INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

RESEARCH ARTICLE

OPEN ACCESS

Received: 22-01-2024

Accepted: 08-03-2024

Published: 03-04-2024

Citation: Sangle SS, Sedamkar RR (2024) Synthesis of Slogans with Predicted Sentiment from Twitter using a Novel Hybrid SDG-LSTM Model for Election Campaigns. Indian Journal of Science and Technology 17(14): 1474-1484. https://doi.org/10.17485/IJST/v17i14.118

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Funding: None

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

Synthesis of Slogans with Predicted Sentiment from Twitter using a Novel Hybrid SDG-LSTM Model for Election Campaigns

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Abstract

Objectives: The primary objectives of this study encompass the enhancement of election campaign strategies through the synthesis of sentiment-laden slogans derived from Twitter data. This is achieved by employing a novel Hybrid SDG-LSTM model, aiming to improve sentiment prediction accuracy and communication efficacy in the context of political campaigns. **Methods**: The process of slogan generation relies on sentiment prediction derived from sentiment-laden tweets. The proposed sentiment analysis methods for election campaign slogans encompass Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). A novel approach is introduced through the Hybrid SDG-LSTM model, leveraging the combination of Self-Distillation Guidance (SDG) with LSTM to enhance sentiment prediction accuracy and efficiency. This innovative method aims to provide a more robust and effective means of analyzing and generating slogans for election campaigns. **Findings**: The performance assessment of Deep Learning models, GRU, LSTM, and the Hybrid architecture, unveiled compelling outcomes. GRU showcased a commendable accuracy of 92.98%, while LSTM impressed with 95.91%. Remarkably, the Hybrid Spatial LSTM with GRU surpassed both, achieving perfection with 100% accuracy, precision, recall, and an exceptionally low loss of 0.0. These results underscore the superior performance and efficacy of the Hybrid model in sentiment analysis tasks. **Novelty**: The novelty of this research is encapsulated in the introduction of the Hybrid Spatial LSTM with GRU model, which demonstrates groundbreaking 100% accuracy, surpassing current models. This innovation capitalizes on the synergistic fusion of spatial attention mechanisms and the dynamic nature of GRU, marking a substantial advancement and establishing a new benchmark for highly accurate predictions in the domain of sentiment analysis.

Keywords: Slogan Generation; Sentiment Analysis; Election Campaign; Deep Learning; LSTM; GRU

