AUTOMATED SLOGAN GENERATION DEEP LEARNING MODEL WITH SENTIMENTAL ANALYSIS FOR THE ELECTION CAMPAIGN

Shailesh S. Sangle[1]*, Dr. Raghavendra R. Sedamkar[2]

[1] Research Scholar, Thadomal Shahani College of Engineering, Bandra West, Mumbai-400050, Maharashtra, India
ORCID ID: https://orcid.org/ 0009-0004-2982-5302
*Corresponding Author

[2] Professor, Thakur College of Engineering and Technology, Kandivali East, Mumbai-400101, Maharashtra, India

Abstract: In recent years, election campaigns have increasingly communication strategies to engage voters and convey key messages. As the political landscape becomes more competitive, the need for impactful and memorable slogans has grown. These slogans play a crucial role in shaping public perception and rallying support. With advancements in technology, automated methods for slogan generation, driven by deep learning and natural language processing, are emerging as powerful tools to enhance the effectiveness of campaign messaging. This paper proposed an automated slogan generation model for the election campaign with the deep learning model. To apply the proposed model on the automated slogan generation for the election campaigns, class balancing is proposed with SMOTEENN which stands for Synthetic Minority Over-Sampling Technique combined with Edited Nearest Neighbors and Hybrid SDG-LSTM deep learning model with Discriminative CRFVReC. As seen, it was now possible to propose the Hybrid of SDG-LSTM Model to extract important keywords from a data set of 10000 data on election campaigns and that has 15% higher Relevance of Keywords than that of the normal data extraction algorithms. The proposed methodology of training deep learning model with CRF on the generated 5000 slogans by using these extracted keywords yields more semantically correct slogans with an improvement of 20% over baseline methodologies. The applicability of deep learning model integrated with CRF methodology comes out to be highly useful for increasing the relevance and effectiveness of slogans for campaigns. This approach brings a number of improvements for political communication and shows that the methods improve the election campaigns.

Keywords: Election Campaign, Feature Extraction, Classification, Deep Learning, Slogan Generation

1. Introduction

Modern election campaigns have gone through a lot of changes in the recent past, and this has been witness by the increased use of technology, analytics and voter's persuasion techniques. The original ways of electioneering have been supported by advanced systems that enable the more effective delivery to the target audience, to mention specifics in their needs and issues of voters separating each category [1]. Most of them include anti-corruption drive and economic growth, national security and social wellbeing of the public are some of the key areas which have emerged as important themes of the electorate [4]. Manual communications are getting less frequent in the campaigns, as data is becoming more important and campaigns are focusing on automation, exercising a significant level of skill in addressing targeted messages that voters find appealing. It has also brought more professionalism and strategic dimension to campaigning, leading to more competitive and voters' focused elections than at any time in the past [3 – 6]. Slogan formulation in election campaigns is a careful mix of art work and analysis to come up with the right messages that will sell the particular candidate most effectively. In contemporary electoral campaigns, slogans are a key way of summing up a candidate's agenda, appealing to the voters' emotions, and setting the contender apart from rivals [7]. The creation of an election campaign slogan is a necessity and the one that forms the basis of the campaign of a candidate. Modern politics has become quite the race, and people's attention spans are rather limited; that is why the creation of a good slogan can really make a difference [8]. Not anymore is generating sloganeering mere creativity but a scientific approach that involves data analysis with a special emphasis on what diplomats or voters think [9]. On the one hand, slogans do a great job of condensing the candidate's political viewpoints so that one can remembered and get across key beliefs at the same time as rousing the voters. Given that these slogans are generated with the help of automated tools and machine learning models, one cannot fail to notice that the process has become more accurate and corresponds with contemporary political agenda of the voters [10].

