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Comparative performance analysis of LSTM, GRU, and bidirectional neural networks for political ideology classification

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ABSTRACT

Political ideology classification is crucial for understanding social polarization, monitoring democratic processes, and identifying bias on online platforms. This study compares the performance of long short-term memory (LSTM), gated recurrent unit (GRU), and bidirectional GRU (Bi-GRU) neural network models in classifying liberal and conservative political ideologies from social media text data. The Bi-GRU achieved the best results with 88.75% accuracy and 89.16% F1-score, highlighting its strength in contextual analysis. These findings suggest their applicability in areas such as election monitoring and the analysis of political discourse. This study contributes to the field of political text classification by offering a comparative analysis of deep learning architectures. The dataset utilized covers a wide range of issues, including social, political, economic, religious, and racial topics, demonstrating its comprehensive nature. Visualizations using WordCloud and uniform manifold approximation and projection (UMAP) reveal distinct ideological patterns, validating the dataset's quality for training models. The findings underscore the importance of utilizing advanced bidirectional architectures for nuanced tasks, such as ideology classification, where contextual understanding is crucial. These insights open avenues for future research, such as the application of Bi-GRU in analyzing multilingual political ideologies or real-time sentiment tracking during election campaigns.

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1. INTRODUCTION

In elections, social media has become a public space where political ideologies evolve and interact. Platforms like X and Facebook have the potential to transform public engagement, significantly influencing individuals' thought patterns, particularly about elections and campaigns [1]. In the context of modern politics, the ideological differences between conservative and liberal groups are becoming more prominent on social media. These ideological trends on social media not only reflect public views but also have the potential to influence political preferences, shape public opinion, and impact election outcomes [2].

A prominent recent case is the political competition between conservative candidate Donald Trump and liberal candidate Kamala Harris in the 2024 United States presidential election. This election not only highlights the policy differences between the two sides but also the social polarization that has been amplified on social media. During election periods, social media often spreads information and disinformation that greatly influences political views [3]. Research shows that social media algorithms can reinforce confirmation bias, causing users to be more frequently exposed to content that aligns with their views, thereby strengthening political polarization [4].

As the volume of data generated from user interactions on platforms like X, Facebook, and Instagram surges, the application of machine learning techniques to analyze trends in political ideology has become increasingly relevant. Machine learning algorithms can effectively monitor, analyze, and predict political conversation patterns, encompassing both conservative and liberal ideologies, that manifest on social media during election periods [5].

The increasing polarization on social media has made political ideology classification an essential task in political and social research. While several approaches have been applied, challenges remain in capturing linguistic nuances and contextual dependencies. Deep learning models such as long short-term memory (LSTM), gated recurrent unit (GRU), and their bidirectional counterparts offer potential solutions by learning sequential features effectively. This study seeks to fill the gap by evaluating their comparative performance in a political context using social media data.

The main finding is that fastText outperforms global vector (GloVe) in most models, except for the LSTM model, where GloVe performs better. Specifically, LSTM with GloVe embeddings achieves higher accuracy and recall than with fastText. While LSTM and bidirectional LSTM (Bi-LSTM) show only small performance differences between embedding types—an average of 0.550 for LSTM and 0.925 for Bi-LSTM per metric—GRU and bidirectional GRU (Bi-GRU) demonstrate notably larger gains using fastText over GloVe [6].

The second study demonstrates that deep learning algorithms, such as recurrent neural network (RNN), LSTM, and GRU, exhibit varying performances in sentiment analysis tasks. In this study, GRU proved to be the best-performing model, showing consistent accuracy improvement at each epoch, reaching 97.7% at the fifth epoch, surpassing LSTM, which remained stable around 95.8%, and RNN, which fluctuated. Based on evaluation metrics, GRU also excelled in balancing classification between positive and negative classes, although a bias toward the positive class remained due to the imbalanced data distribution. Meanwhile, LSTM demonstrated good stability but tended to show less improvement in performance as the number of epochs increased. At the same time, RNN exhibited the lowest performance, struggling to classify the negative class [7].

