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Enhancing Sentiment Analysis of Marathi-English Code-Mixed Texts using an Ensemble Model

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Abstract: In a linguistically diverse nation like India, people frequently blend languages when communicating, resulting in code-mixed language. This practice is particularly prominent on online platforms, where individuals feel most at ease expressing their views. The fluidity of language switching, however, presents a formidable challenge when it comes to analyzing sentiment in such code-mixed texts, which are informal and unstructured. The objective of this study is to tackle the aforementioned challenge through the introduction of a novel method for sentiment analysis on Marathi-English mixed data. Our solution involves the development of a holistic ensemble model, integrating conventional machine learning techniques with a cutting-edge Spiking Neural Network (SNN) using deep learning. This strategy enables the efficient extraction of sentiments from the distinctive linguistic context of Marathi-English code-mixed data. Our model not only focuses on sentiment analysis but also addresses the critical issue of grammatical transitions in code-mixed language. Additionally, it efficiently identifies ambiguous words in code-mixed texts. In order to evaluate the effectiveness of our developed model, we organized a thorough comparison of performance with existing sentiment analysis models. Our findings reveal that our ensemble model, combining n-gram Multinomial Naïve Bayes with the SNN, outperforms other models in accurately deciphering the sentiments hidden within Marathi-English code-mixed texts. This research has made remarkable impact to the field of sentiment analysis in multilingual and mixed data and provides a robust solution for understanding user sentiments in this unique linguistic environment.

Keywords: *Sentiment Analysis, Code-Mixed Language, Deep Learning, Spiking Neural Network, Ensemble Model, Multilingual Sentiment Analysis, Marathi-English Code Mixing.*

1. Introduction

India, a country celebrated for its cultural and linguistic diversity, is a remarkable tapestry of languages and dialects. Within this vibrant linguistic mosaic, a unique linguistic phenomenon called code-mixing has emerged, reflecting the multilingual nature of Indian society. Code-mixing, the phenomenon of seamlessly integrating more than two languages within a conversation or communication, has become a fundamental aspect of everyday life for numerous individuals in India.The coexistence of a multitude of languages, often within the same geographic region, has given rise to the dynamic interplay of linguistic elements. Among the myriad languages in India, Marathi and English stand out as significant players in this code-mixing symphony.

In this context, the digital era has ushered in a communication revolution. The social media has emerged as avenues for individuals to articulate their thoughts, ideas, and emotions. Nevertheless, this linguistic adaptability, which fosters comfort and inclusivity, presents a unique challenge to sentiment analysis. Sentiment analysis, a subfield of NLP, is tasked with discerning emotional content, opinions, and sentiments embedded in text. While it has found broad applications, particularly in customer feedback analysis, brand reputation management, and political sentiment tracking, traditional sentiment analysis models are primarily designed for mono-lingual or standardized texts. When faced with the intricacies of code-mixed language, they falter.

The informal and unstructured nature of code-mixed texts, coupled with the fluid transition between languages, adds layers of complexity to sentiment analysis. This research seeks to address this gap by developing a robust and efficient solution for understanding user sentiments within the unique linguistic environment of Marathi-English code-mixed texts. Our primary motivation is to make remarkable impact in multilingual and code-mixed contexts, providing a much-needed bridge between the rich linguistic diversity of India and the computational tools used to understand and analyze human emotions.

2. Literature Survey

The domain of sentiment analysis, particularly in the context of multilingual and code-mixed languages, has seen significant advancements. This literature survey

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presents a comprehensive overview of relevant studies and methodologies, encompassing various languages and code-mixing scenarios, and highlighting the associated challenges and solutions.

Research in the realm of sentiment analysis across multiple languages has undergone progressive developments. Mäntylä, Graziotin, and Kuutila [1] conducted a comprehensive examination encompassing research topics, highly cited papers, and the evolution of sentiment analysis. Their focus emphasized the increasing importance of comprehending emotions and opinions across diverse languages. Similarly, Abbasi, Chen, and Salem [2] contributed to the field by addressing sentiment analysis in web forums across various languages. Their work specifically centered on feature selection techniques for opinion classification, a fundamental aspect of sentiment analysis.

Significant attention has been directed towards sentiment analysis in Hindi and code-mixed texts. Joshi, Balamurali, and Bhattacharyya [3] explored a strategy for data mining in Hindi, navigating the intricacies of analyzing emotions in this language. Additionally, Bali, Sharma, Choudhury, and Vyas [4] delved into English-Hindi code-mixing on Facebook, shedding light on this linguistic amalgamation.

