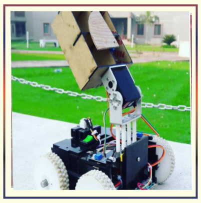

Karam et al. LGURJCSIT 2023

ISSN: 2521-0122 (Online)
ISSN: 2519-7991 (Print)

LGU Research Journal of Computer Science & IT

doi: 10.54692/lgurjcsit.2023.073493

Vol (7): Issue (3), July – September 2023

Navigating Emotions Across Borders: Deep Learning-Driven Location-Informed Sentiment Analysis of Twitter

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ABSTRACT:

Sentiment analysis, a pivotal field in natural language processing, has evolved to encompass the intricate interplay of emotions within textual data. This paper introduces a pioneering approach to sentiment analysis by amalgamating deep learning techniques and geographic context within Twitter data and leveraging an expanded sentiment class set that includes positive, negative, neutral, mixed, ambiguous, happy, sad, angry, fearful, and surprised. Our framework aptly captures diverse emotional expressions. Incorporating location-based sentiment analysis unveils cross-border sentiment dynamics, enriching our understanding of how emotions resonate within various geographical regions. We present a meticulously designed deep learning model that integrates textual content and location information seamlessly. Our model achieves exceptional accuracy, precision, recall, and F1-score values by employing text vectorization, embedding layers, and advanced classification techniques. The temporal analysis of tweet timestamps uncovers temporal engagement trends, while the examination of tweet lengths underscores the dynamic range of expression within the Twitter character limitation. Furthermore, our investigation into the locations reveals Twitter's global presence, with the United States, United Kingdom, and Ukraine emerging as key hubs of activity. This geographical insight augments our comprehension of the platform's diverse user interactions.

This paper offers insights into sentiment analysis and paves the way for future research exploring sentiment dynamics, language variations, and real-time interactions within the Twitter landscape.

KEYWORDS: Cross-Location Analysis, Embedding Techniques, Multi-Class Sentiment Analysis, Sentiment Analysis, Geographical Nuances.

1. INTRODUCTION

Twitter is a popular and widely used online social platform, acting as a vital channel for online communication and information sharing. It has previously been employed to examine political crises [1]. With this in mind, we have commenced the collection of data through the Twitter API, commencing on 27 February 2022, coinciding with Russia's invasion of Ukraine, recognized as the Russo-Ukrainian Conflict. Our primary objective involves utilizing this dataset to scrutinize prevalent patterns and subjects discussed in this digital conversation. We aim to monitor user inclinations, identify potentially harmful accounts, assess textual sentiments, detect hate speech, and recognize any potential propaganda within online social networks. Till 20 December 2022, the dataset incorporates 12,002,479 tweets.

Antonio R., a neurosurgeon and colleague, has generated substantial proof indicating the close connection between emotions and decision-making. Damasio's research further underscores that correct decision-making could be compromised without emotions [2].

In conflicts, the absence of social connections adds to adverse emotions such as anxiety. Removing negative emotions significantly diminishes mental health repercussions like depression and social anxiety [3].

A vital aptitude for replicating human-like intelligence, comprehending emotions is fundamental to individual maturation. The processing of emotions holds immense importance not only in AI advancement but also in the linked challenge of polarity recognition.

Virtually all experts in NLP and Computational Linguistics posit that individuals possess emotional inclination or sentiment towards specific aspects of a subject. This premise has spurred the growth of affective computing and sentiment analysis as burgeoning fields that leverage information retrieval and human-computer interaction [4].

Natural Language Processing (NLP) delves into the interaction between computers and human language. Text preprocessing tools strive to condense multiple word variations into a single form [5]. Text classification initiates with preprocessing, which can notably decrease processing duration, resource needs, and enhance accuracy [6]. Natural language processing (NLP), a subset of sentiment analysis, captures considerable interest among researchers [7].