The study also explores sentiment analysis and emotion detection on cryptocurrency-related tweets, which is crucial because sentiment is often used to predict cryptocurrency market prices. In this study, tweets were collected from Twitter and annotated using TextBlob for sentiment analysis and Text2Emotion for emotion detection. To improve classification accuracy, an ensemble model combining several machine learning and deep learning models, such as LSTM and GRU, was created. Feature extraction techniques, including bag-of-words (BoW), term frequency-inverse document frequency (TF-IDF), and Word2Vec, were applied to the machine learning models. Notably, BoW outperformed TF-IDF and Word2Vec. The proposed model achieved an exceptional accuracy of 0.99 in sentiment analysis, with precision and recall of 0.99 and 0.98, respectively. Furthermore, the LSTM-GRU combination exhibited the best performance in sentiment analysis and emotion detection compared to other models. However, the performance of the LSTM-GRU model was compromised when dataset balancing was achieved through random undersampling, resulting in a reduction in the training data. This study demonstrates the potential of LSTM and GRU in complex sentiment analysis tasks, especially for the cryptocurrency domain [8], [9]. This study aims to identify and classify conservative and liberal ideologies emerging on social media and explore how these trends can be detected using LSTM, GRU, Bi-LSTM, and Bi-GRU approaches.

2. RESEARCH METHOD

This study compares the performance of multiple neural network architectures, specifically LSTM, GRU, and bidirectional networks, in classifying political ideologies from textual data. The steps begin with collecting a dataset of political ideologies, followed by data exploration, including checking the balance of dataset labels and identifying frequently occurring words. Next, data preprocessing is performed, during which the dataset is cleaned and standardized to ensure optimal model training. Subsequently, the model undergoes a training phase followed by a comprehensive evaluation. The overall research methodology is illustrated in Figure 1.

2.1. Data preprocessing

2.1.1. Lowercasing

Lowercasing is the process of converting all letters in a text to lowercase letters. This technique is used to ensure consistency and avoid differences caused by capitalization. For example, the words "Climate" and "climate" will be treated as the same after this process. This is essential in text processing because most text analysis models differentiate between uppercase and lowercase letters.

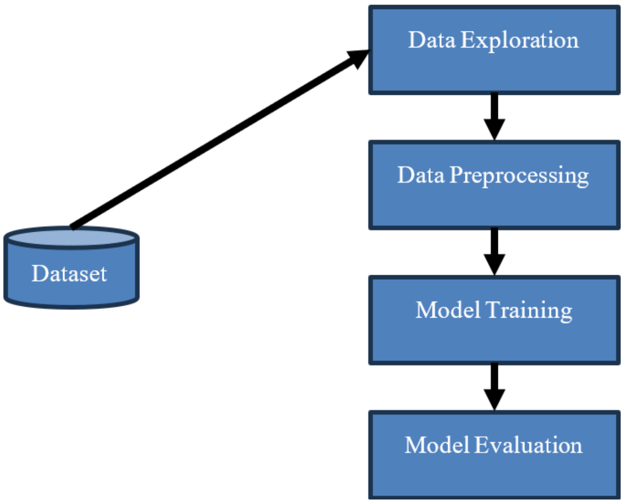

Figure 1. The research method

2.1.2. Punctuation and non-alphabet character removal

Text cleaning is performed by removing punctuation and non-alphabetic characters that do not contribute semantically. This technique aims to eliminate elements such as punctuation marks, numbers, or symbols that are irrelevant for analysis. As a result, the text becomes cleaner and more focused on meaningful words. For instance, the sentence "Climate change, and the escalating environmental degradation..." would become "climate change and the escalating environmental degradation".

2.1.3. Tokenization

Tokenization breaks text into its smallest units, called tokens, typically individual words. This process produces a list of tokens for further analysis, such as word frequency mapping or machine learning applications. For example, the sentence "Climate change and the escalating environmental degradation..." is transformed into ['climate', 'change', 'and', 'the', 'escalating', 'environmental', 'degradation'] [10].

