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A Hybrid Deep Learning Framework using Distil RoBERTa for Sentiment Analysis of Russia–Ukraine War Discourse on Twitter

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ABSTRACT

With over 500 million tweets posted daily, a significant portion reflects opinions on global socio-political events such as the Russia–Ukraine War. Monitoring public sentiment at this scale through manual analysis is time-consuming, inconsistent, and impractical for real-time decision-making. To address this challenge, this study proposes a hybrid deep learning framework for automated sentiment analysis of Twitter discourse related to the Russia–Ukraine conflict. The methodology begins with comprehensive Natural Language Processing (NLP) preprocessing, including tokenization, stopword removal, normalization, and lemmatization, followed by Exploratory Data Analysis (EDA) to examine sentiment distribution, word frequencies, and textual trends. Context-aware semantic features are extracted using Distilled Robustly Optimized BERT Pretraining Approach (DistilRoBERTa), which provides efficient and lightweight transformer-based embeddings while reducing computational overhead. To mitigate class imbalance and improve minority class detection, KMeans-Synthetic Minority Over Sampling Technique (SMOTE) is employed for synthetic oversampling. For performance benchmarking, conventional classifiers such as Logistic Regression (LR), Support Vector Machine Classifier (SVC), and Random Forest Classifier (RFC) are implemented. The proposed model integrates a Deep Neural Network (DNN) for discriminative feature learning with a Greedy Tree-based classifier (GTC) to enhance classification accuracy and generalization. Hereafter, the proposed system named as “SemanticDistilDeepTree”. Experimental results demonstrate that the hybrid approach consistently outperforms baseline models across accuracy and F1-score metrics. The framework offers a scalable, efficient, and reliable solution for real-time sentiment monitoring, supporting policymakers, researchers, and analysts in understanding public perceptions of global conflicts.

Keywords: Twitter data analysis, Sentiment analysis, Natural Language Processing, Transformer-based embeddings, BERT architecture, Greedy tree classifier.

1. INTRODUCTION

The ongoing Russia-Ukraine War (RUW) has become one of the biggest armed conflicts since 1945 in the Europe continent. On 24 February 2022, Russia started marching on the lands of Ukraine to invade and begin the war by attacking major cities such as Chernihiv, Berdyansk, Odesa, Sumy, and Kyiv. The war has shocked the entire globe in many ways, for example, Ref [1] the global inflation rate has increased by 3% and the world’s gross domestic product (GDP) growth reduced by 1.44%, and the USA alone saw its GDP fall by 1.28% since the war began. Studies such as [2] gave two major reasons for this war; first, Ukrainian willingness to join the North Atlantic Treaty Organization (NATO). Second, NATO’s enlargement into eastern Europe. NATO is a group of 30 countries in a security alliance and, according to, “NATO’s fundamental goal is to safeguard the Allies’ freedom and security by political and military means”. Therefore, Ukraine’s prospective intentions and NATO’s foreseen expansion for European security turned this political clash into an armed battle. The RUW is not only affecting eastern Europe but also damaging living standards in the whole world. Despite

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receiving aid from NATO, Ukraine is still in a volatile and unpredictable situation [3]. According to the aforementioned statistics and rationales, it is essential to understand societal emotions. Such emotional expressions in the form of text are helpful to form attitudinal insights. Nowadays, major countries are using both territory and information on social media as part of the war effort. Such social media information dispersion usually turns into information warfare between citizens and politicians of countries participating in the war. For decades there has been antagonism between Ukraine and Russia but in the recent past, the turmoil has flared up belligerently [4]. The year 1991 was revolutionary as with the expiry of the Soviet Union, Ukraine proclaimed its national independence on 24 August 1991.

Fig. 1: Global sentiment distribution of 3.84 million Russian-language tweets.

In 2014, under controversial fraudulent circumstances, the fourth president of Ukraine (Viktor Yanukovych, known as a supporter of Russia) was removed from his post due to the enormous demonstrations and peaceful protests known as Euromaidan which turned into a ferocious Revolution of Dignity. In 2014, under controversial fraudulent circumstances, the fourth president of Ukraine (Viktor Yanukovych, known as a supporter of Russia) was removed from his post due to the enormous demonstrations and peaceful protests known as Euromaidan which turned into a ferocious Revolution of Dignity. The sudden outburst of public demonstration was the reaction to the denial by President Yanukovych to sign a treaty (i.e., EU association agreement) with the European Union (EU) which could have boosted free trade and closer social and economic ties of Ukraine with the EU. With the intrusion of Russia, the pro-Russian separatists in Ukraine's Donbas region proclaimed the Donetsk People's Republic (DPR) and the Luhansk People's Republic (LPR) as independent states, which escalated the unrest in Donbas region [5]. In an attempt to alleviate the hostile environment and the broken ceasefires in the Donbas region, various reformed Minsk agreements were signed in 2014 but for the status quo, all attempts were in vain. However, sustaining harmony in the Donbas region was one of the concerns and agendas of the current Ukrainian president Volodymyr Zelenskyy who was elected in 2019. the increased cooperation and aid to Ukraine from the NATO showcased Ukraine as anti-Russian. For self-protection, Russia started assembling its military nearby to Ukraine's borders at the start of 2021, and the advance of Russian troops to attack Ukraine started on 24 February 2022, which was condemned as a heinous move by the EU, NATO, and worldwide.