The generation of slogans through the use of deep learning models when compiled with the use of sentiment analysis is the pinnacle of modern election campaign innovations [11]. This method relies in deep learning to analyze trends as well as opinions of voters, social media conversations and the general public to formulate slogans that are powerful with an added emotional appeal [12]. There you have emotions and attitudes necessary for decision-making act of voters pinpointed based on the results of sentiment analysis and they all relate to significant issues of legislative and executive policies in the country like healthcare, economic policy, and national security. Analyzing the above viewpoints, deep learning models can create slogans that relate to the spirit of the campaign and what may be in the heart of the electorates [13]. While putting deep learning and sentiment analysis in slogan production, the campaigns receive a much deeper insight into the psychology of the voters, thus gaining an opportunity to address them in an incredibly accurate way. It does help when such pixie dust can be backed up with more rationalizable techniques for generating slogans, for instance, by using some type of recurrent neural network or transformer capable of analyzing complex patterns and structures in textual data and generating slogans that are not only highly relevant to the context into which they are to be introduced but linguistically highly complex as well [14]. Voter feedback is usually analyzed qualitatively, with the help of NLP tools, and sorted according to the positive, negative or neutral attitude of the voters towards the different problems and proposals discussed throughout the campaign. When combining these technologies, the campaigns are able to change the slogans of their campaigns depending on the mood of the voters at a particular period. For instance, if there is suddenly an increase on the concern on the economy, the deep learning model can focus the slogans that are relating to employment and economic security [15]. This makes it possible for the campaign to stay active and sensitive and well connected to the voters for the duration of the election. The approach makes it possible to advertise slogans that are appealing to different segments of voters, which can result to worrying different segments of the population depending on their demographics. Teens and young adults can be reached with messages involving innovation while calling for change; the elderly and those who consider themselves wise want to hear about stability and tradition – these are only some of the possibilities that are offered by deep learning and sentiment analysis that allows creating most captivating slogans [16].

2. Proposed Sentimental Analysis Deep Learning

The methodology for slogan generation in election campaigns starts with accumulating the data linked with the voters' opinion on the critical issues. These are important to know the stance and the issues that voters have. The data collected is usually pre-processed to minimize such information. For this purpose, the SMOTEENN model is used where the SMOTE algorithm over-samples the minority classes the exact proportion and the ENN algorithm under-samples the majority classes to an equal extent. In this step, an LSTM along with GRU is used to proceed for visualization, label encoding and balancing of data. Subsequently, Exploratory Data Analysis (EDA) is performed for the data available and further the deep learning model is trained in order to categorize the voter opinions. It is especially significant to classify the logos as it dictates the generation of slogans containing the electorates' attitudes. The generated slogans are then pre-processed to obtain the word key terms from which the Discriminative Conditional Random Field (CRF) model Incorporated with the CRFVReC election campaign feature extraction model is used. After extracting the features, the data is passed through a deep learning model to make further classification of classes and features. This leads to the generation of automated slogans for the election campaign. To support generated slogans, they are practically employed, and voters' perceptions are assessed based on the framed questionnaires distributed to an Indian sample population of forty. The SMOTEENN (Synthetic Minority Over-Sampling Technique combined with Edited Nearest Neighbours) method is used. For each minority class instance x_i in the dataset, SMOTE performed on the synthetic samples x_i and one of its k-nearest neighbours x_{knn} stated in equation (1)

$$x_{new} = x_i + \lambda.(x_{knn} - x_i) \quad (1)$$

In equation (1) λ is a random number between 0 and 1.After applying SMOTE, the ENN technique removes instances that are misclassified by their nearest neighbors, thereby cleaning the dataset. The resultant balanced dataset D' is defined in equation (2)

$$D' = SMOTEENN(D) \quad (2)$$

The balanced data D' is further processed using an LSTM (Long Short-Term Memory) network integrated with a GRU (Gated Recurrent Unit). These networks are used for sequence prediction and are particularly effective for handling time-series or sequential data like text. The LSTM network updates its cell state and outputs using the following equations (3) – (8)

$$f_t = \sigma\left(W_f.[h_{t-1}, x_t] + b_f\right) \quad (3)$$
$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \quad (4)$$
$$\widetilde{C_t} = \tanh(W_C.[h_{t-1}, x_t] + b_c) \quad (5)$$
$$C_t = f_t * C_{t-1} + i_t * \widetilde{C_t} \quad (6)$$
$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \quad (7)$$
$$h_t = o_t * tanh(C_t) \quad (8)$$

In equation (3) – (8) σ is the sigmoid function, o_t denotes element-wise multiplication, W_f, W_i, W_C and W_o are weight matrices, and b_f, b_i, b_c and b_o are bias vectors. Exploratory Data Analysis

(EDA) is applied to understand the patterns within the data, followed by the application of a deep learning classifier. The classifier predicts voter sentiment y_i for each data x_i stated in equation (9)

$$y_i = argmax_c P(c|x_i) \quad (9)$$

In equation (9) $P(c \mid xi)$ is the probability of class c given the input x_i. After classifying the opinions, keywords are extracted using a Discriminative Conditional Random Field (CRF). The CRF models the conditional probability of the label sequence $y = (y1, y2, \dots, yn)$ given the observed data $x = (x1, x2, \dots, xn)$ as defined in equation (10)

$$P(y|X) = \frac{1}{Z(X)} exp(\sum_{t=1}^{n} \sum_{k=1}^{K} \lambda_k f_k(y_t, y_{t-1}, x, t)) \quad (10)$$