2.1.4. Stopword removal

Stopword removal is a technique used to remove common words that frequently appear but do not carry significant semantic value, such as 'and', 'the', 'is', and similar words. This technique aims to reduce the amount of data processed, allowing the analysis to focus more on words that hold important meaning. For example, the token list ['climate', 'change', 'and', 'the', 'escalating', 'environmental', 'degradation'] would become ['climate', 'change', 'escalating', 'environmental', 'degradation'] [10].

2.1.5. Lemmatization

Lemmatization is a technique used to replace each word with its base form (lemma) based on its grammatical context. For example, the word 'running' is changed to 'run', but 'better' remains 'better' to preserve its semantic context. Lemmatization helps simplify text data without losing its meaning. In the sentence 'The escalating environmental degradation requires immediate attention.', the lemmatized result will be ['escalate', 'environmental', 'degradation', 'require', 'immediate', 'attention'] after lemmatization [10].

2.2. Model training

2.2.1. FastText

FastText, a word representation method employed in natural language processing (NLP), treats each word as a combination of character n-grams. This approach enables FastText to extract morphological information from words, enabling it to better handle unfamiliar or uncommon words compared to conventional word representations, such as Word2Vec [11]. A key feature of FastText is its ability to treat each word as a combination of character n-grams. For example, for the word 'apple', FastText can generate n-grams like 'app', 'ap', 'pp', 'pl', 'le', and so on. This approach allows the model to capture both morphological and contextual information of the word, making it effective in handling out-of-vocabulary words [11]. In FastText, vector learning is performed using an approach similar to Word2Vec, where the vector representation for words is learned based on their context in a sentence. However, instead of using words as single entities, FastText also considers the generated character n-grams. This helps produce richer and more informative representations [12]. FastText can be implemented with two main models, continuous bag of words (CBOW) and Skip-Gram are two popular word embedding models. In CBOW, the surrounding words are used to predict the target word, while in Skip-Gram, the target word is used to predict the surrounding context words. Each word is represented as a vector derived from the average of its n-gram vectors. This approach allows FastText to provide better representations for unknown words by building vectors based on their n-gram components [12].

2.2.2. Uniform manifold approximation and projection

Uniform manifold approximation and projection (UMAP), a recently proposed manifold learning method, seeks to accurately represent the local structure of data while simultaneously integrating global structure more effectively than other methods such as t-SNE. One of its key advantages is its scalability in handling large datasets. This method is based on three fundamental assumptions: that data is uniformly distributed on a Riemannian manifold, the Riemannian metric is locally constant, and the manifold is locally connected. Under these assumptions, UMAP effectively represents the manifold using a fuzzy topological structure of high-dimensional data points [13]. The embedding process is carried out by finding the fuzzy topological structure of the low-dimensional projection, enabling UMAP to capture both fine details and the global structure of the data. UMAP uses neighbor probabilities in both the input space and the embedding space, and optimizes the cost function with attractive and repulsive forces between neighboring and non-neighboring points [14]. Although the combination of FastText and UMAP is well-established, the contribution of this study lies in its comparative evaluation of sequence models in political ideology classification, which remains underexplored.

2.2.3. Long short-term memory

LSTM is a type of artificial neural network designed to address the issues of vanishing gradient and exploding gradient that often arise in traditional neural networks, especially when processing sequential data. This algorithm was developed by computer scientists Hochreiter and Schmidhuber in 1997. LSTM has become one of the most popular architectures for various tasks, including language modeling, machine translation, speech recognition, image captioning, sentiment analysis, and time series prediction, such as stock price forecasting [15]. The equations used in the LSTM algorithm are shown in (1)–(6):

$$f_i = \sigma\left(W_f.[h_{t-1}, x_t] + b_f\right) \tag{1}$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{2}$$

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \tag{3}$$

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \tag{4}$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t \tanh(C_t) \tag{6}$$

Where: h_{t-1} represents the previous output message, x_t represents the new input message, σ refers to the sigmoid activation function, W_f and b_f refer to the weight matrix and bias vector for the forgotten gate, W_i and b_i refer to the weight matrix and bias vector for the input gate determined by σ, W_c, and b_c refer to the weight matrix and bias vector for the input gate determined by the tanh function, tanh refers to the hyperbolic tangent activation function, W_o and b_o refer to the weight matrix and bias vector for the output gate, and o_t represents the output gate at time t [16].