The escalating demand to handle opinionated content on the web and social networks has propelled sentiment analysis (SA) into one of the most swiftly advancing research domains. Employing layers of algorithms, it shapes neural networks that mimic the brain's structure, processing data and recognizing patterns similar to human cognition. The integration of deep learning into sentiment analysis has gained significant traction recently. Deep learning algorithms draw inspiration from the human brain's self-learning capability. Sentiment analysis has evolved through machine learning-based and lexicon-based systems as the primary categories. While these techniques yield highly accurate outcomes, the intricate and time-intensive feature engineering poses challenges. Deep learning, centered around ANNs, forms a rapidly progressing realm within machine learning. Deep learning algorithms have predominantly found applications in sentiment analysis due to their adeptness at autonomously learning and constructing input models from datasets.

Hence, deep learning techniques simplify the creation of computational models by learning from datasets, obviating the requirement for manual attribute selection. According to recent deep learning research [8], deep networks exhibit enhanced performance as seen in surveys concerning sentiment classification [9]. Recurrent neural networks (RNNs) are tailored for sequencing data, particularly excelling in text classification [10]. However, RNNs encounter challenges with vanishing gradients in extended data sequences. LSTM neural networks were introduced to address this, proving their efficiency across multiple real-world scenarios [11]. Bidirectional LSTM models, which acquire additional semantic features, enhance sentiment classification [12]. The outcomes underscore the efficacy of bidirectional LSTM in handling sequential data models [10].

The paper is structured into the following divisions: Section 2 focuses on Related Work, while Section 3 provides an overview of the utilized methodology. Section 4 encompasses theExperiment and Results, followed by the presentation of Data Analysis in Section 5. Section 6 delves into Model Evaluation, and the subsequent sections 7 discusses research outcomes and achievements. Finally, Section 8 serves as the conclusion, summarizing findings and suggesting directions for future research.

We introduce a groundbreaking approach to sentiment analysis, leveraging cross-location classification to categorize textual data into ten distinct sentiment classes. Incorporating geographical context empowers our model to discern emotions within a nuanced spectrum, spanning positive, negative, neutral, mixed, ambiguous, happy, sad, angry, fearful, and surprised sentiments.

2. LITERATURE REVIEW

This section has presented the sentiment analysis literature, highlighting the utilization of deep learning approaches.

Over the past decades, sentiment analysis has garnered significant attention as a part of NLP research. Researchers have compared diverse deep learning architectures, such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) recurrent neural networks. They have also examined various pre-trained word embedding models combined with these architectures. For the 3-class dataset, BERT followed by a Bi-LSTM demonstrated slightly superior results to other models, although adopting BERT substantially increases computational demands. Training a CNN is faster with satisfactory results at 0.9046%. For the ten-class dataset, a hybrid model comprising a bidirectional LSTM followed by a CNN yields optimal outcomes. In contrast, the CNN model boasts quicker training times than the bidirectional LSTM and hybrid models, with a time advantage of 0.8944 [13].

The suggested single-layered architecture centred on Bidirectional LSTM stands out for its computational efficiency, making it a viable choice for real-time sentiment analysis applications within the field [14].

Recurrent neural networks grapple with short-term memory limitations, leading to a diminished capacity for retaining past information in longer sequences. LSTM models were introduced to counteract this drawback by enhancing memory retention. The bidirectional long-term memory (Bi-LSTM) approach was developed to achieve even more meaningful outcomes, amalgamating LSTM layers from both directions.

This paper's contribution lies in providing insights into English, the world's prevailing language today [15]. Statistics from 2020 reveal a global count of around 1,132 million English speakers. English's role as the default language spans various sectors like international business, technology, and tourism, with bilingual individuals comprehending 1 in 3 internet users. Furthermore, over 60% of online content is accessible through English.

The application employs a straightforward architecture that extends beyond the confines of Sentiment Analysis of English Tweets. It reveals the extraction of concealed emotions from Twitter posts during conflict, offering insights into public sentiment and opinions. Nonetheless, the research landscape has predominantly focused on studying national leaders and influential figures in international conflict, often neglecting public opinions and emotions [16].