Fig. 2: Global geographic distribution of Ukrainian-language tweets.

2. LITERATURE SURVEY

The landscape of sentiment analysis (SA) has recently shifted toward analyzing complex global events, such as wars and public health crises, by leveraging transformer-based models and hybrid machine-learning frameworks.

2.1 Sentiment Analysis in Geopolitical Conflicts

Global conflicts like the Russia-Ukraine War (RUW) and the Israel-Palestine conflict have become primary focal points for studying societal emotions. Vyas et al. [6] developed the RUemo framework using Emoroberta and Multilayer Perceptron (MLP) to identify 27 distinct emotions on Twitter, finding that while many users remain neutral, there is significant evidence of social bot activity. Liu et al. [7] enhanced feature extraction in this context by combining RoBERTa with a Convolutional Neural Network (CNN) and a domain-specific sentiment lexicon, demonstrating that hybrid models better capture the nuances of "bullet screen" texts during hot events. Furthermore, the linguistic gap in war-related discourse was addressed by Pratibha et al. [10], who curated a specialized Hinglish (Hindi-English) dataset of war-related tweets, validated by human experts to facilitate deep pragmatic analysis of conflict psychology.

2.2 Financial Forecasting and Market Dynamics

Beyond social sentiment, recent research highlights the profound impact of public discourse on financial markets. Kim et al. [9] utilized FinBERT to analyze news summaries from *The New York Times*, integrating these sentiment scores into an LSTM model to significantly improve stock price prediction accuracy. This interplay between geopolitics and finance is further explored by Gude et al. [15], who used ensemble learning and MLP to predict how corporate positions on the Israel-Palestine conflict influence abnormal stock returns. In the energy sector, Santos et al. [11] conducted a systematic review following PRISMA standards, confirming a consensus that sentiment analysis—extracted from sources like Reuters and Twitter—is an essential tool for mitigating the volatility of oil price forecasting during exogenous shocks like pandemics and wars.

2.3 Information Integrity and Cybersecurity

As social media platforms become battlegrounds for information, detecting misinformation and threats has become critical. Al-Tarawneh et al. [8] investigated the efficacy of word embeddings for fake news detection, noting that while Word2Vec and FastText capture semantic nuances, TF-IDF remains highly effective for models like SVM and CNN in highlighting discriminative features. From a proactive security stance, Arora et al. [13] proposed the deployment of AI-based conversational chatbots on social media to predict cyber-attacks by analyzing the sentiment of users discussing vulnerabilities.

2.4 Public Health and Anomaly Detection

The integration of SA into epidemiology has provided new tools for crisis management. Thakur et al. [12] conducted a multi-virus study using the VADER approach to analyze over 60,000 tweets discussing COVID-19 and MPox simultaneously, revealing a high prevalence of negative sentiment (46.88%) during concurrent outbreaks. To aid in early warning systems, Kumar et al. [14] developed a framework using Latent Dirichlet Allocation (LDA) and sentence transformers to detect "unusual" clusters of healthcare tweets, successfully identifying pandemic-like emergencies through anomaly detection with up to 78.57% accuracy.

Table 1: Summary of Methodological Trends

Research Theme	Key References	Primary Models/Techniques	Key Findings
Geopolitical Emotion	[6], [7], [10]	Emoroberta, RoBERTa+ CNN, Hinglish Dataset	High neutral sentiment; bot detection; necessity of multi-

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			lingual data.
Financial/ Market Prediction	[9], [11], [15]	FinBERT, LSTM, Ensemble Learning	Sentiment improves stock and oil price forecasting accuracy.
Crisis & Health Monitoring	[12], [14]	VADER, LDA, NMF, Sentence Transformers	Negative sentiment dominates health crises; effective anomaly detection.
Security & Fake News	[8], [13]	TF-IDF, SVM, Conversational AI	Model performance depends heavily on embedding choice; SA can predict cyber threats.