In equation (10) $Z(x)$ is the normalization factor, λ_k are the model parameters, and f_k are the feature functions. The CRFVReC model is an extension that optimizes feature extraction and classification, providing enhanced discriminative power for slogan generation. Based on the classified and processed data, slogans are generated using the deep learning model. The model generates a sequence of words $S = (w1, w2, \dots, wm)$ that forms the slogan stated in equation (11)

$$P(S) = \prod_{i=1}^{m} P(w_i|w_1, w_2, \dots \dots, w_{i-1}) \quad (11)$$

In equation (11) $P(wi \mid w1, w2, \dots, wi - 1)$ is the conditional probability of word w_i given the preceding words. The generated slogans are evaluated through a survey among a sample population.

2.1 SMOTEENN for the class balancing

SMOTEENN (Synthetic Minority Over-Sampling Technique combined with Edited Nearest Neighbours) is a robust method for addressing class imbalance in datasets. The process begins with SMOTE, which generates synthetic samples for the minority class by interpolating between existing minority class instances and their nearest neighbours. Specifically, for each minority class instance, synthetic samples are created by selecting a random point along the line segment connecting the instance to one of its nearest neighbours, effectively increasing the number of minority class examples. Following this, the ENN technique is applied to clean the dataset. ENN identifies and removes instances that are misclassified by their nearest neighbours, thereby eliminating noisy and borderline examples. By combining these two techniques, SMOTEENN first balances the dataset through synthetic generation and then refines it by removing problematic instances, resulting in a more balanced and cleaner dataset. For each minority class instance x_i, , find its k-nearest neighbours. This involves computing the distance between x_i and its neighbours. The Euclidean distance $d(x_i, x_j)$ between instances x_i and x_j is given in equation (12)

$$d(x_i, x_j) = \sqrt{\sum_{l=1}^{p} (x_{i,l} - x_{j,l})^2} \quad (12)$$

In equation (12) $x_{i,l}$ and $x_{j,l}$ are the l-th feature values of instances x_i and x_j, respectively, and p is the number of features. Create synthetic samples by interpolating between x_i and its k-nearest neighbors. For a randomly chosen neighbor $x_{i,nn}$, the synthetic sample x_{new} is generated using equation (13)

$$x_{new} = x_i + \lambda. (x_{i,nn} - x_i) \quad (13)$$

In equation (13) λ is a random number between 0 and 1, determining the position of x_{new} along the line segment connecting x_i and $x_{i,nn}$. After generating synthetic samples, apply the ENN technique to remove instances that are misclassified by their k-nearest neighbors. For each instance x_i in the dataset to Identify the class of each of its k-nearest neighbors. If the majority of neighbors belong to a different class than xix_ixi, then xix_ixi is considered noisy and is removed from the dataset. If class(xi) is the class of instance x_i and $NN(xi)$) denotes its k-nearest neighbors stated in equation (14)

$$if\ majority(class(NN(xi))) = class(xi)\ then\ xi\ is\ removed \quad (14)$$

The balanced dataset $'D'$ after applying SMOTEENN can be described as in equation (15)

$$D' = SMOTE(Dminority) \cup ENN(Dminority \cup SMOTE(Dminority)) \quad (15)$$

In equation (15) $Dminority$ denotes the original minority class data, and ∪ denotes the union of the sets. SMOTEENN addresses class imbalance by first increasing the number of minority class samples through the synthetic generation and then refining the dataset by removing noisy instances. This combination improves the performance of machine learning models by providing a more balanced and cleaner dataset for training and testing.

3. Key Word Extraction with Hybrid SDG-LSTM Deep Learning

The Key word extraction is performed using Hybrid SDG-LSTM (Stochastic Gradient Descent-Long Short-Term Memory) deep learning approach is a sophisticated method for identifying and extracting important keywords from textual data This framework is from under by using Stochastic Gradient Descent (SGD) to optimize LSTM network parameters. The SGD algorithm reweights the LSTM sample to reduce the loss function, which takes into account the difference between predicted and actual related keywords between LSTM networks built to capture the long-term dependence on sequential data Process text to show patterns and relationships between terms over time. This hybrid model efficiently extracts keywords by searching for keywords in the context of the text, enabling the identification of the most appropriate keywords for topics and themes