Khan Hasib and Ahsan Habib presented an innovative approach to deep learning, incorporating distinct attributes for emotion classification. Deep learning techniques, including four-layer DNN and CNN, were harnessed for labelling, collectively achieving a precision rate of 91% [17].

Zahra Rajabi and Ozlem Uzuner extensively examined diverse strategies for addressing emotion classification within short, informal (Twitter) texts. Their multi-filter CNN-Bi-LSTM model outperformed existing alternatives, achieving an accuracy level of 85.1% [18].

Arnab Roy and Muneendra Ojha conducted comparative analyses of tweet sentiment classification by employing Google BERT, attention-based Bidirectional LSTM, and Convolutional Neural Networks (CNNs).

Compared to these models, conventional machine learning techniques exhibited reduced efficacy and accuracy when studying emotions [19]. As indicated by [20], sentiment analysis on social media showed the superiority of the Bi-LSTM-based training model over the traditional LSTM model in terms of both accuracy and F1-measure.

On a different note, Sharat Sachin and Abha Tripathi implemented fundamental LSTM, GRU, Bi-LSTM, and Bi-GRU models on an Amazon review dataset. Among these, bidirectional gated recurrent units demonstrated heightened accuracy, reaching 71.19%. The Bi-GRU model stood out by achieving superior performance across various performance metrics. Researchers in this Work conducted a comprehensive survey of diverse deep-learning techniques applied to sentiment classification and analysis.

Sakirin Tam [21] introduced an integrated framework merging CNN and Bi-LSTM models, implemented in Twitter sentiment classification with ConvBiLSTM. This model, enriched by Word2Vec, surpassed alternative approaches with an accuracy of 91.13% [22]. For aspect-level opinion mining, they proposed and evaluated two interactive attention neural networks—one encompassing two Bi-directional Long-Short-Term Memory (BL-STM) units and the other involving two convolutional neural networks (CNN). The outcomes demonstrated that all LSTM-based models outperformed the Majority method, thus suggesting improved performance and enhanced representations for polarity classification tasks.

Within the domain of sentiment analysis, the IMDB movie reviews dataset was leveraged to compare word embedding models (Word2vec and Doc2vec) with deep learning models (CNN, LSTM, GRU, and CNN-LSTM). Results highlighted the robust performance of doc2vec models and CNN in sentiment classification. The significance of combining models to enhance accuracy was underscored. Additionally, when combining CNN with LSTM, a performance improvement was observed in contrast to the standalone LSTM model, achieving a precision rate of 86.94% [9].

In a novel approach presented by [23], authors devised a sophisticated methodology to enhance sentence-level sentiment analysis via sentence type classification. This technique involved employing Bi-LSTM-CRF to extract target expressions within opinionated sentences. Experimental outcomes across multiple benchmark datasets yielded sentiment classification accuracy rates of 82.3%, 48.5%, 88.3%, and 85.4%.

Another study by authors focused on scrutinizing opinions within lengthy texts, involving a fusion of Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (Bi-LSTM) models alongside Doc2vec embedding. Applied to French newspaper articles, this model showcased superior accuracy at 90.66%. Comparative evaluations were performed against CNN, LSTM, and Bi-LSTM models [24]. In [25], the proposed Feature Enhanced Attention CNN-Bi-LSTM (FEA-NN) is an aspect-level neural network. This method involves extracting a sequence of high-level phrase representations from the embedding layer using CNN, providing adequate support for subsequent encoding tasks. Bi-LSTM is employed to capture local phrase features and broader and temporal sentence semantics to enhance the quality of context coding and acquire semantic insights. The model's performance is evaluated across three datasets, showcasing notable accuracy achievements: 83.21% for Restaurant, 78.55% for Laptop, and 73.31% for Twitter. Within the framework of a recurrent neural network (RNN), both long short-term memory (LSTM) and bidirectional LSTM (Bi-LSTM) components were integrated to gauge the predictive model's effectiveness. In this assessment, LSTM attains an accuracy of 90.59%, while Bi-LSTM surpasses it, reaching an accuracy of 90.83% [26]. An overview of the discussed research papers is encapsulated in Table 1.