The main characteristic of LSTM is the presence of a memory cell that allows the network to retain information over a long period of time. This advantage is supported by gate mechanisms that control the flow of information in and out of the memory cell. There are three main types of gates in LSTM: the forget gate, which determines which information should be forgotten from the memory cell, helping the network discard irrelevant data; the input gate, which manages new information to be added to the memory cell, ensuring that only important information is retained; and the output gate, which controls which information will be released from the memory cell to generate output at a specific time step. With this structure, LSTM can selectively store or discard information, making it highly effective in understanding long-term dependencies in sequential data [17].

2.2.4. Gated recurrent unit

GRU is a variant of LSTM [18]. GRU uses a pair of reset gate and update gate. The reset gate is responsible for controlling the retention or deletion of past information in the model. By considering the previous state and the potential future inputs, this gate determines which information should be preserved. On the other hand, the update gate helps the model determine how much of the previous information from the previous time step should be retained for the future. When an input enters the GRU model, it is first processed by the update gate. The update gate serves as a mechanism that determines how much past information will be passed to the future using an activation function [19].

$$u_{pdate}g_{ate} = sigmoid\left(W_{ug}X_t + W_{ug}h_{t-1}\right) \tag{7}$$

$$r_{est}g_{ate} = sigmoid\left(W_{rg}X_t + W_{rg}h_{t-1}\right) \tag{8}$$

$$\tilde{h}_t = \tanh\,(W(r_{est}g_{ate})_t \otimes + Wh_{t-1}, X_t) \tag{9}$$

$$h_t = (1 - \left(u_{pdate}g_{ate}\right)_t) \otimes h_{t-1} + (u_{pdate}g_{ate})_t \otimes \tilde{h}_t \tag{10}$$

In (7), the update gate controls how much content or information is updated. Similarly, in (8), the reset gate functions similarly to the update gate; when this gate is set to zero, the model reads the input sequence and forgets the previously computed state. Additionally, h_t serves the same function as in the recurrent unit, and the value of h_t in the GRU at time t represents the linear interpolation between the current h_t and the previous activation state h_{t-1}, as explained in (9) and (10) [20].

2.2.5. Bidirectional neural networks

Bidirectional neural networks are a type of neural network architecture designed to process information in two directions: from the past (forward) and from the future (backward). This allows the network to consider a broader context. In NLP tasks, such as segmenting address elements in Chinese or sentiment analysis, this approach is highly effective because it can simultaneously capture information from both preceding and following contexts. One example of its implementation is the Bi-GRU, which calculates the states before and after each moment in the sequence data, thereby producing more accurate representations compared to unidirectional networks that process information in only one direction [21].

Bidirectional models often employ separate LSTM or GRU layers for each direction, enabling them to handle long input sequences and mitigate vanishing and exploding gradient problems. By integrating information from both directions, these models provide richer representations, enhancing performance in various NLP tasks such as sentiment analysis, text segmentation, and more [22].

2.3. Model evaluation

Classification model evaluation metrics are used to measure the performance of the model in classifying data into predefined categories. The equations for accuracy, precision, recall, and F1-score are presented in (11)–(14) [23]:

$$Accuracy = \frac{Tp+Tn}{Tp+Tn+Fp+Fn} \tag{11}$$

$$Precision = \frac{Tp}{Tp+Fp} \tag{12}$$

$$Recall = \frac{Tp}{Tp+Fn} \tag{13}$$

$$F1 - Score = 2 \times \frac{Recall \times Precision}{Recall + Precision} \tag{14}$$

These metrics encompass a range of measurements, including accuracy, precision, recall, and F1-score. Each metric offers a unique perspective on the model's performance. Accuracy quantifies the proportion of accurate predictions compared to the total number of predictions. Precision measures the number of positive predictions that are actually positive. Recall calculates the percentage of all positive cases that the model correctly identifies. The F1-score is the harmonic mean of precision and recall, striking a balance between these two metrics [24], [25].