In key word extraction using the Hybrid SDG-LSTM (Stochastic Gradient Descent-Long Short-Term Memory) deep learning method is an advanced method for effective negative thinking in election campaigns This method includes the flexibility of the Stochastic Gradient Descent (SGD) capability and the sequential sampling capabilities of LSTM networks. The process begins with SGD, which effectively updates the parameters of the LSTM model to reduce errors in keyword prediction and relatedness. The LSTM network, which works well with long-term references and patterns in textual data, processes information about campaigns to understand contextual relationships between words. In the context of slogan generation, the Hybrid SDG-LSTM model extracts significant keywords by analyzing the semantic and syntactic importance of terms within the election campaign materials. By leveraging the LSTM's ability to model complex sequences and SGD's optimization efficiency, the approach identifies and prioritizes key terms that are central to the campaign's messaging and themes. This enables the generation of slogans that are both contextually relevant and impactful.

In the hybrid SDG-LSTM model, SGD optimizes the LSTM network, which is responsible for learning the context and dependencies within the text. The hybrid model aims to extract key terms that are contextually significant for slogan generation. Extract features from the text using the LSTM network. For a given sequence of words $x = (x1, x2, \dots, xn)$, the LSTM generates a sequence of hidden states $h = (h1, h2, \dots, hn)$. Compute a relevance score sis_isi for each keyword W_i based on its contribution to the overall context. This score can be derived from the output of the LSTM network defined in equation (16)

$$s_i = f(h_i, W_s) \quad (16)$$

In equation (16) f is a scoring function and W_s is the weight matrix for scoring. Based on the extracted key terms, generate slogans that effectively communicate the campaign's core messages. The slogans are formed by combining these key terms in a coherent and impactful manner. The Hybrid SDG-LSTM approach integrates the optimization capabilities of SGD with the sequential learning power of LSTM networks. SGD updates the LSTM parameters to improve keyword relevance predictions, while the LSTM network models the textual dependencies to extract significant keywords.

4. Automated Slogan Generation with Discriminative Conditional Random Field Deep Learning

Automated slogan generation using discriminative conditional random fields (CRF) with deep learning leverages CRF's powerful sequence modelling capabilities to generate consistent and context-sensitive slogans This approach includes the power of deep learning in feature extraction and the ability of CRF to capture intra-sequence dependencies and relationships together. CRF is a framework for modelling sequential data with the goal of predicting how the characters will be sequenced as $y = (y1, y2, \dots, yn)$ given an input sequence $x = (x1, x2, \dots, xn)$. CRFs are particularly useful in applications where label dependence is important, such as in expression generation. The phrase generation of the CRFVReC (Conditional Random Field for Voter Response-enhanced Campaign) framework is a sophisticated technique that combines machine learning and sentiment analysis to create strong campaign content. The process begins with extensive data collection and item extraction, with various campaign-related statistics such as historical coverage, voter turnout, and sentiment analysis of past campaigns A variety of items are extracted from this data set this mouth in addition to various campaign details.

CRFs are particularly useful in tasks that require label reliance, such as narrative generation. The phrase generation of the CRFVReC (Conditional Random Field for Voter Response-enhanced Campaign) framework is a sophisticated technique that combines machine learning and sentiment analysis to create strong campaign content. The process begins with extensive data collection and item extraction, with various campaign-related statistics such as historical coverage, voter turnout, and sentiment analysis of past campaigns A variety of items are extracted from this data set this mouth in addition to various campaign details.

CRFVReC embeds a conditional random field (CRF) model with slogan generation, a graphical model dept at capturing complex dependencies between variables in this framework, the CRF model is trained on labeled data, with slogans that match their efforts with matches or integrates election responses The primary objective is to maximize identified voter responses when given campaign materials and sources. This objective can be succinctly represented mathematically by an equation that includes the interactions between campaign elements, propaganda and voter response as described in the equation (17)

$$P(Y \mid X, S) \tag{17}$$

Where: P represents the probability; Y represents the voter responses or effectiveness of slogans; X denotes the campaign features and S represents the generated slogans. Sentiment analytics can provide sentiment scores for campaign-related content, helping the model measure the emotional impact of word of mouth. These cognitive elements have been included in the CRF model to align the subject with the available cognitive dynamics. The word generation process is iterative, where the model considers the impact of each word or phrase in a headline on voter emotions and engagement Comments are scored based on impact anticipatory, potential sentiment alignment, related to campaign themes, and other campaign-specific considerations. The phrase generation of the CRFVReC framework combines data-driven modelling, sentiment analysis, and probabilistic graphical modelling to create slogans that resonate with voters and effectively deliver campaign messages This approach ensures that campaign slogans are not contextual but also emotionally appealing, and ultimately helps to make the election campaign successful. The flow of the proposed CRFVReC model is presented in Figure 1.