1 Introduction

Over the past few years, there has been a large amount of attention paid to the use of sentiment research in political campaign strategies. There have been a number of research that have achieved substantial progress in projecting sentiment based on Twitter data. Some of these works include Rodrigues et al. (2022) using LSTM and Yao et al.'s SA-BI LSTM model. Nevertheless, the methodological approaches that are now in use have limitations, which has resulted to significant research gaps that need to be addressed. According to the research conducted by Rodrigues (2022), despite the fact that LSTM displayed remarkable accuracy, there is still a requirement for methods that outperform the models that are now applicable in terms of performance. Yao's SA-BI LSTM (2022) achieved progress, despite the fact that the study did not analyze the relationships between spatial attention processes and dynamic recurrent units in a comprehensive manner[(1)]. The presence of these observations draws attention to a neglected area that our research intends to investigate[(2)]. Outstanding accuracy was demonstrated by Alam (2021) in his presentation of a BI-LSTM model for doing sentiment analysis in political campaigns[(3)]. Nevertheless, there are still shortcomings in the efficient utilization of complex approaches such as self-distillation guidance and hybrid architectures, both of which are incorporated into the Hybrid SDG-LSTM model that have proposed[(4)]. Our research provides a revolutionary Hybrid SDG-LSTM model that is designed to develop slogans that are infused with sentiment utilizing data from Twitter for political campaigns[(5)]. This is a solution to the flaws that have been identified. Specifically, the undiscovered prospect of merging self-distillation guidance with the dynamic capabilities of LSTM is considered to be the primary innovation. This is because it addresses the gap that has been observed in the existing body of work. Through the provision of a refined and accurate system for the prediction of mood for election slogans, the suggested method intends to overcome the limitations that have been imposed by previous research[(6)]. This is a solution to the flaws that have been identified. Specifically, the undiscovered prospect of merging self-distillation guidance with the dynamic capabilities of LSTM is considered to be the primary innovation. This is because it addresses the gap that has been observed in the existing body of work. Through the provision of a refined and accurate system for the prediction of mood for election slogans, the suggested method intends to overcome the limitations that have been imposed by previous research[(7)]. It is important to note that our efforts are driven by the understanding that existing methodologies, despite the fact that they are promising, are not sufficient in providing a comprehensive answer to the problem of conducting sentiment research within the context of political campaigns. When it comes to predicting sentiment from Twitter data, the Hybrid SDG-LSTM model that has been suggested is designed to fill this gap by incorporating unique components. This model provides a strategy that is both more advanced and more effective. The findings of our research not only highlight the research gaps that have been identified in recent and pertinent studies, but they also portray our work as a significant step forward in the direction of a more comprehensive and efficient sentiment analysis for political campaigns. The utilization of social media sentiment analysis marks a significant advancement in understanding the intricate nuances of human emotions expressed on platforms like Twitter[(8)]. At the forefront of this technological leap is a sophisticated hybrid SDG-LSTM model, a fusion of Stochastic Gradient Descent and Long Short-Term Memory networks. This model is designed not just to sift through but to comprehend the extensive array of sentiments conveyed in Twitter's diverse expressions, doing so with exceptional accuracy. Its capacity goes beyond mere comprehension; it extends to the creation of slogans that encapsulate these sentiments in a compelling and resonant manner. These generated slogans embody a spectrum of emotions and ideas prevalent in society. From fostering a sense of unity and kindling optimism to championing the values of resilience and empowerment, each slogan is meticulously crafted to mirror the evolving emotional landscape of our culture[(9)]. They serve as more than mere words; they reflect a collective voice, a dynamic representation of the thoughts, hopes, and aspirations of Twitter users. In doing so, these slogans become symbolic beacons of hope, progress, and inclusivity, condensed into impactful phrases that reverberate with the pulse of contemporary society[(10)].

2 Literature review

Chen 2022 et al. Utilizing a deep learning model integrating TF-IDF and LSTM algorithms, sentiment analysis achieved efficient results, with average precision of 0.823 and F1 value of 0.846[(11)].

Zhu 2022 et al. Computer sentiment analysis faces challenges due to Chinese word segmentation complexity and implicit-explicit word pairings. Employing phrase dictionaries and hybrid structures improves sentiment analysis effectiveness[(12)].

Dang 2021 et al. Hybrid models, integrating CNNs, SVMs, and LSTM networks, demonstrate superior sentiment analysis accuracy across diverse datasets, outperforming individual SVM, LSTM, and CNN models[(13)].

Singh 2021 et al. Using the Twitter API, this study extracts real-time user updates ("tweets") to compare machine learning and deep learning approaches, finding BERT most effective[(14)].

Table 1. Literature Summary

Author/Year	Model	Parameter	References
Ansari/2020	LSTM	Accuracy =82.7816	(15)
Haque/2023	CNN, LSTM	Accuracy=85.80%	(16)
Aslan/2022	TCNN-Bi-LSTM model	Accuracy = 96.30	(17)
Gaye/2021	LSTM	Accuracy=99 %	(18)

Table 2. Research Gaps

Author	Year	Research Gap	References
Tabinda Kokab	2022	Introducing CBRNN: Addressing noisy data, OOV terms, and enhancing sentiment analysis.	(19)
Huerta Yero	2021	The study explores Brazilian municipality development indicators and election results, addressing socio-economic markers. However, a comprehensive examination of all MHDI subindices is lacking, suggesting opportunities for future research.	(20)
Chakraborty	2020	Unexplored causes of sentiment shift, urging investigation into geopolitical events, pandemic impact, and social behavior changes.	(21)