3. RESULTS AND DISCUSSION
3.1. Dataset
The dataset used in this study comprises a collection of texts classified by ideology (liberal or conservative) and the issues discussed, including social, political, economic, religious, racial, and immigration-related topics. The dataset was obtained from the Hugging Face website (https://huggingface.co/datasets and customized for binary ideology labels). The research process involves several key stages: data understanding, data preprocessing, modeling, and evaluation. The dataset contains three primary columns: statement, which represents the text to be trained; label, indicating the ideology (liberal or conservative); and issue_type, categorizing the issues into groups such as social, political, economic, family, and others. Table 1 presents sample data points, illustrating the ideological diversity across issues. The dataset was manually annotated by three independent annotators using predefined ideological criteria. A majority voting scheme was applied to finalize each label. The dataset contains an equal number of data points for each label class (liberal/conservative), with 1,280 data points each, as shown in Figure 2, eliminating the need for data balancing.

Table 1. The top six data entries from the dataset used

No.	Statement	Label	Issue_type
1	“Climate change, and the escalating environmental degradation we witness daily, is an urgent issue that requires immediate attention and collective effort...”	1	1
2	“I believe in the foundational importance of the nuclear family structure in society; it has historically been the bedrock upon which stable and prosperous communities are built...”	0	2
3	"Firmly believe that the principle of separation of church and state is a cornerstone of our democracy, ensuring the freedom of individuals to practice their faith without interference from governmental authorities, or conversely, that the government is not influenced by religious institutions...”	1	6
4	“I firmly believe in the separation of church and state as a fundamental principle that ensures the sanctity of individual freedom and belief in our diverse society. Access to essential services, such as healthcare or education, should not be limited or influenced by religious institutions or doctrines...”	1	6
5	“I firmly believe in the power of free markets as the key driver of prosperity and growth, encouraging competition, innovation, and consumer choice. Policies such as excessive taxation and regulation can stifle these markets, inhibiting entrepreneurship and business expansion...”	0	0
6	“While I fundamentally believe in the importance of environmental stewardship, I also value the principles of limited government intervention, individual liberty, and free market capitalism to drive innovation and technological advances...”	0	1

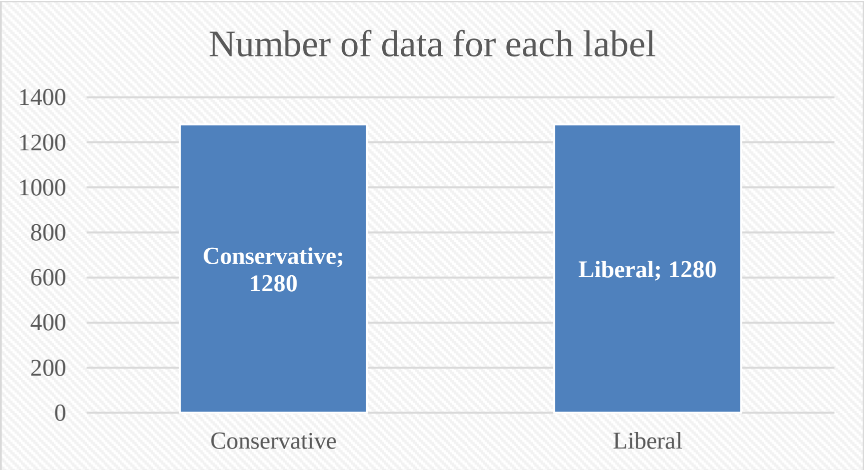

Figure 2. Number of data for each label

The distribution of data across each issue_type class is relatively balanced. The issue types with the lowest number of data points are race, justice, and immigration (309 data points), while the issue type with the highest number of data points is religion (327 data points). The difference in the number of data points among these issue types is small enough that it does not affect the overall balance of the dataset. Although the dataset is balanced, we acknowledge that real-world data often exhibits class imbalance. No artificial balancing techniques were applied as the dataset was originally constructed with equal distribution. The distribution of data amount across issues is shown in Figure 3.