3. PROPOSED METHODOLOGY

The proposed methodology in Fig. 3 presents a hybrid deep learning framework designed to analyze public sentiment surrounding the Russia–Ukraine war using Twitter data. The system integrates Natural Language Processing (NLP), contextual feature extraction using a pre-trained Distil RoBERTa model, and an ensemble of machine learning classifiers for accurate sentiment categorization. The workflow begins with the collection of war-related tweets, which are processed through the Distil RoBERTa model to extract high-dimensional contextual embeddings. These embeddings are then passed to an ensemble of machine learning classifiers that collaboratively determine the sentiment polarity—Positive, Negative, or Neutral. A graphical user interface allows for interactive visualization of inputs and predictions, while the final classified sentiments are stored in a Redis database for real-time retrieval and monitoring.

Step 1: Data Acquisition and Input Processing: The first stage involves the collection of war-related tweets from the Twitter platform using API-based data scraping. The input dataset contains text messages expressing users' emotions, opinions, and perspectives regarding the Russia–Ukraine conflict. These tweets represent the unstructured textual input that forms the foundation for subsequent analysis. The raw data is fed into the system, where preprocessing steps such as tokenization, removal of stopwords, and lemmatization ensure the textual information is clean, standardized, and ready for feature extraction.

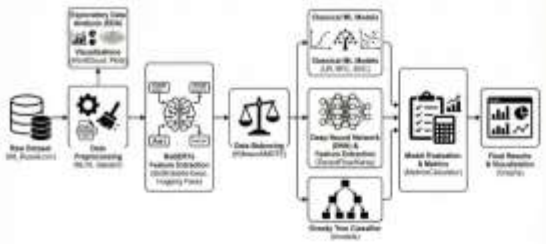

Fig. 3: Proposed System Architecture for analysing public sentiment on the Russia Ukraine war via twitter.

Step 2: Deep Contextual Feature Extraction using Distil RoBERTa: After preprocessing, the cleaned tweets are passed through the

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Distil RoBERTa model for deep contextual feature extraction. Unlike traditional bag-of-words or TF-IDF (Term Frequency – Inverse Document Frequency) approaches, RoBERTa captures the contextual meaning of each word based on its surrounding words. The output of this stage is a dense vector representation (embedding) that encodes both semantic and syntactic properties of the tweet text. These embeddings serve as the rich feature input for the downstream classification models. By leveraging Distil RoBERTa's transformer-based architecture, the system ensures high accuracy in understanding sentiment nuances and linguistic subtleties present in conflict-related discussions.

Step 3: Ensemble of Machine Learning Classifiers: The extracted embeddings are then forwarded to an ensemble of machine learning classifiers, each trained to specialize in identifying sentiment polarity. The ensemble typically includes algorithms such as LR, RFC, and SVC, which work collaboratively to improve classification performance. The ensemble approach ensures that the system benefits from both linear and non-linear learning mechanisms—balancing interpretability, robustness, and accuracy. The outputs from individual classifiers are combined through a voting or stacking mechanism, producing a final sentiment prediction for each tweet. This collective decision-making process minimizes model bias and enhances generalization across varied linguistic expressions.

Step 4: Sentiment Classification and Output Storage: Once the ensemble determines the sentiment class, the final output—categorized as Positive, Neutral, or Negative—is stored in a Redis database. This database supports high-speed data retrieval, making it suitable for real-time sentiment tracking. It allows the system to serve as a backend for dynamic dashboards or policy-monitoring applications where instant sentiment updates are crucial. Each classified tweet entry is stored along with its timestamp, sentiment score, and textual content for further analysis or visualization.

Step 5: User Interaction and Visualization Interface: The system includes a Django framework that enables end-users to interact with the model effortlessly. Through this frontend, users can input new tweets, view predicted sentiments, and observe overall sentiment trends. The GUI acts as both an input gateway and an output display, linking user queries to the backend classification system. It provides an intuitive way to visualize the impact of global events on public sentiment and facilitates user-friendly exploration of real-time analytics.

Step 6: Overall Integration and Workflow: Collectively, this multi-stage pipeline combines deep learning and traditional machine learning within a unified framework. Distil RoBERTa ensures deep semantic understanding, while the ensemble of classifiers contributes robustness and interpretability. The integration of Redis as a database and Django as a frontend ensures end-to-end operability—from tweet ingestion to real-time sentiment output. This hybrid architecture not only enhances classification accuracy but also offers scalability, enabling continuous monitoring of public emotions during rapidly evolving geopolitical events.

4. RESULTS AND DISCUSSION

Figure 4 reveals a marked class imbalance in the Russia-Ukraine War Twitter dataset. Negative (Class 0) and Neutral (Class 1) sentiments each account for over 3,500 tweets, while Positive (Class 2) tweets number approximately 2,500, indicating a lower prevalence of optimistic discourse. This skewed distribution underscores the predominantly critical or neutral tone in public reactions to the conflict. Such imbalance necessitates advanced oversampling techniques like KMeans-SMOTE to ensure robust model training.