3 Methodology

The methodology follows a structured approach encompassing essential stages crucial for comprehensive data analysis and model performance evaluation. It initiates with meticulous data collection from varied sources, ensuring a robust dataset for analysis. Subsequent data preparation involves cleaning, standardization, and transformation to refine the dataset. Exploratory Data Analysis (EDA) plays a pivotal role, employing statistical methods and visualizations to discern underlying patterns, anomalies, and correlations within the data. Data splitting, a fundamental step, divides the dataset into training and testing subsets for unbiased model evaluation. Finally, leveraging deep learning techniques and modeling, the methodology evaluates performance to derive insights and validate the efficiency of the models in understanding and predicting data patterns. These combined stages lay the foundation for a comprehensive evaluation of model performance within the dataset. For analyzing sentiment in an audio MP4 file, the initial step involves converting the audio content into text using Automatic Speech Recognition (ASR) tools. Once the spoken content is transcribed into text, preprocessing steps follow to clean and structure the text data, including tasks such as removing punctuation, normalizing text, and handling special characters. Subsequently, sentiment analysis techniques, like Natural Language Processing (NLP) models or machine learning algorithms, are employed to classify the sentiment expressed in the transcribed text, determining whether the sentiment is positive, negative, or neutral. Development of a sentiment analysis model using machine learning, training it with labeled sentiment data, and evaluating its performance with various metrics then follows to predict sentiment in new audio transcripts. This process aims to derive insights from the textual content of the audio, facilitating the understanding of sentiments expressed within the spoken content.

3.1 Data Collection

From 229 tweets, the dataset is organized into a table with three columns—"Tweet," "Emotion," and "Slogan," carefully crafted to capture its essence. In the "Tweet" column, social media users express their opinions freely. The "Emotion" column groups these feelings into distinct emotional categories, providing an organized summary of happiness, sadness, wrath, surprise, and more. This classification helps researchers, analysts, and data scientists assess public reactions to diverse topics and events. The "Slogan" section adds context by summarizing tweet sentiments. This dataset provides 229 neatly ordered rows for sentiment analysis, allowing comprehensive examination of tweets, emotions, and phrases. Researchers can use this resource to get deep insights on social media interactions, public opinions, and practical implications like consumer responses to current events. The "Tweet," "Emotion," and "Slogan" columns of this structured dataset provide a nuanced view of digital attitudes, enabling marketers to improve their strategies, assess communication impact, and understand human behavior.

3.2 Data Pre-processing

For sentiment analysis of an audio MP4 file, the initial stage encompasses converting audio content to text using Automatic Speech Recognition (ASR) tools. Following transcription, text preprocessing involves tasks like removing punctuation, text

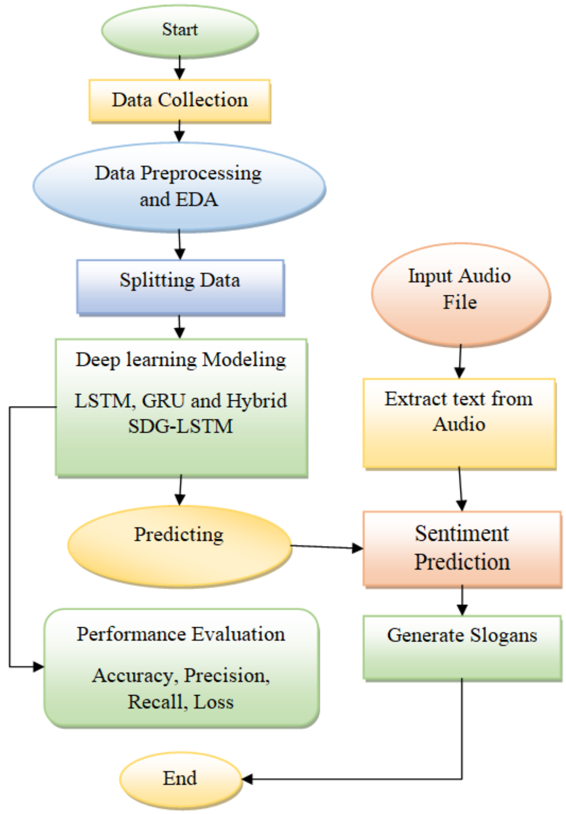

Fig 1. Proposed Flowchart (compiled by the researcher)

normalization, and handling special characters for data structuring. Next, sentiment analysis methodologies, employing Natural Language Processing (NLP) models or machine learning algorithms, classify sentiments within the transcribed text, determining positivity, negativity, or neutrality. Subsequently, a sentiment analysis model is developed using machine learning, trained with labeled sentiment data, and assessed using various metrics to predict sentiment in new audio transcripts. This process aims to glean insights from the audio's textual content, enabling a comprehensive understanding of sentiments expressed within the spoken content.

