} (a_t \quad a_t) = 0 \tag{11}$$

$$\frac{@}{@_t} = 0 \ ! \quad c \quad a_t \quad _t = 0 \tag{12}$$

$$\frac{@}{@_t} = 0 \ ! \quad c \quad a_t \quad _t = 0 \tag{13}$$

As a result, after embedding of equation (3) in equation 2, the dual (1) is yielded as below,

$$\max\ a; a^1\ J_D(a_1 a^1) = \frac{1}{2} w^T w \quad e \sum_{t=p+1}^{T} (a_t + a_t) + \sum_{t=p+1}^{T} z_t (a_t \quad a_t) = \sum_{t=p+1}^{T} : \sum_{t=p+1}^{T} (a_t \quad a_t)(a_k \quad a_k) z_t z_k$$

$$e \sum_{t=p+1}^{T} (a_t + a_t) + \sum_{t=p+1}^{T} z_t (a_t \quad a_t) \tag{14}$$

S.T.

$$\sum_{t=p+1}^{T} z_t (a_t \quad a_t) = 0 \quad \text{where} \ 0 \quad a_t; a_t^2 \quad c \tag{15}$$

To obtain the value of W_0, KKT method has been used.

$$a_t (e + \ _t \quad z_t + w^{(}T)(z_t) + W_0) = 0 \tag{16}$$

$$a_t (e + \ _t + z_t \quad w^{(}T)(z_t) + W_0) = 0 \tag{17}$$

After some simple calculations, we can get,

$$w_0 = z_t \quad w^{(}T) z_t \quad e \quad a_t\ [0; c]\ _t = 0 \tag{18}$$

$$w_0 = z_t \quad w^{(}T) z_t \quad e \quad a_t\ [0; c]\ _t = 0 \tag{19}$$

So that,

$$\hat{w}_0 = \frac{1}{jsj} \sum_{1} (z_t \quad w^T z_t \quad Sign(a_t \quad a_z) e) S = t : 0 < a_t \quad a_1^{0} < c \tag{20}$$

Then we have,

$$\hat{z}_t = \sum_{k=p+1}^{T} (\hat{a}_k \quad \hat{a}_k) z_k^T z + \hat{w}_0 \tag{21}$$

If $z_t = w^T\ (z_t) + w_0$ where : R^P ! R^n then we have,

$$\hat{z}_t = \sum_{k=p+1}^{T} (a_k \quad a_k)\ ^T(z_k)\ (z_t) = \sum_{k=p+1}^{T} (a_k \quad a_k) K(z_k; z_t) \tag{22}$$

k is indicating a kernel function. But in place of the above model, we can use the below model.

$$Z_t = \sum_{J=p+1}^{T} W_j K_h(z_{j;} z_t) + W_0 \tag{23}$$

The above model contains various characteristics, such as,

SVM algorithm yields the target equation.

As estimate coe cients Loss function is used, rather than errors $(\varepsilon^{1})_t$.

In the model, dual equations employ the kernel function K_h.

When using programming to determine the coefficient values of the aforementioned equation, there are less time twists.

Either the generalized Wasserman cross-validation criterion or the trial-and-error approach can be used to get the smoothing constant.

When h is smoothing constant in the loss function is set to its ideal value of many outlier data and modifications in non-linear or linear Z_t modes can be taken into account.

All $Z_p; Z_{p+1}$ observations via function

$$\sum_{J=p+1}^{T} W_j K_h(z_j; z_t) \tag{24}$$

Z_t is estimated using the weighted sum of the neighborhood to the center Z_t and radius h. In addition, the GCV criterion's smoothing constant, h, is present. In addition, apply the objective equation shown below to determine w_0 and w:

$$(\hat{W}; W_0) = \min_{w;w_0} \frac{w^T w}{2} + C \sum_{t=p+1}^{T} \ell\left(z_t - \sum_{J=p+1}^{T} w_j k(z_J; z_t)\right) \tag{25}$$

ℓ indicating the loss function. The mean least squared error (ℓ_{LS}), is a commonly used loss function for analyzing and modelling time-dependent data, which gauges the gap between expected and actual values. There are times when the data is set up so that the predicted values have a tendency to resemble the outlier data, or are “crooked”. In this instance, the loss function indicated above causes issues with parameter estimation and response variable prediction. This issue is resolved by using Huber's loss function (ℓ_H). We must decide predictions are whether uncertain or certain in the majority of modelling situations involving real-world data. For solving problems in the actual world, it is essential to understand the range of possible variances for expected values. The quantile loss function (ℓ_q) offers the advantage of predicting response variable for an interval as opposed to a single value. Table I provides a summary of the aforementioned function's forms.