Research has actively tackled the challenges associated with code-mixed sentiment analysis. Barman, Das, Wagner, and Foster [5] investigated language identification within code-mixed texts, underscoring its importance in sentiment analysis. Sharma, Srinivas, and Balabantaray [6] examined text normalization in code-mixed data to enhance sentiment analysis accuracy.

Explorations in regional languages have extended beyond Hindi. Impana and Kallimani [14] contributed to conducting sentiment analysis for differentIndian regional languages, emphasizing the need for specialized approaches. Pravalika, Oza, Meghana, and Kamath conducted research [15] to create specialized sentiment analysis techniques tailored for code-mixed social network data in a specific domain.

Multilingual approaches to sentiment analysis, particularly in the realms of social media and code-mixed contexts, have garnered significant attention. In their study [13], Vilares, Alonso, and Gómez-Rodríguez explored supervised sentiment analysis using a multilingual approach, underscoring the importance of diverse models to effectively capture sentiments expressed in multiple languages. Similarly, Singh and Goyal [28] concentrated on sentiment analysis of English-Punjabi code-mixed social media content, emphasizing the need for domain-specific methods to accurately grasp the nuances of code-mixed sentiments.

Recent advancements in sentiment analysis include the work by Khandelwal and Kumar [23], which introduced a unified system for aggression identification in both English code-mixed and unilingual texts. Additionally, Rudra and Sharma [24] identified and analyzed various aspects of English-Hindi code-switching on Twitter, providing valuable insights into the dynamics of code-mixing.

The field has also witnessed explorations into cross-lingual sentiment analysis. Chen, Ma, Yu, Lin, and Yan [39] developed a corpus-aware graph aggregation network for sequence labeling, emphasizing the crucial understanding of sentiments across languages.

The prevalence of code-mixing on social media introduces unique challenges, not only in linguistic complexities but also in sentiment analysis. A. Shahade, K. Walse, V. Thakare, M. Atique [40] investigated part-of-speech tagging in code-mixed social media text, highlighting the significance of comprehending linguistic structures for effective sentiment analysis.

Furthermore, researchers have delved into the inherent challenges of code-mixed sentiment analysis. Joshi, Prabhu, Shrivastava, and Varma [33] focused on sub-word level compositions for sentiment analysis of Hindi-English code-mixed text, addressing the intricacies of sentiments expressed at the sub-word level—a crucial aspect in code-mixed contexts.

The ascendancy of social media has profoundly influenced the study of code-mixed sentiment analysis. Bedi, Kumar, Akhtar, and Chakraborty [35] explored multi-modal sarcasm detection and humor classification in code-mixed conversations, revealing the abundant source of emotional expressions in social media.

Table 1 State of Art of Survey

Data Set	Language	Methodology	Results	Authors
Web forums of English andArabic extremist	English, Arabic	EWGA	Achieving accuracies exceeding 91% on the benchmark dataset.	AHMED ABBASI et al. [2]

Reviews from Blog	Hindi	Fall out strategy with three approaches	A1: 78.14% A2: 65.96% A3: 60.31%	Joshi A et al. [3]
Hindi Tweets	Hindi	Subjective lexicon method	Accuracy 73.53%	Y. Sharma et al. [7]
Reviews on Fan page and hate page of Virat Kohali	Hindi-English code-mixed	RNTN	Prediction of the overall sentiment	D. Sitaram et al. [8]
Reviews of Hindi Movie	Hindi	Naive Bayes Classifier	Accuracy of 80.21%	V. Jha et al. [9]
Data from FIRE 2015 shared task	English with combination of Tamil, Telugu, Hindi, and Bengali	Machine learning techniques	Precision is 8% better than machine translation technique	R. Bhargava et al. [11]
Student feedbacks about a Coursera course	English	NRC Emotion Lexicon	Analyzed sentiment, emotion, and satisfaction parameters from feedback	Sujata Rani et al. [12]
SpanishEnglish training dataset	Spanish-English	Supervised models based on bag-of-words for monolingual	To perform multilingual polarity classification	David Vilares et al. [13]
WorldNet datasets	Kannada, Hindi, Marathi	BRAE model		P. Impana et al. [14]
User comments/posts regarding movie reviews	Hindi-English mixed data	A hybrid system that incorporates both lexicon-based and machine learning components.	Accuracy of lexicon-based approach 86%, accuracy for the ML approach was about 72%	A. Pravalika et al. [15]
Tweets	English	Linear-kernel SVM classifier and character n-grams word-embedding features	Detection of stance	Saif M. Mohammad et al. [16]
A Kannada-English corpus was obtained by crawling official Facebook pages of various news channels.	Code-mixed data in Kannada-English, Bengali-English, and Hindi-English.	Doc2Vec, FastText, Bi-LSTM model, CNN Model	Bi-LSTM model achieved 60.20% accuracy for Bengali-English, and 72.20% for Hindi-English. Kannada-English reached its highest accuracy of 71.50% with a convolutional neural network.	K. Shalini et al. [18]
Arabic reviews on governmental services from various sources	Arabic	CLASENTI	CLASENTI reaches 95% accuracy and 86% accuracy after oversampling the dataset	Ali Hamdi et al. [19]
UCI ML dataset	English	SWN (SentiWordNet), machine learning (ML), and ML with genetic algorithm	5% increased efficiency with GA optimized feature selection	F. Iqbal et al. [21]