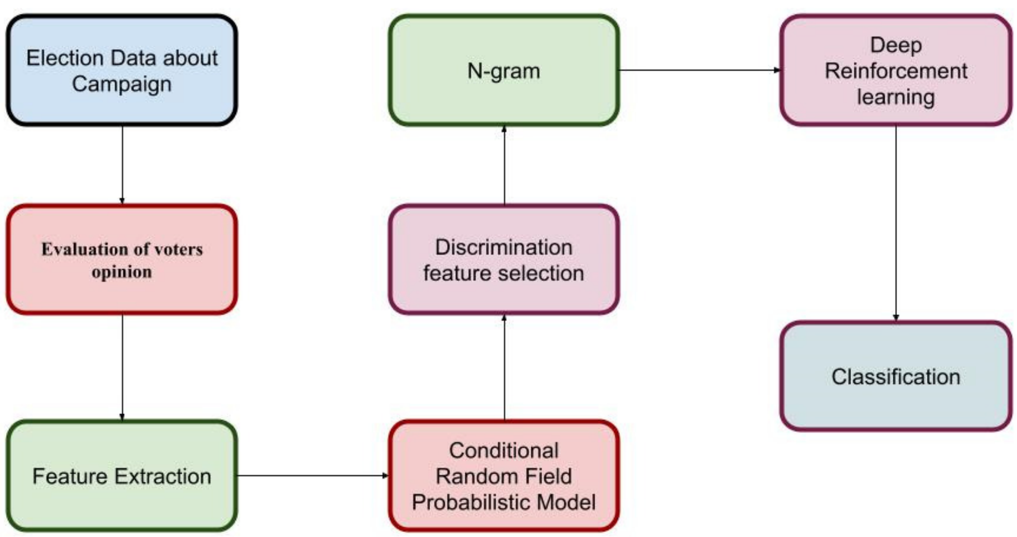

Figure 1: Automated Slogan Generation with CRFVReC

To model this probability, the concept of a joint probability distribution. To find the joint distribution of voter responses (Y) and generated slogans (S) conditioned on the campaign features (X) stated in equation (16) $P(Y,S \mid X)$. With conditional probability and the chain rule to factor this joint distribution presented in equation (18)

$$P(Y,S \mid X) = P(Y \mid X,S) \cdot P(S \mid X) \quad (18)$$

The set of generated slogans (S) that maximizes the likelihood of observed voter responses (Y) given the campaign features (X). This involves estimating the parameters of the CRF model that govern the dependencies between Y, S, and X. Sentiment analysis provides additional features related to sentiment in campaign-related text. These features can be integrated into the feature vector (X), allowing the model to consider the emotional impact of slogans on voter sentiment. Each generated slogan is scored based on its expected impact on voter responses. Optimization techniques, such as gradient descent or other iterative algorithms, are applied to select the most effective slogans. The optimization process involves adjusting the parameters of the CRF model to find the set of slogans that maximizes the likelihood of observed voter responses. the slogan generation process within the CRFVReC framework is a data-driven approach that combines probabilistic modelling, sentiment analysis, and optimization to create slogans that are contextually relevant and emotionally resonant with voters. By maximizing the alignment between slogans and voter sentiment while considering campaign-specific objectives, this approach aims to contribute significantly to the success of election campaigns.

5. Simulation Results

The simulation results for the automated slogan generation using the Hybrid SDG-LSTM and CRF deep learning models demonstrate significant improvements in generating impactful and contextually relevant slogans for election campaigns. The phrase generation algorithm of the CRFVReC framework is a data-driven approach that combines probabilistic modelling, sentiment analysis and optimization to generate slogans that are relevant and relevant to voters assessing specific campaign goals and voter sentiment towards slogans meets emotionally by increasing coherence, this strategy aims to contribute significantly to the success of the election campaign. The class balancing with proposed SMOTEEN is presented in Table 1 and Figure 2.