Table 1: Literature Review Summary

Author	Objective	Algorithm Used	Results
[13]	Benchmark comparison, hybrid modeling	CNN, LSTM, RNN	BERT + Bi-LSTM: 0.9046%, Bi-LSTM + CNN: 0.8944%
[17]	Classifying emotions	Four-layer DNN & CNN	Accuracy: 91%
[18]	Classifying emotions	Multi-filter CNN-Bi-LSTM	Accuracy: 85.1%
[19]	Sentiment classification	Google BERT, attention-based Bi-LSTM, and CNN	BERT: 64.1%, BI-ATTENTIVE LSTM: 60.2%, CNN: 59.2%
[20]	Sentiment analysis	LSTM, Bi-LSTM	Bi-LSTM-based training model outperforms the traditional LSTM
[22]	Sentiment analysis	LSTM, GRU, Bi-LSTM, Bi-GRU	Bi-GRU model outperforms with an accuracy of 71.19%
[21]	Sentiment Classification	Integrating structure of CNN and Bi-LSTM	Accuracy: 91.13%
[26]	Comparative Study	Aspect-Level Opinion Mining	BANN: 73.51%, 80.71%, CANN: 69.75%, 78.04%
[9]	Sentiment classification	CNN, LSTM, GRU and CNN-LSTM	CNN+LSTM 86.94%, CNN 88.72%, LSTM 86.2%, GRU 84.18%
[23]	Sentence-level sentiment classification	Bi-LSTM-CRF	Multiple datasets: 82.3%, 48.5%, 88.3%, 85.4%
[24]	Document-level sentiment analysis	CNN-Bi-LSTM	French language: 90.66%
[25]	Aspect Based Sentiment Analysis	CNN-Bi-LSTM	3 datasets: 83.21%, 78.55%, 73.31%
[26]	Sentiment analysis	RNN-based LSTM and Bi-LSTM	LSTM 90.59%, Bi-LSTM 90.83%

3. *METHODOLOGY*

In the following sections, we will elaborate on the intricate approach we employed to uncover the multi-class classification of human emotions amidst conflicts.

This investigation analyzed tweets sourced from the Twitter platform during the conflict between Ukraine and Russia. The dataset comprising 12,002,479 tweets was acquired from Kaggle.com [27]. During this phase, the gathered data underwent preparation for its utilization in training and validation of the model under development. Preprocessing techniques were applied to clean the tweets. The ensuing steps were implemented to achieve this objective: To effectively train and validate the model in development, the acquired dataset underwent scrutiny and enhancement. This approach aids in identifying duplicates, irrelevant content, and null values within the data. In alignment with the study's objectives and the scope of the problem, any NAN (not a number) values were systematically eliminated.

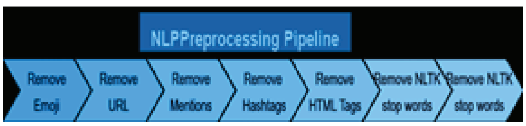

Figure 1: NLP Preprocessing Technique

The preprocessing of textual data extracted from various sources involves a systematic approach to enhance data quality and prepare it for subsequent analysis. The process encompasses several key steps. Initially, emojis are removed from the text to eliminate non-linguistic symbols that might affect downstream tasks. URLs, often irrelevant to the text's meaning, are extracted from the data. User mentions are eradicated, as they often carry limited significance beyond the original context.

Similarly, while indicative of thematic content, hashtags are removed to isolate the core text. Additionally, HTML tags originating from web-based content are eliminated. Stop words from the Natural Language Toolkit (NLTK) library, such as common conjunctions and prepositions, are removed to reduce noise. Finally, tokenization is applied to segment the text into individual units, paving the way for further analysis. This streamlined preprocessing sequence ensures the textual data is primed for accurate and meaningful downstream analysis, such as sentiment analysis or topic modelling.