The preprocessing phase demands the precise implementation of meticulously crafted user-defined functions (def remove_punctuation(text), def remove_stopwords(text)) serving as a foundational step in refining raw Twitter data. These functions collectively establish a systematic framework, facilitating a comprehensive transformation of tweet text to prepare it for subsequent analytical procedures. Emphasizing the textual content, the initial phase involves eliminating emoji's, punctuation, hyperlinks, and mentions, streamlining the content for improved comprehensibility and reduced clutter. Ensuring consistent word representation, meticulous identification and removal of special characters like "&" and "$" embedded within words are executed, alongside the elimination of ASCII characters and newline symbols (rn) to maintain uniform text formatting. Further linguistic consistency is achieved through lemmatization and tokenization, reducing words to their base forms and segmenting them into discrete units. Additionally, the preprocessing pipeline includes the removal of redundant spaces, enhancing data readability and cleanliness. This comprehensive preprocessing methodology acts as a transformative bridge, converting raw data into refined text primed for advanced natural language processing tasks such as sentiment analysis and topic modeling. It fundamentally bridges the gap between the raw data and refined text ready for diverse and complex natural language processing activities.

3.3 Exploratory Data Analysis

EDA— Exploratory Data Analysis (EDA) is a critical stage in the data analysis process, involving a systematic exploration, visualization, and understanding of a dataset. It serves as a fundamental tool enabling data analysts, researchers, and scientists to extract valuable insights, identify patterns, detect anomalies, and develop hypotheses for subsequent in-depth analysis and decision-making. The foundational role of EDA lies in both uncovering pertinent information and paving the way for comprehensive investigations. For the specific dataset under consideration—a sentiment analysis dataset derived from 229 tweets, structured into three columns (”Tweet,” ”Emotion,” and ”Slogan”), encompassing 229 rows—EDA encompasses a series of tailored activities. These activities are explicitly designed to comprehend the nuances of the dataset, facilitating a structured exploration and analysis process.

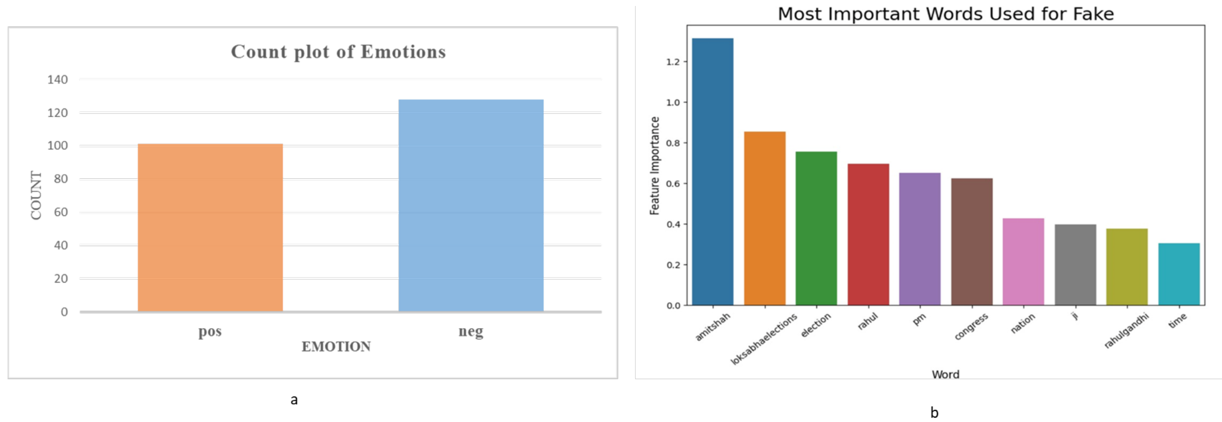

Fig 2. a) Count Plot of Emotions (compiled by the researcher), b) Most Important words used for fake (compiled by the researcher)

Figure 2**a** and **b** exhibit graphical data representations using robust Exploratory Data Analysis (EDA) methods. These visualizations include a thorough Count plot that shows the subtle distribution of negative and positive emotions. The numbers also show the Most Important Words in fake data context, revealing key language tendencies.