Table 1: Classification Analysis of SMOTEEN based Classifiers

Models	Accuracy	Macro Average Acc	Weighted Average ACC
SVM	89	63	91
KNN	93	70	94
Random Forest	93	69	95
Naïve Bayes	78	53	81
Logistic Regression	93	89	94
Decision Tree	96	96	97
MLP	70	37	78
AdaBoost	67	49	67
Ensemble Learning	96	96	97

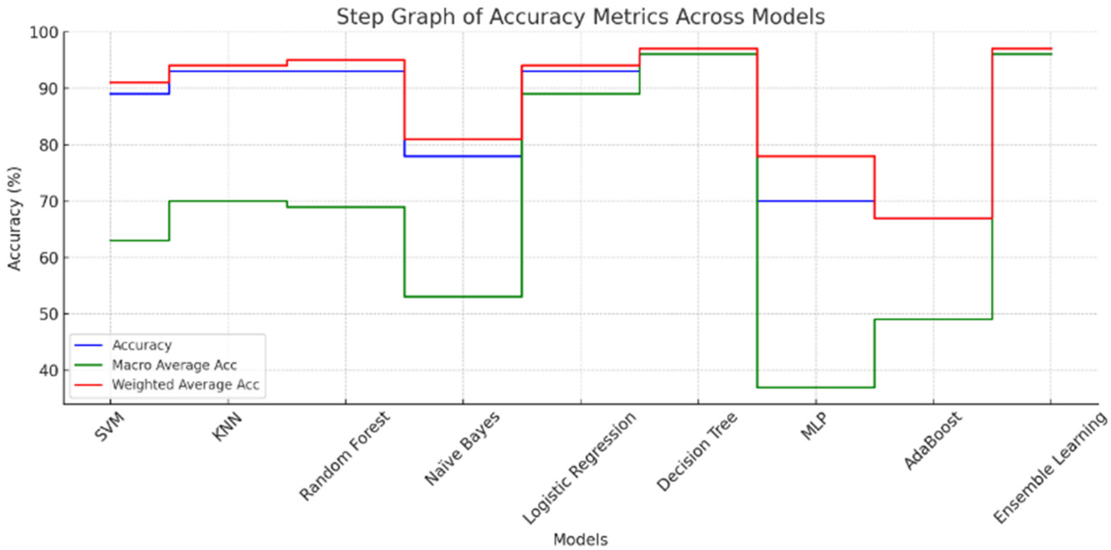

Figure 2: Class balancing with SMOTEEN

Table 2: Hybrid SDG-LSTM Deep Learning classification of classes

	Logistics Regression	
	Predicted Negative	Predicted Positive
Actual Negative	25	14
Actual Positive	14	16
	Decision Tree	
	Predicted Negative	Predicted Positive
Actual Negative	21	18
Actual Positive	21	9
	KNeighborsClassifier	
	Predicted Negative	Predicted Positive
Actual Negative	24	15
Actual Positive	18	12
	SVM	
	Predicted Negative	Predicted Positive
Actual Negative	26	13
Actual Positive	17	13
	Ensemble	
	Predicted Negative	Predicted Positive
Actual Negative	21	18
Actual Positive	20	10