Methods	Loss function
Least-Squares	$\ell_{LS}(e) = e^2$
Huber	$\ell_H(e) = \begin{cases} \frac{1}{2}e^2 & for \lvert e \rvert \le k \\ k\lvert e \rvert - \frac{1}{2}k^2 & for \lvert e \rvert > k \end{cases}$
Quantile	$\ell_Q(e) = e(Q - I_{(e<0)})\ 0 \le Q \le 1)$

TABLE I. Loss Function

4. Methodology

The objectives to develop the proposed methodology is deep learning based, to analyze the sentiments so that the ”hope” and ”fear” during the 2022 RUW can be measured.

Figure 2. Overview of proposed methodology

There are multiple phases of the proposed system behind this, such as,

i Dataset collection
ii Preprocessing of data
iii Feature representation
iv Generation of sentiment score
v Polarity calculation
vi Use of LSTM-CNN model
vii Model testing
viii Evaluation of metrics and
ix Analysis of result

The framework of proposed methodology is applied in the current investigation is shown in Figure 2.

Datasets: During the March 2022 the prominent topic of X was the war between Russia and Ukraine. The related tweets of the war between Russia and Ukraine were collected related and separated by the location. After that the tweets are separated and identified on the basis of

”hope” and ”Fear” with the help of sentiment analysis. Approx. 1640,000 English tweets are collected against the keyword Ukraine during month of March, 2022 related to the RUW and to get the tweets from dierent countries applied geotag. As the data are collected from the web, the data is having irregularity, that's why the data preprocessing is required. After the preprocessing the data we have created a balanced data set.

Data Preprocessing:For data cleaning dierent preprocessing steps were implemented after that the data processing are easy. Below are the various preprocessing methods performed on the data sets at the same time. All words of tweets are converted into the lowercase.

Removal of Stop word: The words like ”an”, ”a”, “is”, “the” and “are” do not carry any kind of information. So, these kinds of words were removed from the tweets.

TRemoval of Punctuation: Punctuation marks are also removed from tweets.

Elimination One-Word tweet: That kind of tweets that contains only one word were eliminated from this process.

Removal of Contraction: This is a kind of process in which the short form of the written sentences is in short form like ”I'll” becomes ”I will”.

Tokenization: Tweets are broken down into small pieces of text.

Tagging of tweets: This is the steps in which the sentences were tagged with POS tag, like ”AJ” for adjective, ”N” for noun, and ”VB” for verb.

Score Generation: An evaluation of the tweet's sentiment produced a score. The dataset was matched with opinion data to determine the sentiment score. lexicon [44] comprising 4,500 negative words and 5,000 positive words, each with a corresponding score. Depending on the lexical notes, a feeling score was obtained for each review text. If the score was higher than 0, the review text would be labeled as hop, while if it was not, it would be labeled as fear.

Word Embeddings: ”Word embeddings” method is used to calculate the numerical vectors for preprocessed tweets. For word indices, all the tweets are turned into sequences. These indices are obtained using the tokenizer ered by Keras [45]. Ensure that the tokenizer has no zero-indexed terms or words and maintain the vocabulary properly, each word in the testing and training sets is indexed separately, which can be used to produce numeric vectors of all tweets in the dataset.

5. LSTM-CNN Integration Model

The LSTM-CNN integration model used for the analysis of ”expectations” and ”fears” of sentiment relative to X data for the RUW dataset is shown in Figure 3.

Figure 3. LSTM-CNN structure

A. Embedding Layer

By the use of this layer the tweets sentiment transformed and constructed into the numerical form, means that transform the words into an actual-valued vector. The process is called as word embedding. Each word of the training dataset has an embedding learned by the Embedding layer, which begins with random weights. It is a layer that is exible and can be utilized in various applications, such as.

It can be loaded into a transfer learning technique known as a pre-trained word embedding model.

Learning a word embedding can be achieved by using it alone, which can be preserved and used in a di erent model later.

The embedding can be learned concurrently with the model in a deep learning model.

There are three components for this embedding layer that includes,

Size of the vocabulary is 15,000 words,

Dimension word is 50, as well as,

Length of input sequence is 400 words.