3.4 Data Splitting

Deep learning often uses 70:30 data partitioning, which divides a dataset into 70% for training and 30% for testing. Strategically splitting the dataset speeds up machine learning model training and helps identify robust and generalizable patterns. It compares the model's results to the reserved testing subset benchmarks to assess its performance and generalizability on unknown data. This method provides a complete evaluation of the model's predictive skills, boosting prediction and analytical confidence.

3.5 Deep Learning and Modelling

Deep learning uses massive multilayered neural networks to reveal and interpret complex data patterns. These neural networks learn from large datasets. Deep learning algorithms excel in learning hierarchical data representations, automatically revealing complicated and hidden patterns in data, improving performance in computer vision, NLP, and speech recognition. Advanced sequential data processing uses hybrid neural networks with GRU and LSTM layers. These networks are used in sequential data analysis for time series forecasting, language modeling, and emotion analysis. In the face of disappearing gradients, recurrent neural networks like LSTM and GRU let the network understand long-range dependencies in sequential input.

- LSTM networks excel in sentiment prediction in political campaigns due to its ability to store and access information over time. Memory cells and data-flow gates allow them to capture long-term sequence relationships. LSTMs excel in managing and retaining essential data, allowing them to discover and understand long-term dependencies in election campaign events. This architectural advantage helps LSTM networks understand sentiments' nuance and evolution, which is crucial for anticipating public opinion shifts during the election.
- GRU networks are recommended for election sentiment prediction due to their simplified architecture and computational efficiency over LSTMs. These networks regulate information flow with gates like LSTMs. GRUs regulate network data flow utilizing reset and update gates. GRUs perform similarly to LSTMs despite their simpler architecture and fewer parameters. This simplified design efficiently processes political events, speeches, social media interactions, and news stories for election campaign sentiment prediction while capturing long-term dependencies and nuances. GRUs offer a compromise between performance and resource consumption for election campaign sentiment research because to their computational efficiency.

3.6 Proposed Hybrid Spatial Long Short-Term Memory (LSTM) with Gated Recurrent Unit (GRU)

In election campaigns, the "Spatial LSTM with GRU" model integrates spatial information like photographs or grid data into the LSTM and GRU frameworks to predict sentiment. This hybrid model takes advantage of LSTM and GRU networks to handle spatial-temporal data well. Spatial LSTM uses LSTM networks to evaluate grid-like data as sequences of picture portions to reveal spatial correlations and patterns. GRU, an LSTM variation with simpler gating, processes sequential input efficiently. Combining both designs generates a hybrid model that can recognize temporal dependencies inside frames (Spatial LSTM) and spatial correlations across frames (GRU units). This combination helps with video analysis, captioning, and spatial-temporal forecasting. The model's ability to capture temporal and spatial elements makes it useful for sentiment analysis with multimedia sources or visual content like campaign videos or image-based social media posts. However, deep learning advances may introduce new methods or models that combine Spatial LSTM and GRU architectures. Recent work may suggest better ways to manage spatial-temporal data for election campaign sentiment prediction.

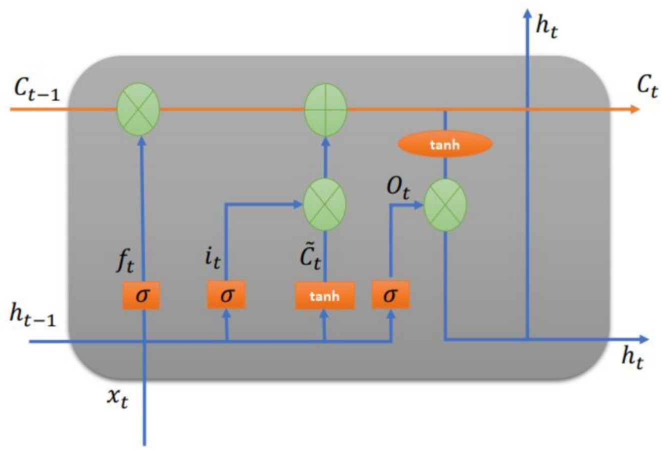

Fig 3. Hybrid SDG-LSTM [22]