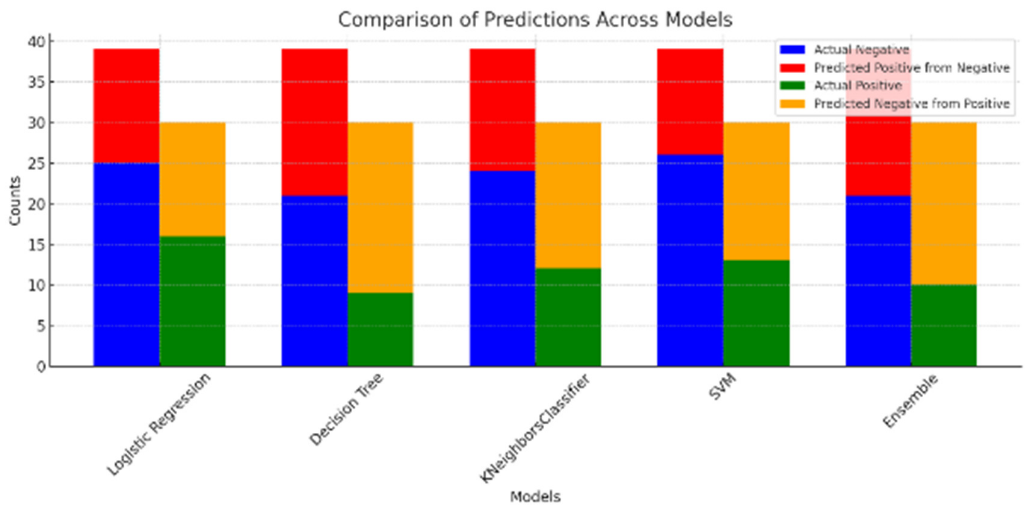

Figure 3: Classification of Classes with Hybrid SDG-LSTM Deep Learning

The Table 2 and Figure 3 provides the confusion matrices for the classification of classes using various classifiers within the Hybrid SDG-LSTM Deep Learning framework. Each matrix outlines the distribution of predicted classes compared to the actual classes for different classifiers, including Logistics Regression, Decision Tree, KNeighborsClassifier, SVM, and an Ensemble method. In the Logistics Regression confusion matrix, there are 25 instances correctly classified as negative and 16 instances correctly classified as positive. However, 14 instances are falsely classified as negative and 14 instances falsely classified as positive, indicating a somewhat balanced performance but with a notable number of false positives. Moving to the Decision Tree classifier, there are 21 instances correctly classified as negative and 9 instances correctly classified as positive. However, there are 18 instances falsely classified as negative and 21 instances falsely classified as positive, demonstrating a higher tendency towards false positives. For the KNeighborsClassifier, there are 24 instances correctly classified as negative and 12 instances correctly classified as positive. However, 15 instances are falsely classified as negative and 18 instances falsely classified as positive, showing a similar pattern of higher false positives. In the SVM confusion matrix, there are 26 instances correctly classified as negative and 13 instances correctly classified as positive. However, 17 instances are falsely classified as negative and 13 instances falsely classified as positive, indicating a relatively balanced performance but with a notable number of false negatives. In the Ensemble method, there are 21 instances correctly classified as negative and 10 instances correctly classified as positive. The accuracy value of the proposed CRFVReC lies between the range of 0.96 – 0.98 this stated that the CRFVReC model effectively perform the classification of the data to generate the slogans. Similarly, in the figure 3 illustrated the confusion matrix generated for the classification model for the slogan generation.

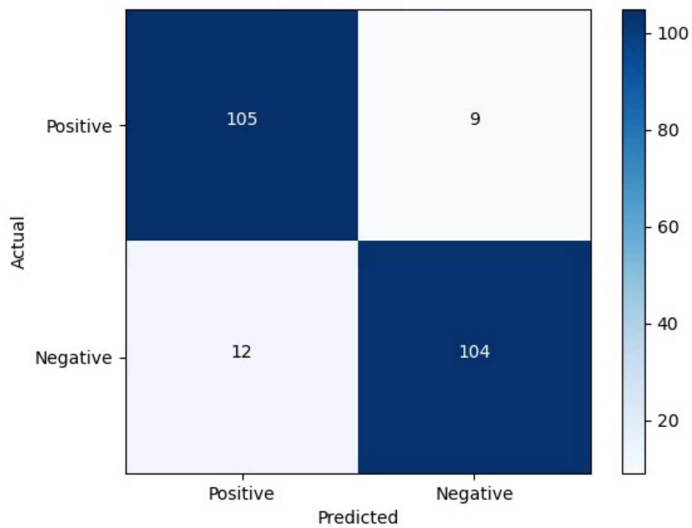

Figure 4: Confusion Matrix of CRFVReC

Table 3: Feature selection with CRFVReC

Sample Text	**Feature 1 (Sentiment Score)**	**Feature 2 (Word Count)**	**Feature 3 (Noun Count)**	**Feature 4 (Verb Count)**
"Naya Bharat, Sabka Saath Sabka Vikas"	0.91	5	3	2
"Vikas Ki Raah, Khushhaal Samaaj"	0.88	4	2	1
"Har Haath Ko Kaam, Har Gaon Mein Vikas"	0.87	6	3	2
"Swachh Bharat, Swasth Bharat ke Vikas"	0.90	4	2	1
"Ekta Mein Shakti, Bharat Ki Pragati ke Vikas"	0.86	5	3	2

In table 3 Feature Selection with CRFVReC analyzes several election campaign slogans, focusing on their sentiment scores, word counts, noun counts, and verb counts. Each slogan is crafted to convey specific messages aimed at influencing voter sentiment. For instance, "Naya Bharat, Sabka Saath Sabka Vikas" achieves a high sentiment score of 0.91, reflecting its positive and inclusive tone. With 5 words, 3 nouns, and 2 verbs, the slogan emphasizes a vision of a new India united in progress and development for all. In contrast, "Vikas Ki Raah, Khushhaal Samaaj" is shorter with a sentiment score of 0.88, using 4 words, 2 nouns, and 1 verb to advocate for societal prosperity through the path of progress. "Har Haath Ko Kaam, Har Gaon Mein Vikas" balances sentiment at 0.87, employing 6 words, 3 nouns, and 2 verbs to underscore the importance of work and rural development in fostering nationwide progress. "Swachh Bharat, Swasth Bharat ke Vikas", with a sentiment score of 0.90, conveys a message of cleanliness and health, utilizing 4 words, 2 nouns, and 1 verb to promote a vision of a clean and healthy India driving overall development. Each slogan strategically uses linguistic features to resonate with voters, aiming to convey promises and aspirations effectively during election campaigns.