B. Dropout Layer

The over tting dropout model [46] is employed in the model to prevent this. The dropout rate parameter in this case is 0.4, which falls between 0 and 1. Arbitrarily deactivating a group of neurons in the embedding layer is one of the primary duties of the dropout layer. each neuron explains the emotional elements in a sentence in a speci c way. CNN is used in a variety of deep learning applications, including computer vision, natural language processing, and medical picture processing.

C. Convolution Layer

Using the third layer, features are extracted from the input matrix. The input sequence matrix elements are used by n convolution lters to determine the convolutions for each sequence. We made the choice to use a lter kernel that was 3 by 3 in size and had 64 lters.

D. Max Pooling Layer

Along with the spatial dimensions of the provided input sequences, this layer does down-sampling. Each lter kernel's pool of input features is taken into account to the fullest extent possible. The assignment of the 5 x 5 kernel has been made.

E. LSTM Layer

A type of RNN, LSTM is utilized for long-term learning dependency [46]. We applied an LSTM layer with 50 hidden units as the next layer. Employing a convolutional neural network as a feature extraction technique is one of the main advantages. The reduction in features that need to be aggregated is more signi cant compared to a traditional LSTM. These characteristics (words) are used by a sentiment classi cation model throughout the feature extraction process to determine if the tweet is a kind of "hope" or "fear". Before sending the output to the network's last layer, LSTM performs pre-calculations for the input sequences. The four gates input, output, candidate, and forget, provide the foundation for the four discrete calculations that take place in each cell. Figure 4 presented the LSTM model structure. And the equations of all the gates are as follows.

Figure 4. LSTM model

RNN Equation:

$$h_t = \tanh(M^t_{hh} h_{t1} + M^t_{xh} h_t) \tag{26}$$

$$y = M^t_{hy} h_t \tag{27}$$

where, h_t indicates the hidden state calculated by the RNN at timestamp t.

$M_h h$ indicates the mass matrix from one state to state that is calculated by RNN at timestamp t both the states are hidden.

$M_x h$ indicates mass matrix from the input to the state that is hidden.

$M_y h$ indicates mass matrix from the input to the output state.

LSTM Equation

$$\text{forgetgate}: f^{(t)} = sig(M_f x^t + U_f h^{(t1)}) \tag{28}$$

$$\text{inputgate}: i^{(t)} = sig(M_i x^t + U_i h^{(t1)}) \tag{29}$$

$$c^{(t)} = \tanh(M_c x^t + U_c h^{(t1)}) \tag{30}$$

$$\text{outputgate}: o^{(t)} = sig(M_o x^t + U_o h^{(t1)}) \tag{31}$$

$$\text{hiddenstate}: h^{(t)} = o^{(t)} \quad \tanh(c^{(t)}) \tag{32}$$

$$\text{cellstate}: c^{(t)} = f^t c^{(t\ \ 1)} + i^t c^{(t)} \tag{33}$$

$$\tanh(x) = \frac{1e^{2x}}{=} 1e^{2x} \tag{34}$$

where, Weight matrix of the input layer is indicated by M_i and U_i.

Weight matrix associated with the forgotten layer is indicated by M_f and U_f.

Weight matrix about the output layer is shown by M_o and U_o.

Weight matrix associated with the LSTM cell is shown by M_c and U_c.

F. The Dense Layer

A collection of 512 artificially linked neurons makes up this hidden layer of the LSTM-CNN model, which connects the network's accessible neurons. The equation below uses rectified linear units for this layer.

$$f(x) = max(o; x) \tag{35}$$

G. Activation of Sigmoid Function

From the dense layer, there are some outputs. Now the time is to detect and classifies means that positive and negative sentiment through this layer. The formula for the sigmoid function is given below that is used in LSTM-CNN model configuration:

$$Sig(\ ) = 1 = 1e^{2x} \tag{36}$$

H. Evaluation Metrics

For the purposes of the evaluation of the proposed LSTM-CNN model and comparison with the LSTM model, certain measurements have been used as a reminder, precision, F1- score, precision and specificity. The following are the performance measurements shown as,

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Performance Measurements

Precision = (TP / (FP + TP)) × 100%
Accuracy = ((TN + TP) / (FN + FP + TP + TN)) × 100%
Specificity = (TN / (TN + FP)) × 100%
F1 score = 2 (precision × sensitivity) / (precision + sensitivity)) × 100%
Recall = (TP / (TP + FN)) × 100%
where TP (true positive) = Total number of positive (hope) sentiment samples
FP (false positive) = Total number of incorrectly classified negative (fear) sentiment samples
TN (true negative) = Total number of negative (fear) sentiment samples, and
FN (false negative) = Total number of incorrectly classified positive (hope) sentiment samples.