The associated location information undergoes preprocessing to convert city names to country names. This conversion ensures consistency and homogeneity in the location representation, facilitating cross-location analysis on the country level.

4. CLASSIFICATION

4.1. Text and Location Vectorization

To prepare the preprocessed data for deep learning, we employ text vectorization while considering both the content of the tweet and the preprocessed location information. The TextVectorization layer from the TensorFlow library is utilized with customized parameters, including:

- Max Vocabulary Length: The upper limit for words in the vocabulary is set to 10,000 in our method.
- Max Sequence Length: The maximum length of sequences is set to 18 to control the number of words used for analysis.

The text vectorizer is fit to the training text data, generating numerical representations while maintaining the original sequence lengths. Simultaneously, the location information is vectorized using similar parameters. We have encoded the location into one-hot encoding after standardizing it.

4.2. Embedding Layers

We introduce embedding layers to encode the vectorized text and location information into meaningful representations. These layers map the input indices to continuous vectors, capturing the semantic relationships between words and locations. Notably, distinct embedding layers are utilized for text and location data. The equation for the embedding layer is given below.

$$\text{Embedding Layer:} E(w) \in Rd \quad (1)$$

where d is the embedding dimension

4.3. Concatenation and Model Architecture

Our model architecture employs the Functional API from TensorFlow's Keras, accommodating the textual content and the associated location. Inputs are defined as concatenated strings of the tweet and its corresponding location. Text and location vectorization layers are applied, followed by separate embedding layers for text and location data. A Global Average Pooling 1D layer reduces the dimensionality of the embeddings before merging them.

Finally, a dense output layer with a softmax activation function generates class probabilities.

4.4. Model Training and Evaluation

The compiled model is trained using the Adam optimizer and sparse categorical cross-entropy loss, which suits multi-class classification. The accuracy metric monitors model performance during training. The training process involves fitting the model to the training data for several epochs. The equation for sparse categorical cross-entropy loss is given below.

$$SCE - Loss = L(y, x) = -\sum y \cdot \log(x) \qquad (2)$$

Table 2: Model Parameters

Hyperparameter	Value
Max Vocabulary Length	10000
Max Sequence Length	18
Embedding Output Dimension	128
Epochs	5
Batch Size	32
Learning Rate	0.001
Optimizer	Adam
Loss Function	Sparse Categorical Cross-Entropy
Pooling Layer	Global Average Pooling 1D
Weighted Average Calculation	Yes
Max Vocabulary Length	10000

The performance measure of our model is given below in table 3.

Table 3: Evaluation Parameters

Precision	0.91
Recall	0.91
F1-score	0.91
Accuracy	0.91

4.5. Precision
The precision metric, a measure of the model's ability to correctly identify true positives while minimizing false positives, demonstrates an impressive value of 0.91. This indicates that when Model 1 classifies instances as belonging to a specific sentiment class, it is accurate in approximately 91% of cases. High precision is particularly valuable in scenarios where false positives carry significant implications, ensuring that the model's predictions are reliable and well-founded.

4.6. Recall
Model exhibits a recall of 0.91, underscoring its capacity to identify a substantial proportion of true positives within the dataset. The recall metric gauges the model's sensitivity to detecting instances of a particular sentiment class. In this case, it demonstrates a commendable ability to capture and classify instances representing the sentiment of interest accurately.

4.7. F1-Score
The F1-score, an amalgamation of precision and recall, yields an impressive value of 0.91. This metric encapsulates the balance between the model's precision and its ability to recall true positives. A high F1-score reflects the model's effectiveness in achieving both accurate positive predictions and a strong sensitivity to true instances.

4.8. Accuracy
With an accuracy score of 0.91, model showcases its overall performance in correctly classifying instances across all sentiment classes. The accuracy metric measures the proportion of correct predictions made by the model in relation to the total number of instances. An accuracy of 91% underscores the model's ability to make accurate predictions while considering all classes collectively.