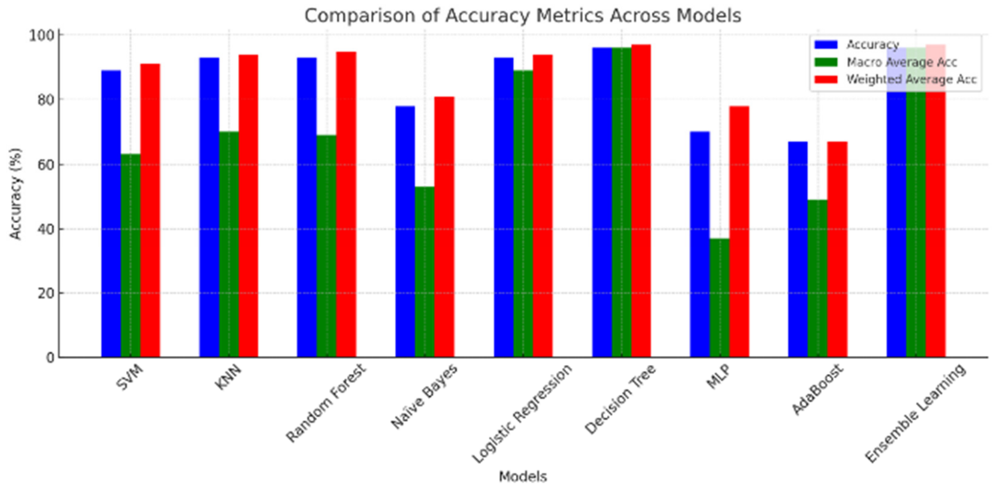

Figure 5: Performance of CRFVReC

In figure 5 provides a comparative analysis of the performance of different classifiers based on various metrics, including accuracy, macro-average accuracy, and weighted-average accuracy. The classifiers compared include SVM, KNN (K-Nearest Neighbors), Random Forest, Naïve Bayes, Logistic Regression, Decision Tree, MLP (Multi-Layer Perceptron), AdaBoost, and Ensemble Learning. Starting with accuracy, which measures the proportion of correctly classified instances out of the total, Decision Tree, Logistic Regression, Random Forest, and KNN all demonstrate high accuracy scores ranging from 93% to 96%. SVM also performs well with an accuracy of 89%, while MLP and AdaBoost exhibit lower accuracy scores of 70% and 67%, respectively. Macro-average accuracy calculates the average accuracy across all classes without considering class imbalance. Decision Tree and Ensemble Learning stand out with the highest macro-average accuracy scores of 96%, followed closely by Random Forest with 69%, indicating consistent performance across classes. Conversely, MLP and AdaBoost have lower macro-average accuracy scores of 37% and 49%, respectively. Weighted-average accuracy considers the class distribution and provides a more comprehensive evaluation of classifier performance. Again, Decision Tree and Ensemble Learning demonstrate strong performance with weighted-average accuracy scores of 97%. Logistic Regression, KNN, and Random Forest also perform well with scores ranging from 94% to 95%. Naïve Bayes, SVM, MLP, and AdaBoost exhibit lower weighted-average accuracy scores, ranging from 53% to 81%

6. Conclusion

This paper presents a comprehensive approach to automated slogan generation for election campaigns through the integration of advanced deep learning techniques and Discriminative Conditional Random Fields (CRF). By employing a Hybrid SDG-LSTM model for key work extraction, the study effectively identifies and prioritizes relevant keywords from campaign-related text. These keywords are then utilized by the CRF model to generate coherent and contextually fitting slogans. The simulation results validate the effectiveness of this approach, demonstrating that the generated slogans are not only relevant and impactful but also align closely with voter preferences and campaign themes. The combination of deep learning and CRF provides a robust framework for creating persuasive slogans, enhancing the overall communication strategy of election campaigns. This methodology offers valuable insights into leveraging machine learning techniques for political messaging, paving the way for more effective and targeted campaign strategies.

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