LSTM-CNN model Configuration

Input training = x_train and targets = y_train
Hyperparameters like
embedding_dimension = 50 as em;
input_length = 400 as il; vocabulary_size = 20000 words as vs; dropout_rate = 0.5 as dr;
activation_function = Relu as af; number_filters = 64 as nf; strides = 5; kernel_size = 33 as ks; number_epochs = 5 as ne; pool_size = 55x20 as ps; lstm_units = 50 as lu; num_classes = 2 as nm; batch_size = 32 as bs; Adam optimizer.
Step 1 : Sequential model() initialization;
Step 2 : Set input layer as embedding layer
Step 3 : Add embedding model (vs; il; em);
Step 4 : Add convolutional model 1D (ks; nf);
Step 5 : Add max_pool layer (strides; ps);
Step 6 : Add LSTM_layer (recurrent_activation; af; dr; lu; return_sequences);
Step 7 : Add Dropout (dr);
Step 8 : Add Dense_layer (af = " $= \frac{1}{1\ e^{2x}}$ ", nm);
Step 9: Compile = (e (optimizer, loss_function);
Step 10: Result = $x_t$rain; $y_t$rain; bs; ne):

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6. Experimental Results

The LSTM-CNN model's experimental results for sentiment analysis of X data from RUW are displayed in this section. The proposed system employed evaluation metrics such as recall, specificity, F1-score, precision, and accuracy to examine the result.

A. Data Splitting

In this phase, we divided the collected dataset using keywords Ukraine, # UkraineNATO, # UkraineWar, # StandwithUkraine, # RussiaInvade, etc. that consisted of 1640000 opinions (tweets) into 72% training, 8% validation, and 20% datasets testing. The LSTM-CNN and LSTM models were utilized to detect and categorize the review texts as either hope or fear. The dataset has been divided, as shown in Table II.

Total number of reviews	Training set at 72%	Validation set at 8%	Testing set at 20%
1640000 (316,184 positive; 1323,816 negative)	1180800	131200	328000

TABLE II. Splitting of the dataset

B. Results and Discussion

In this work, all implementations are used the Python programming language. Each country's tweets were identified by it geotags, and on the basis of each nation's tweets a sentiment analysis was carried out. Retweets were removed at this point to prevent redundancy. The rate of positive as hope and negative as fear sentiment throughout the first four weeks of the war is shown in Figure 5 and 6 for each nation. Users appear to have a bad opinion of the situation in Ukraine, as evidenced by the fact that the rate of negative tweets outweighs the rate of positive tweets in every country. Additionally, with European states making up 50% of the countries, the proportion of nations that shared enough tweets on the conflict is higher in Europe. Asian countries, which made up roughly 30% of the nations, came in second. The ratio of negative to positive tweets is higher in Portugal, Switzerland, Ukraine, Austria, Spain, Italy, Singapore and Turkey, showing a more pessimistic view of the events surrounding the RUW. On the other hand, in countries like Denmark, Belgium, Argentina, China, Sweden, and the Philippines there are more positive tweets than negative ones. This ratio suggests that during the

Figure 5. Rate of negative and positive tweets for ”Hope” in the rst four weeks of the war

Figure 6. Rate of negative and positive tweets for ”Fear” in the rst four weeks of the war

rst month of the con icts, citizen's perceptions of these countries were less negative.

C. Time Series of Clustered Countries

The 34 countries which is listed in the table (III) with the most tweets are subject to the suggested clustering model. In the end, these 34 countries are divided into ve groups. The clustering of the nations is shown in Figure 7 - 12. Clusters 1 and 5 contain the largest number of nations. Figure 8 shows the majority of the countries from Western Europe, the United States, Canada, England, and India make up Cluster 1. All nations, excluding India, have supported Ukraine wholeheartedly during the con ict. Figure 9 re ects the cluster 2 only has Ukraine in it. Understandably, that their perspective on this war di ers from that of other countries given that their country has been assaulted. Figure 10 shows the cluster 3, the model obtained for Japan is unique compared to any other nation, even though the restrictions that the Japanese government imposed on Russia. Figure 11 re ects the Spain, Australia, and Italy make up Cluster 4. Finally, Cluster 5 is made up of China, the United Arab Emirates, Argentina, the Czech Republic, Estonia, Poland, Brazil, Russia, Singapore, the Philippines, Finland, Portugal, Mexico, Denmark, Switzerland, Belgium, Sweden and South Africa, all of which had views that were somewhat similar to those of Russia is in Figure 12. The majority of these countries are found in Eastern Europe, Southern and Central Africa, Asia, and Scandinavia. It is crucial to keep in mind the following two points, which also highlight the work's limitations when evaluating the clustering:

- According to the tweets made by users during the rst month of the war, the countries were clustered. Naturally, as the ght went on and di erent things happened, the type of clustering may change.
- The time series of both negative and positive tweets showed a dynamic pattern that was grouped. As a result, both the time frame and the subject's relevance over time have been somewhat taken into consideration.

Index	Country	Index	Country
1	USA	18	DENMARK
2	GERMANY	19	BELGIUM
3	TURCKY	20	BRAZIL
4	CANADA	21	CZECHIA
5	IRELAND	22	POLAND
6	INDIA	23	INDONESIA
7	FRANCE	24	ESTONIA
8	AUSTRALIA	25	SWITZERLAND
9	UKRAIN	26	FINLAND
10	SPAIN	27	CHINA
11	UK	28	SOUTH AFRICA
12	ITALY	29	PORTUGAL
13	NETHERLAND	30	PHILIPPINES
14	JAPAN	31	MEXICO
15	AUSTRIA	32	RUSSIA
16	UAE	33	SINGAPORE
17	ARGENTINA	34	SWEDEN

TABLE III. List of Countries

Figure 7. Dendogram

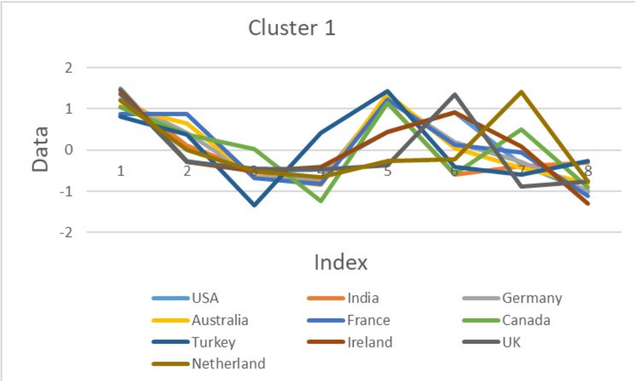

Figure 8. Cluster of 10 countries

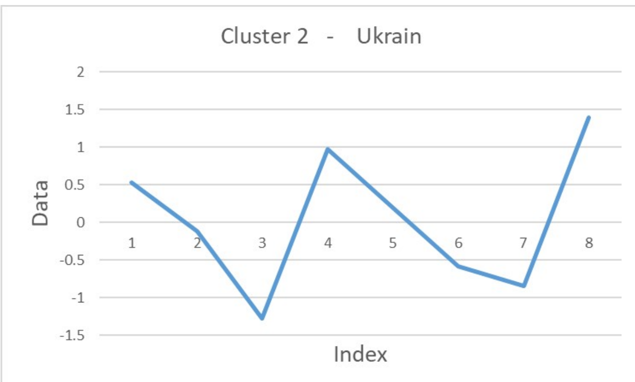

Figure 9. Index of Ukrain

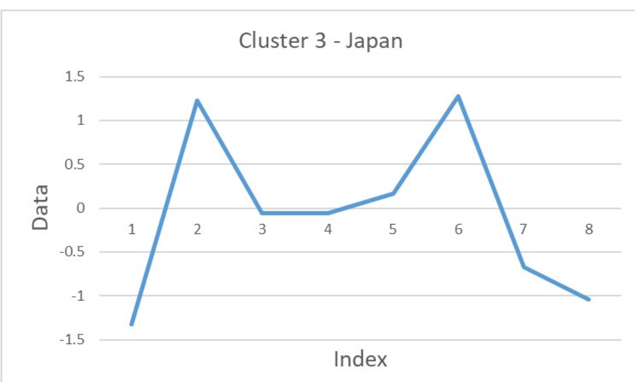

Figure 10. Index of Japan

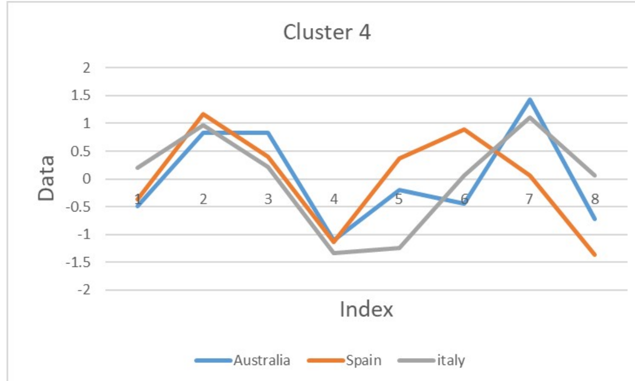

Figure 11. Index of Australia, Spain, and italy

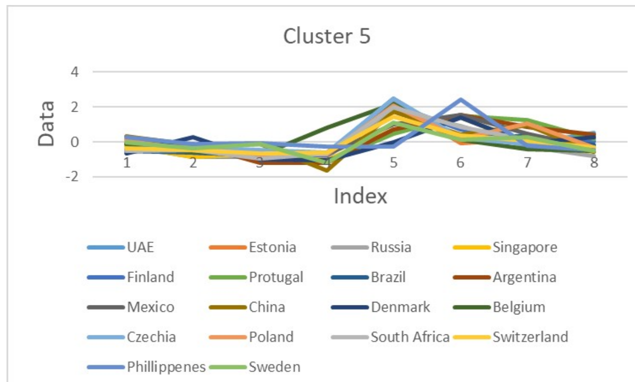

Figure 12. Cluster of 18 countries

D. Outcome

The deep learning techniques outcomes are displayed in Table IV to Table IX.

Table IV Compare on different models on overall data that reflects the 96% accuracy, 97.05% of F1-Score, 99.00% Recall and 98.08% of Precision is achieved by the LSTM-CNN model. Table V shows the 97.09% accuracy, 96.0% of F1-Score, 95.07% Recall and 97.03% of Precision is achieved by the LSTM-CNN model when the comparing the tweets from the cluster 1 countries by the different models. When comparing the tweets from the cluster 2 countries by the different models in table VI, the 99% accuracy, 98.07% of F1-Score, 98.02% Recall and 96.08% of Precision is achieved by the