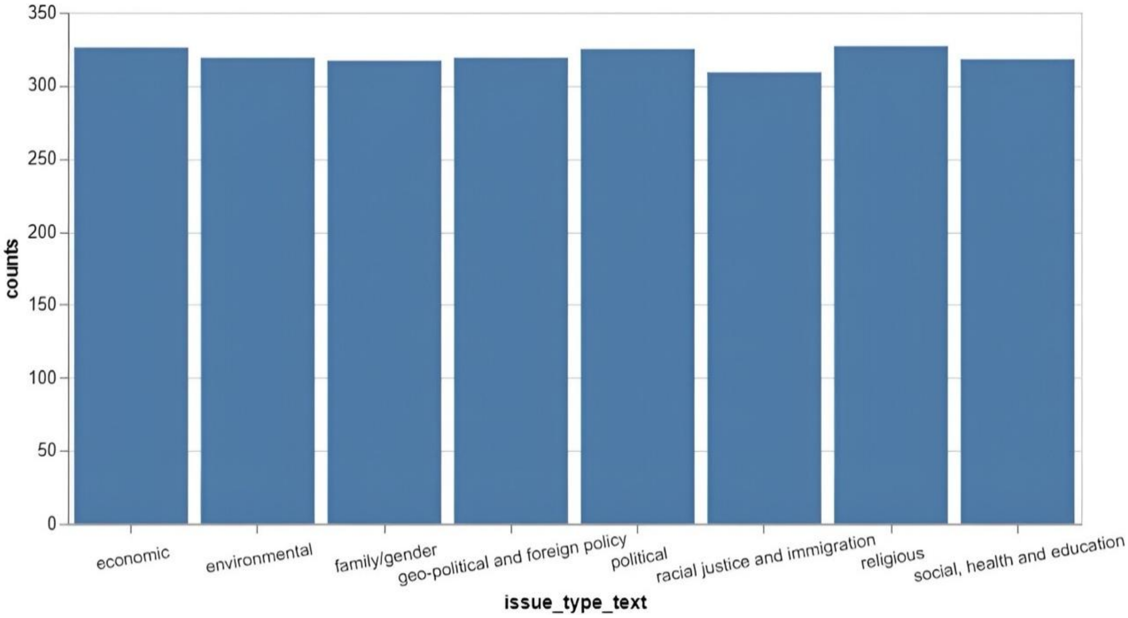

Figure 3. Distribution of data amount across issues

When visualized using a WordCloud as shown in Figure 4, words such as "society," "believe," "firmly," "right," and "crucial" appear most frequently. This is evident from the larger font size of these words compared to others.

Figure 4. Word visualization using WordCloud

3.2. Data preprocessing

The text is represented as numerical vectors using the FastText algorithm. After representation, the vector dimensions are projected into two dimensions using the UMAP algorithm, allowing the data to be visualized in a two-dimensional space (x and y axes). UMAP was used strictly for 2D visualization and exploratory analysis, not as a dimensionality reduction step in the model pipeline. As shown in Figure 5, liberal opinions are typically located at the bottom, while conservative opinions are primarily located at the top. However, there are exceptions for liberal opinions related to geopolitical issues, foreign policy, and religion.