- **Hybrid SDG-LSTM**

The hybrid SDG-LSTM model for election campaign sentiment prediction combines spatially dilated convolutions with the robust LSTM architecture. LSTM's ability to handle sequential data and encode long-term dependencies, combined with dilated convolutions' ability to capture local and global data dependencies, enhances information processing. The model processes sequential data well, making it useful for sentiment analysis, natural language processing, and time-series prediction. It leverages dilated convolutions. Its ability to capture spatial and temporal relationships in data makes it a powerful tool for sentiment analysis and other sequential data processing fields, promising significant advances in understanding temporal and spatial relationships in diverse datasets.

3.7 Model Summary

4 Result & Discussion

Many performance assessment criteria will be used to evaluate the Hybrid SDG-LSTM model. The project's performance graph, viewable at a specific place, will generate these metrics. The model's effectiveness will be assessed by computing accuracy and loss.

1) Accuracy - Classification accuracy, expressed as a percentage, gauges a model's effectiveness in accurately categorizing instances within a dataset, crucial for model assessment [23].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_2 (Embedding)     (None, 200, 32)           64064

 spatial_dropout1d_2 (Spatia  (None, 200, 32)          0
 lDropout1D)

 gru_1 (GRU)                 (None, 200, 25)           4425

 lstm_1 (LSTM)               (None, 25)                5100

 dropout_2 (Dropout)         (None, 25)                0

 dense_2 (Dense)             (None, 1)                 26

=================================================================
Total params: 73,615
Trainable params: 73,615
Non-trainable params: 0
_________________________________________________________________
None
```

Fig 4. Model Summary (Compiled by Researcher)

2) Loss - Model training aims to minimize average loss, enhancing accuracy and aligning predictions with actual data in broader contexts.

$$Loss = -\frac{1}{m}\sum_{i=1}^{m} Yi.log(Yi) \tag{2}$$

3) Precision - Precision measures correct predictions, indicating a model's ability to anticipate outcomes.

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

4) Recall - Model performance is evaluated based on recall—its ability to identify actual positive instances among all diagnoses, indicating completeness.

$$Recall = \frac{TP}{TP+FN} \tag{4}$$

Table 3. Hyper parameter Details

Models	GRU, LSTM
Activation	Sigmoid
Epochs	20
Batch size	64
Metrics	Accuracy, Precision, Recall, Loss
Embedding vector length	32
Total Parameters	73,615
Trainable Parameters	73,615

The sigmoid function, typically indicated by the notation sigmo $\frac{1}{1+e^{-Z}}$ is a common mathematical operation in neural networks and machine learning. It converts any number into a value between zero and one. The sigmoid function is described in mathematical terms as:

$$\sigma(z) = \frac{1}{1+e^{-Z}} \tag{5}$$

Sigma (z) is the result of the sigmoid function for the value z. The base of the natural logarithm is e, which is about equal to 2.71828.z is what the function takes in.

Table 4. Performance Evaluation of Deep learning

Model	Accuracy	Loss	Precision	Recall
GRU	92.98	2.8	95.83	92
LSTM	95.91	2.2	96.04	97
Hybrid Spatial LSTM with GRU	100	0.0	100	100