LSTM-CNN model. Table VII depicts the 97% accuracy, 97.38% of F1-Score, 97.00% Recall and 98.89% of Precision is achieved by the LSTM-CNN model by comparing the tweets from cluster 3 countries by the different models. Table VIII reflects the 97% accuracy, 97.00% of F1-Score, 98.00% Recall and 98.08% of Precision is achieved by the LSTM-CNN model when the comparing the tweets from cluster 4 countries by the different models. Table IX reflects the 96% accuracy, 96.00% of F1-Score, 98.00% Recall and

99.00% of Precision is achieved by the LSTM-CNN model when the comparing the tweets from cluster 5 countries by the different models.

Figures 13 and 14 display the LSTM and LSTM-CNN model's confusion matrices. The sample's TN, FP, TP, and FN rates are displayed using the confusion matrix. The LSTM-CNN model, which uses hidden data to predict people's sentiments, used these rates to compute the assessment metrics (accuracy, specificity, F1-score, recall, and precision). LSTM produced a TP of 83.24% whereas LSTM-CNN produced a TP of 94.87%. In terms of misclassification, LSTM-CNN achieved 0.89% FP whereas LSTM achieved 6.39% FP, showing that the LSTM-CNN model performed better than the LSTM model. The accuracy performance of LSTM for the validation and training datasets is shown in Figure 15 and Figure 16. The accuracy of LSTM models increased from 86% to 94% during the training phase, and it achieved 91% accuracy after 10 iterations during the testing phase. The LSTM model's loss fell from 0.35 to 0.17 during the training phase and from 0.3 to 0.27 during the validation phase. During the training phase, the LSTM-CNN accuracy performance grew from 87.50% to 97%. The accuracy performance in the validation phase was 94% as shown in Figure 17. Figure 18 shows that the LSTM-CNN model experienced a loss of 0.20 during the validation stage. 94% accuracy achieved by the LSTM-CNN model.