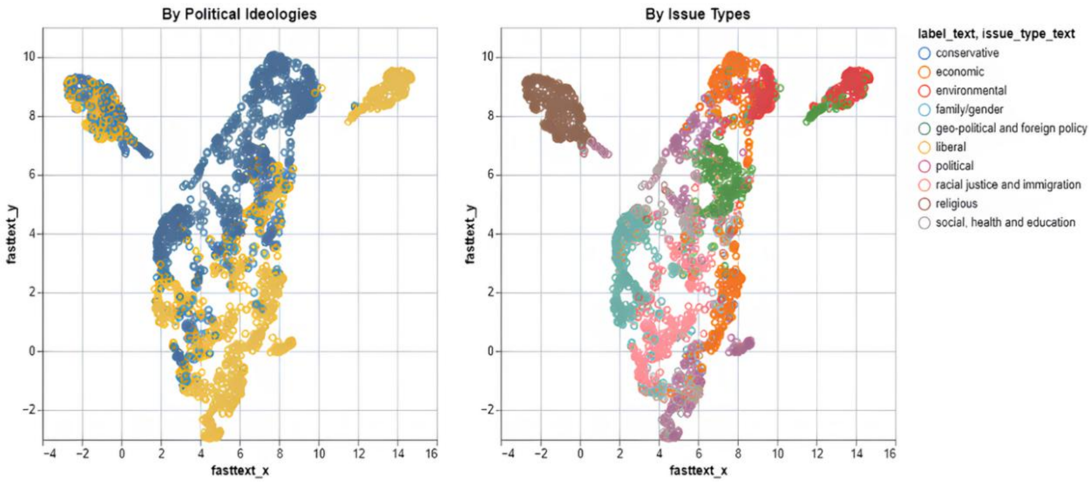

Figure 5. UMAP for the spread of political ideology

3.3. Model building

The deep learning models used in this study are LSTM, GRU, Bi-LSTM, and Bi-GRU with the following configurations: 64 units with rectified linear unit (ReLU) activation function, 50% dropout, an output layer consisting of 2 neurons with a SoftMax activation function, and regularization of 0.001 applied to both the GRU layer and the output layer to prevent overfitting. The configuration of 64 units, ReLU activation, and 50% dropout follows previous work showing effective generalization in text classification tasks. The overall architecture is detailed in Table 2.

Table 2. Model architecture

Type of model	L1	Activation L1	Regularization L1	Dropout	L2	Activation L2	Regularization L2
LSTM	64	ReLU	0.001	0.5	2	SoftMax	0.001
GRU	64	ReLU	0.001	0.5	2	SoftMax	0.001
Bi-LSTM	64	ReLU	0.001	0.5	2	SoftMax	0.001
Bi-GRU	64	ReLU	0.001	0.5	2	SoftMax	0.001

3.4. Model evaluation

During the training process, the accuracy of the models on both the training and validation datasets consistently improved. As shown in Figure 6, the Bi-GRU model demonstrated the best performance on the training dataset, as indicated by the consistently highest line compared to other models. The GRU model ranked second, followed by the Bi-LSTM, and finally the LSTM. On the validation dataset, the performance of the four models was generally similar, with minor differences.

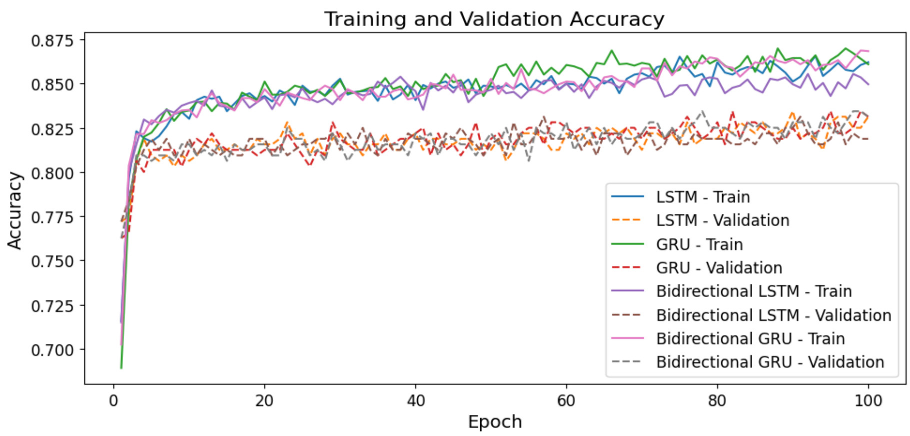

Figure 6. Accuracy on training and validation data

For the loss during training on the training data, as shown in Figure 7, the Bi-GRU model again showed the best performance, similar to the accuracy results on the training data. This model was followed by GRU, LSTM, and Bi-LSTM in that order. A similar pattern was observed on the validation data, with the performance order of loss from best to worst being Bi-GRU, GRU, LSTM, and Bi-LSTM.