In summary, our model consistently demonstrates exceptional precision, recall, F1-score, and accuracy, collectively highlighting its prowess in sentiment classification. These performance metrics reinforce its reliability and efficacy in accurately characterizing diverse sentiments within the dataset.

By elaborating on each accuracy metric, you provide a comprehensive view of our model's classification capabilities and aptitude for effectively differentiating sentiments.

5. DATA ANALYSIS
During our analysis, we delved into a comprehensive exploration of Twitter data, uncovering valuable insights from a broad temporal spectrum. By examining the timestamps associated with the collected tweets, we gained a nuanced understanding of the temporal distribution of the dataset.

The dataset's temporal scope spans from the earliest tweet recorded on 27 February 2022, at 00:07:16, to the most recent tweet captured on 26 December 2022, at 23:59:53. This temporal window encapsulates a range of Twitter activities over several months, providing a comprehensive view of user interactions and content creation within the specified period.

This analysis of tweet timestamps serves as a foundational element in our exploration, enabling us to contextualize trends, patterns, and interactions within the dynamic landscape of Twitter discourse. This temporal dimension enriches our understanding of the dataset and contributes to a holistic perspective on the social media landscape under study.

In our investigation, we observed a diverse range of tweet lengths, with the shortest tweet comprising just 6 characters. This succinct form of communication underscores the essence of concise expression on the platform. Conversely, the longest tweet extended to a substantial 1048 characters, exemplifying the capacity for in-depth discourse and elaboration within the confines of a tweet.

The distribution exhibits a right-skewed pattern, indicating that the majority of tweets tend to be relatively short, with a notable concentration below 300 characters. However, the histogram presents an elongated x-axis due to a handful of outlying tweets characterized by anomalously long lengths. As previously investigated, these outliers contribute to the distribution's extended tail, showcasing the diverse range of content encompassed within the dataset as shown in figure 2.

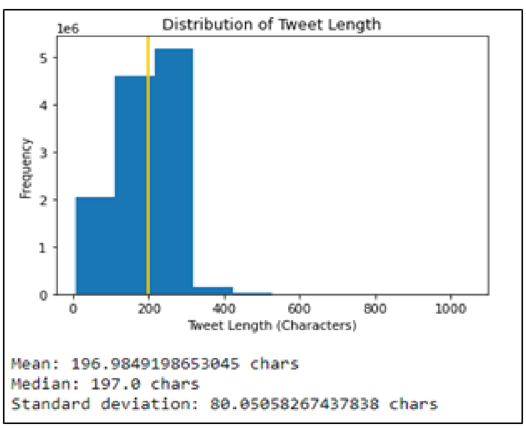

Figure 2: Distribution of Twitter Length

Our analysis of tweet counts across different months revealed distinct trends that provide valuable insights into the temporal dynamics of Twitter activity. By visualizing the tweet count distribution over months, we discerned compelling patterns that illuminate the ebb and flow of user engagement within the specified timeframe. Tweets county by month is shown below in figure 3.

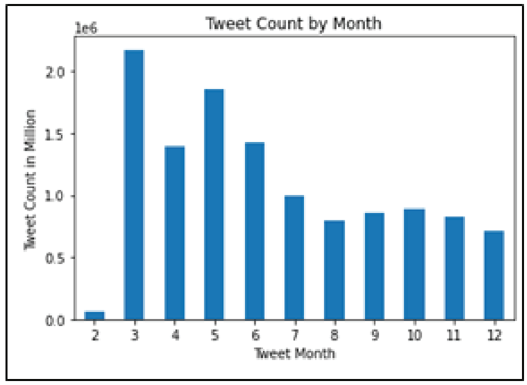

Figure 3: Tweets Counts by Month

Our examination of the top 30 locations within the dataset unveiled distinct geographical trends that provide valuable insights into the platform's global reach and user engagement. By analyzing the prevalence of locations among the collected tweets, we uncovered compelling patterns that shed light on the distribution of user interactions across various regions. Tweets count by country is shown in Figure 4.