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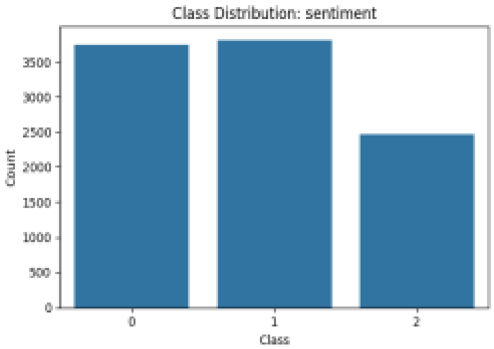

Fig. 4: Distribution of sentiment classes in the Russia-Ukraine war twitter dataset.

Table 1 presents a comprehensive comparison of four classification models—LR, RFC, SVC, and the proposed SemanticDistilDeepTree evaluated on the Russia-Ukraine War Twitter sentiment dataset using DistilRoBERTa-WE embeddings. The proposed SemanticDistilDeepTree model achieves the highest performance across all metrics, with an accuracy of 93.659%, precision of 93.686%, recall of 93.675%, and F1-score of 93.609%, significantly outperforming the baseline models. Among the traditional classifiers, LR ranks second with balanced metrics around 79.5%, demonstrating robust linear separability in the high-dimensional embedding space. RFC follows with moderate performance (~74–76%), while SVC records the lowest scores, particularly in recall (62.817%) and F1-score (61.850%), suggesting sensitivity to class imbalance or kernel parameter tuning. These results, likely computed on a balanced test set (post KMeans-SMOTE application), validate the efficacy of DNN-based feature selection and greedy tree optimization in enhancing sentiment classification accuracy and robustness. The substantial margin of improvement underscores the proposed SemanticDistilDeepTree hybrid framework as a scalable and superior solution for real-time public sentiment monitoring in geopolitical discourse.

Table 1: Performance evaluation obtained using Distil RoBERTa-WE LR, RFC, SVC and proposed SemanticDistilDeepTree classification models.

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Distil RoBERTa-WE LR [Sentiment]	79.524	79.473	79.570	79.192
Distil RoBERTa-WE RFC [Sentiment]	74.593	76.598	74.685	74.310
Distil RoBERTa-WE SVC [Sentiment]	62.616	75.412	62.817	61.850
SemanticDistilDeepTree [Sentiment]	93.659	93.686	93.675	93.609

Fig. 5(a) shows the user-facing text input section where users can submit tweets or statements related to the Russia–Ukraine conflict for analysis. It illustrates a clear and interactive field enabling users to enter data easily. The layout presents buttons or triggers for initiating the prediction process. This figure depicts the system's primary interaction point that initiates real-time sentiment classification. Fig. 5(b) presents the output interface displaying the predicted sentiment based on the user's submitted text. It illustrates the results produced by the underlying hybrid deep learning model, categorizing sentiment such as positive, negative, or neutral. The interface shows a clean and readable format that highlights the final analytical outcome. This figure depicts how the system transforms raw text into meaningful sentiment insights for the user.

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(a)

(b)

Fig. 5(a)(b): Prediction page of the Sentiment analysis of Russia Ukraine war.

5. CONCLUSION

This study presents a scalable hybrid deep learning framework for real-time sentiment analysis of Twitter discourse on the Russia-Ukraine War, overcoming the inefficiencies of manual analysis and limitations of traditional classifiers. By integrating DistilRoBERTa for efficient contextual embeddings, KMeans-SMOTE to address severe class imbalance, and a novel DNN-guided Greedy Tree mechanism for optimized feature selection and classification, the proposed SemanticDistilDeepTree model achieved 93.66% accuracy, 93.69% precision, 93.68% recall, and 93.61% F1-score—significantly outperforming LR (79.52%), Random Forest (74.59%), and SVC (62.62%) on a balanced test set. Exploratory analysis revealed a dominance of negative and neutral sentiments, with positive expressions underrepresented, reflecting the conflict's emotional weight. Despite data artifacts from URLs and metadata, rigorous preprocessing and transformer representations enabled robust insight extraction. The framework's high performance and computational efficiency make it ideal for real-time monitoring of public opinion during geopolitical crises, empowering policymakers and analysts. Future enhancements should include multilingual support, temporal modeling, and multimodal integration to further strengthen predictive fidelity and global applicability. This work bridges advanced NLP with social science, delivering a powerful, actionable tool for understanding collective sentiment in times of war. Future work will extend the framework to multilingual sentiment analysis, incorporate temporal dynamics for tracking opinion shifts, and integrate multimodal data (images/videos) to enhance contextual understanding and predictive accuracy.

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