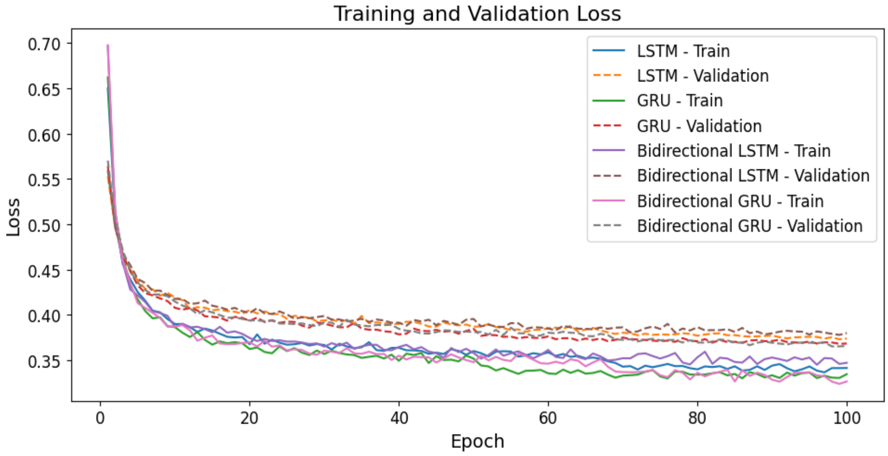

Figure 7. Loss on training and validation data" to match Figure 6's style

During the model training phase, we conducted an evaluation on several RNN architectures, including LSTM, GRU, Bi-LSTM, and Bi-GRU, using accuracy, precision, recall, and F1-score metrics. The evaluation results revealed that the Bi-GRU achieved the highest performance, with an impressive accuracy of 88.75%. This finding aligns with previous research by [7], [8], which demonstrated the superiority of GRU-based models in classification and sentiment analysis tasks. Moreover, the Bi-GRU model demonstrated remarkable precision and recall, reaching 86.05% and 92.5%, respectively. These metrics indicate that the model effectively minimizes false positives and captures a substantial portion of the positive data. Table 3 presents the detailed accuracy, precision, recall, and F1-score values for each evaluated model.

Table 3. Accuracy, precision, recall, and F1-score values

Model	Accuracy	Precision	Recall	F1-score
LSTM	86.88	83.15	92.5	87.57
GRU	87.19	83.24	93.12	87.91
Bi-LSTM	87.5	84.88	91.25	87.95
Bi-GRU	88.75	86.05	92.5	89.16

The Bi-GRU model achieved the highest F1-score at 89.16%, demonstrating superior balance between precision and recall. In comparison, the GRU and LSTM models attained accuracies of 87.19% and 86.88%, respectively, but exhibited lower precision and recall. Specifically, GRU achieved a precision of 83.24% and a recall of 93.12%, while LSTM recorded a precision of 83.15% and a recall of 92.5%. The F1-scores for GRU and LSTM were 87.91% and 87.57%, respectively.

4. CONCLUSION

This study confirms the superiority of the Bi-GRU model in the task of political ideology text classification, achieving the highest accuracy (88.75%) and F1-score (89.16%) among all evaluated models. These results highlight its ability to balance precision (86.05%) and recall (92.5%), which is crucial for minimizing false positives while effectively capturing relevant data. Specific applications of this approach include real-time classification of political content on social media platforms, automated political profiling in digital journalism, and early detection of ideological extremism in online forums. However, this study is limited to monolingual datasets and predefined labels, which may not fully capture the dynamic, multilingual nature of real-world political discourse. Future work can extend the model's scope by incorporating multilingual corpora, context-aware embeddings, and real-time deployment strategies. Overall, this research underlines the significant impact of deep learning models, particularly Bi-GRU, in advancing the field of NLP. The findings strengthen the evidence that DL-based architectures are pivotal in enabling accurate and scalable text classification systems for complex sociopolitical analysis. A limitation of this study is the absence of classical ML baselines such as SVM or random forest. These will be included in future work to enable broader comparative insights.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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