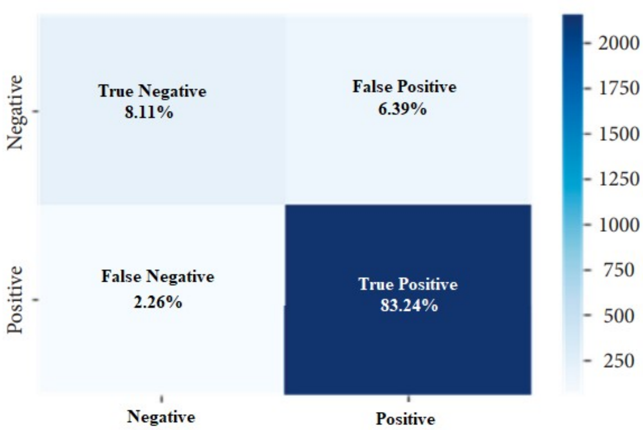

Figure 13. Confusion matrix of the LSTM

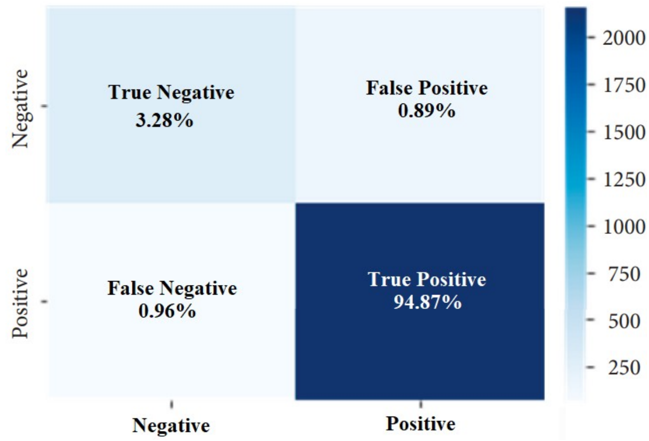

Figure 14. Confusion matrix of the LSTM-CNN models

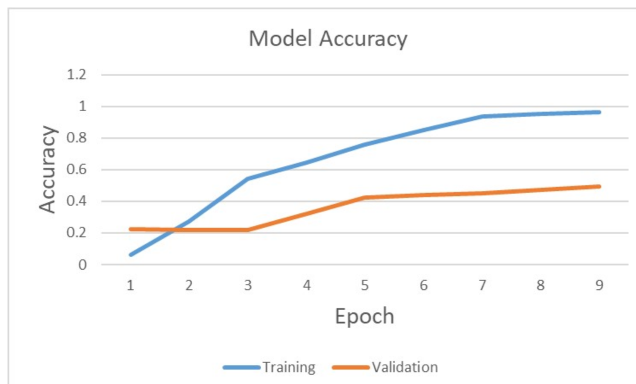

Figure 15. Performance of the LSTM model (Epoch vs Accuracy)

Figure 16. Performance of the LSTM model loss (Epoch vs Loss)

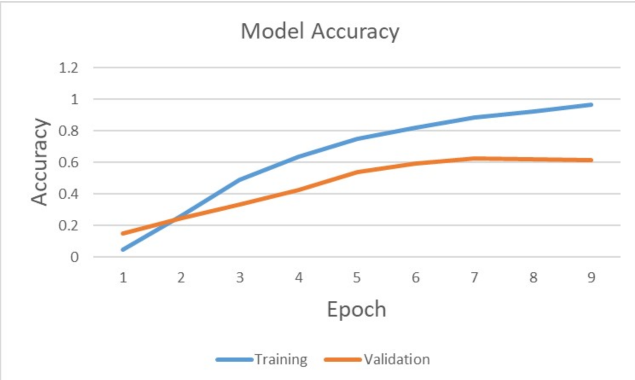

Figure 17. Performance of the LSTM-CNN model (Epoch vs Accuracy)

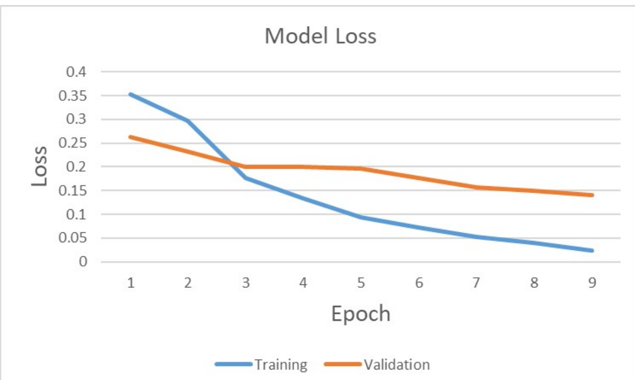

Figure 18. Performance of the LSTM-CNN model (Epoch vs Loss)