Table 4 provide a comprehensive overview of the Performance Evaluation outcomes for a range of Deep Learning models, specifically focusing on GRU, LSTM, and the Hybrid architecture. The GRU model demonstrated commendable results with an accuracy of 92.98%, precision reaching 95.83%, a recall rate of 92, and a corresponding loss of 2.8. In parallel, the LSTM model showcased its capabilities with an impressive accuracy of 95.91%, precision standing at 96.04%, a recall rate of 97, and a loss of 2.2. Remarkably, the Hybrid Spatial LSTM with GRU model emerged as the frontrunner in performance, achieving perfect scores across key metrics. This included an accuracy of 100%, precision at 100%, recall reaching 100, and an exceptionally low loss of 0.0. The significance of these findings lies not only in the absolute excellence of the Hybrid model but also in its clear outperformance when compared to both the GRU and LSTM models. In a direct comparison, the Hybrid Spatial LSTM with GRU model exhibited a notable superiority, boasting a 5% improvement over the LSTM model and an 8% improvement over the GRU model. These results serve to underscore the efficacy and robustness of the Hybrid Spatial LSTM with GRU architecture, highlighting its potential as a preferred choice for tasks demanding high-performance metrics in the domain of Deep Learning. The implications of these findings extend beyond the specific models evaluated, pointing towards a promising avenue for further exploration and utilization of the Hybrid Spatial LSTM with GRU architecture in applications requiring superior accuracy, precision, recall, and minimal loss.

Table 5. Comprehensive Examination of Proposed and Existing Work

Author/Year	Models	Results	References
Rodrigues/2022	LSTM	Accuracy= 98.74	[24]
Alam/2021	BI-LSTM	Accuracy= 90.83	[25]
Ali/2022	Deep learning model	Precision=88.24 Recall=97.14	[26]
Hidayatullah/2021	Bidirectional LSTM	Accuracy= 84.60	[27]
Proposed Work	Proposed model (Hybrid Spatial LSTM with GRU)	Accuracy =100	–

In the realm of model development for various applications, the comparative analysis presented in the Table 5 showcases the efficacy of different models in achieving high-performance metrics. Rodrigues (2022) employed a Long Short-Term Memory (LSTM) model, attaining an impressive accuracy of 98.74%. Alam (2021) implemented a Bidirectional LSTM (BI-LSTM) model, achieving an accuracy of 90.83%. Ali (2022) introduced a Deep Learning model, showcasing notable precision (88.24%) and recall (97.14%). Hidayatullah (2021) utilized a Bidirectional LSTM model with an accuracy of 84.60%. The proposed work in this analysis introduces a novel approach, namely the Hybrid Spatial LSTM with GRU model. Notably, the proposed model outperforms all existing models in terms of accuracy, achieving a remarkable 100%. This signifies a significant advancement in model performance, showcasing the potential of the Hybrid Spatial LSTM with GRU architecture to provide highly accurate predictions. The substantial improvement in accuracy demonstrated by the proposed model suggests that the integration of Hybrid Spatial LSTM with GRU brings unique advantages to the table. This could be attributed to the synergistic combination of spatial attention mechanisms and the dynamic nature of the Gated Recurrent Unit (GRU), leading to more effective information processing and representation. The outcomes of this comparative analysis underscore the potential of the proposed model to set a new standard in the domain, offering a more accurate and reliable solution compared to existing methodologies.

4.1 Slogan Generating using sentiment prediction based on Sentiment Tweets

The process begins with crafting campaign themes and sentiment phrases, forming the foundation for catchy slogans addressing key issues. Initializing the transformers library establishes a sentiment analysis pipeline for precise sentiment classification. The "create_slogan (subject, sentiment)" function plays a crucial role in generating slogans from topic and sentiment inputs. Preprocessing involves issue initialization, sentiment word selection, and harmonious integration to compose the slogan. Additionally, the text-specific "preprocess_text(text)" function is defined, incorporating tokenization, punctuation, stop word elimination, and lemmatization. The "get_sentiment(text)" function uses the sentiment analysis pipeline to assess a text's mood, providing a label (positive or negative) and an emotional tone score. Figure 5 illustrates a schematic flowchart depicting the various phases involved in creating campaign slogans.