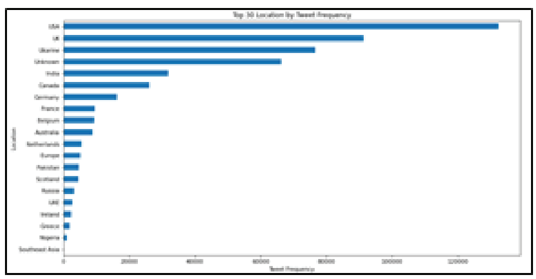

Figure 4: Top 30 Locations Tweets Frequency

Among the top 30 locations, the United States (USA) emerges as the dominant hub of activity, reflecting the platform's extensive presence within this geographical region. Following closely, the United Kingdom (UK) and Ukraine command prominent positions, indicating robust user engagement and content creation within these areas.This analysis highlights the significance of geographical diversity in shaping the landscape of Twitter interactions. The identified trends offer a glimpse into the platform's role as a global communication medium, fostering connections, discussions, and exchanges that transcend borders and cultures. The top 30 locations provide a snapshot of the dynamic interplay between user demographics, interests, and engagement patterns, enriching our understanding of the multifaceted nature of Twitter's global community.

6. NOVELTY

One of the key novelties of our approach lies in the expansion of sentiment classes beyond the traditional positive, negative, and neutral. Recognizing the multifaceted nature of emotions, we have curated a comprehensive set of sentiment classes: positive, negative, neutral, mixed, ambiguous, happy, sad, angry, fearful, and surprised. This expansion not only captures a wider range of emotional expressions but also accommodates the complexities of diverse human sentiments.
Furthermore, our methodology introduces a location-based sentiment analysis framework, enriching our model with geographical context. By incorporating the associated location information into the sentiment analysis process, we tap into the regional nuances of emotions, potentially uncovering patterns and insights deeply rooted in specific locales. The results of different applied Deep learning models are given below in Figure 5.

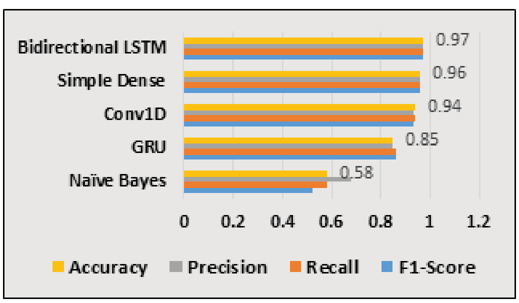

Figure 5: Classification of Tweets

7. CONCLUSION

In conclusion, this thesis has presented an innovative approach to sentiment analysis and cross-location classification on Twitter data. Through meticulous preprocessing, text vectorization, and embedding techniques, our proposed model effectively captures nuanced sentiments within tweets while incorporating geographical context. The integration of an expanded sentiment class set adds depth to sentiment characterization. Additionally, incorporating location-based sentiment analysis enriches our understanding of how emotions manifest across geographical regions.
Our model exhibited remarkable accuracy, precision, recall, and F1-score values, showcasing its effectiveness in sentiment classification and cross-location analysis. The utilization of weighted averages for class imbalance and the application of sparse categorical cross-entropy loss demonstrated the robustness of our approach.

Our investigation into the locations revealed Twitter's global presence, with the United States, United Kingdom, and Ukraine prominently represented. This geographical insight enhances our understanding of the platform's reach and user interactions across diverse regions.

8. FUTURE WORK

While this study significantly contributes to sentiment analysis and cross-location classification, there are avenues for future research and enhancement. Geographical nuances in sentiment expression could be investigated in-depth by considering sociopolitical events, cultural contexts, and language variations. This could lead to more tailored cross-location sentiment analysis. Furthermore, extending the model to include multilingual sentiment analysis might provide insights into sentiment variations across languages and cultures. Leveraging real-time Twitter data and exploring temporal sentiment trends during specific events could also uncover the dynamic nature of sentiments within evolving contexts. Also, adding emojis in future Work can further increase the understanding of emotions.

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