Models	F1-Score %	Recall %	Precision %	Accuracy	Specificity
CNN	79.03	74.00	83.00	71.09	82.00
LSTM	94.50	96.73	91.07	90.03	95.02
LSTM-CNN	97.05	99.00	98.08	96.00	97.07

TABLE IV. Comparison on different models on overall data

Models	F1-Score %	Recall %	Precision %	Accuracy	Specificity
CNN	74.13	78.00	91.00	71.09	79.00
LSTM	95.02	91.07	96.00	92.23	97.05
LSTM-CNN	96.00	95.07	97.03	97.09	99.00

TABLE V. Comparison on different models on country cluster 1

Models	F1-Score %	Recall %	Precision %	Accuracy	Specificity
CNN	77.89	69.00	82.09	71.09	76.00
LSTM	94.50	93.18	3.00	90.03	85.02
LSTM-CNN	98.07	98.02	96.08	99.00	93.07

TABLE VI. Comparison on different models on country cluster 2

Models	F1-Score %	Recall %	Precision %	Accuracy	Specificity
CNN	76.09	74.00	82.08	74.00	82.70
LSTM	89.00	93.09	91.07	89.00	95.02
LSTM-CNN	97.38	97.00	98.89	97.00	97.80

TABLE VII. Comparison on different models on country cluster 3

Models	F1-Score %	Recall %	Precision %	Accuracy	Specificity
CNN	79.00	69.00	83.00	72.00	83.00
LSTM	93.00	96.73	91.07	91.00	96.00
LSTM-CNN	97.00	98.00	98.08	97.00	98.00

TABLE VIII. Comparison on different models on country cluster 4

Models	F1-Score %	Recall %	Precision %	Accuracy	Specificity
CNN	79.00	72.00	82.00	73.00	82.02
LSTM	93.00	96.00	93.00	90.03	93.00
LSTM-CNN	96.00	98.00	99.00	96.00	97.07

TABLE IX. Comparison on different models on country cluster 5

7. Conclusions and Future Work

This research work, investigates user opinions on the RUW throughout its first month. In March 2022, 1640,000 relevant English tweets mentioning Ukraine were gathered for this purpose. Following that, each tweet geotag was used to pinpoint its position. We employed a combination of LSTM-CNN, a language-based model that outperformed competing models in terms of sentiment analysis of tweets, and compare the performance with LSTM and CNN which performed better in any kind of situation. The rate of positive as hope and negative as fear tweets from nations with a significant quantity of tweets were then analyzed across a weekly time period. The examination of these time series revealed important information about user's thoughts on the situation between Russia and Ukraine. It is likely to assume that most users have an unfavorable perspective of this war because there were more negative tweets than good tweets in every country means that people have a fear of the war results. The trend of the country's favorable and negative tweets was also clustered, which explained how the subject gained relevance over time. The results of this work enable us to highlight the similarity of opinions held by users on first month of the war based in South America, Scandinavia, Asia and Eastern Europe during, as well as the similarity of beliefs held by users in the United States, Canada, and Western Europe. Additionally, user's perspectives in Ukraine and Japan were unique and different from those of any other country. Users of the many counties not able to speak English fluently and they post the tweets other than English language, this article has several limitations. One of them is that it does not take into account tweets in languages other than English. If the tweets take from other languages, then the output may vary in positive or in negative direction. In addition, we exclusively used X for polling and left out other social media sites. Finally, because only tweets containing the phrase Ukraine, # UkraineNATO, # UkraineWar, # StandwithUkraine, # RussiaInvade, etc. were gathered, not all pertinent tweets may have been included. Other that these phrases might be various tweets are available on X, that can create a big impact on the results. Future research can cluster the coefficients produced from the suggested model for each country using a variety of techniques, and the outcomes can be compared. In addition, social network users can be used to analyze how this war has affected economic, political, and other issues as well as international relations. Moreover, how the COVID-19 affected the economic condition of the various countries and compared to RUW can also be analyzed and compared.

8. Data availability statement

The data set used in this manuscript can be found at: https://www.kaggle.com/datasets/foklacu/ukraine-war-tweets-dataset-65-days?select=StandWithUkraine.csv.

9. Declaration of Competing Interest

The authors state that there are no known competing financial interests or personal relations that could have influenced the work reported in this document.

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