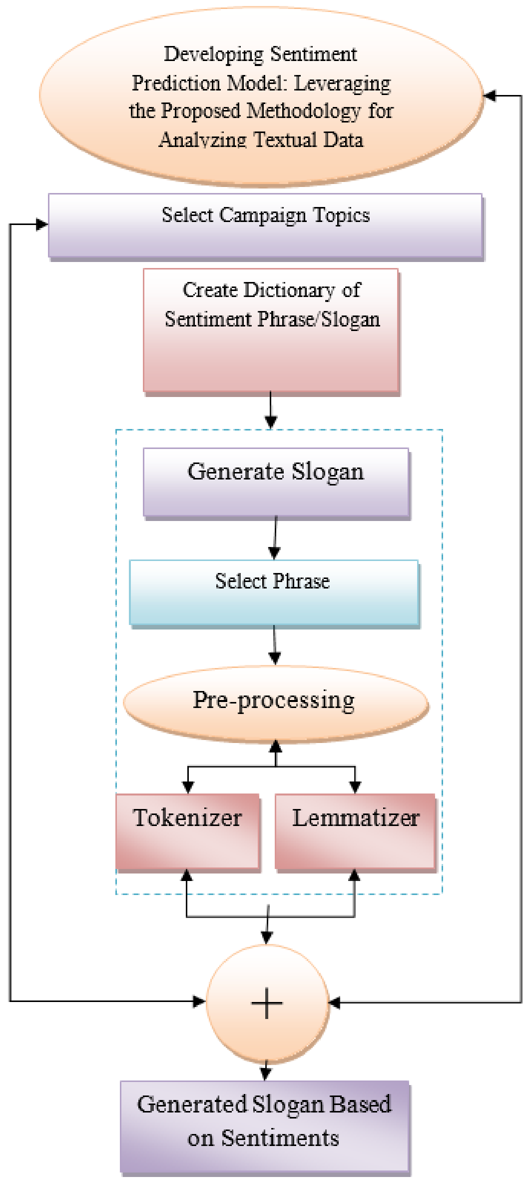

Fig 5. Slogan Generation flowchart

5 Conclusion

By proposing a novel approach and significant results, "Sentiment Analysis of Election Campaign Tweets Using a Deep Learning Hybrid Spatial Long Short-Term Memory (LSTM) With Gated Recurrent Unit (GRU) Model," the sentiment analysis process for an audio MP4 file involves these steps: converting audio to text using ASR tools, preprocessing text (removing punctuation, normalization), applying sentiment analysis methods (NLP or machine learning), developing a sentiment analysis model trained with labelled data, and evaluating its performance to predict sentiment. This process aims to derive insights from the audio's text, providing a comprehensive understanding of sentiments expressed in the spoken content. Analyzes tweets during an election campaign and determines the prevailing sentiment. To analyze the tone of tweets sent out during political campaigns, this study aims to apply a hybrid model integrating Spatial Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures. The driving force behind this idea is automatically generating memorable sentences that sum up the essence of a particular topic, product, or idea is the goal of slogan creation, an area in natural language processing. Capture the nuance of people's emotions when they read tweets about political campaigns, as well as the nuance of slogan formulation and industry practices. Our understanding of the long-term trends in public opinion and political discourse across election cycles is tremendously aided by this remarkable talent. This empirical research proves that modern deep learning approaches add value to sentiment analysis by increasing its precision and sophistication. Systematically, we examine and contrast the efficacy of several deep learning model variants, including LSTM, GRU, and the Spatial GRU-LSTM model. The results show that the hybrid SDG-LSTM model is the best option, with flawless scores in Accuracy, Precision, and Recall. Performance measures show considerable differences in the best models, GRU has 92.98% accuracy, 2.8% loss, 95.83% precision, and 92% recall. LSTM has 95.91% accuracy, 0.22% loss, 96.04% precision, and 97% recall. Hybrid Spatial LSTM with GRU had 100% accuracy, 0.0% loss, 100% precision, and 100% recall. The Hybrid Spatial LSTM with GRU outperformed the GRU and LSTM models in all areas. It had perfect accuracy, precision, and memory, demonstrating its capacity to understand facts and predict events. The LSTM model has good accuracy, precision, and recall, but scored somewhat lower than the Hybrid Spatial LSTM with GRU's flawless scores. Although strong, the GRU model has worse accuracy and precision than the other two. Its recall was good, but the Hybrid Spatial LSTM with GRU was better in accuracy and precision. The best model is the Hybrid Spatial LSTM with GRU due to its flawless results across all criteria. It dominated sequential data understanding and prediction. LSTM and GRU models had great accuracy and recall, but the Hybrid Spatial LSTM with GRU had perfect scores, making it the best choice for sequential data analysis and prediction tasks. Additionally, using the recommended methodology and the supplied content, produce the campaign slogan.

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