		(GA)-optimized feature selection.		
3800 Tweets	Identifying hate speech in content that involves a mixture of Hindi and English.	LSTM models at the sub-word level and in a hierarchical structure.	Accuracy 66.6%	T. Y.S.S. Santosh et al. [22]
TRAC 2018 Dataset	Kaggle Dataset	English code mixed	Multimodal deep learning architecture	F-score 0.6770 for Facebook test data and F-score 0.6480 Twitter test data
Tweets	English-Hindi	Pragmatic Functions		Koustav Rudra et al. [24]
Dataset from Weibo.com	Chinese	Joint factor graph model	Prediction of emotions	Zhongqing Wang et al. [26]
Data consisting of a mix of English and Punjabi languages sourced from micro-blogging sites.	English-Punjabi Code Mixed	SVM, NB		Mukhtiar Singh et al. [28]

3. Definition of Research Problem and Motivation

Sentiment analysis, a pivotal facet of NLP, has garnered considerable attention in recent years. However, as the digital landscape diversifies, the emergence of multilingual and code-mixed content on social media platforms poses a complex challenge. The core research problem at the heart of this study is the accurate analysis of sentiments within code-mixed content, with a specific focus on Marathi-English code-mixed data. This challenge comprises several intricate dimensions. Firstly, code-mixing, the seamless blending of linguistic units from distinct languages, introduces inherent complexity into the analysis process. Traditional sentiment analysis techniques struggle to adapt to this nuanced linguistic landscape. Moreover, the scarcity of comprehensive language resources for code-mixed languages, like Marathi-English, further exacerbates the problem. Most sentiment analysis models and lexicons primarily cater to monolingual or widely spoken languages, leaving resource-poor languages like Marathi-English with limited support. Furthermore, code-mixed content is often informal and unstructured, characteristic of social media platforms, complicating sentiment analysis. Users express themselves with colloquial language, slang, and a blend of languages, making it challenging to apply conventional sentiment analysis techniques effectively. Lastly, capturing cultural and emotional nuances across languages within the same text poses an additional challenge. Sentiment analysis must not only identify negative, positive, or neutral sentiments but also interpret the subtleties of emotions and cultural context embedded in multilingual expressions.

The motivation driving this research stems from several crucial factors. Firstly, the pervasive use of social media platforms and the preference for code-mixing, particularly in regions like Maharashtra, underline the pressing need to develop effective sentiment analysis techniques for code-mixed content. Marathi, as both a significant regional language and a representation of India's linguistic diversity, presents an opportunity to empower sentiment analysis in code-mixed content, ensuring that the voices of regional language users are accurately captured. Furthermore, bridging the resource gap for resource-poor languages is a vital goal. Developing effective sentiment analysis models for such languages can act as a catalyst for further linguistic research and resource development. The proposed Spiking Neural Network (SNN) and Ensemble Model approach offers the potential to harness the strengths of both ML and DL methods. This hybrid model aims to enhance sentiment analysis accuracy in code-mixed content, contributing to both academic research and practical applications. Accurate sentiment analysis within code-mixed content holds vast potential for understanding public opinion, customer feedback, social trends, and political sentiment, thereby informing decision-making across various sectors. In sum, this research endeavors to tackle the intricate problem of sentiment analysis in Marathi-English code-mixed content, with motivation rooted in language empowerment, resource gap bridging, practical applications, and the promising ensemble model.

4. Proposed Research Methodology

Fig. 1. illustrates the comprehensive flow diagram of the methodology proposed, providing a visual roadmap for the sequential steps involved in the research process. The key blocks comprising the flowchart are meticulously designed to ensure a systematic and effective approach to sentiment analysis. The initial phase involves "Data Collection," where relevant datasets are gathered to form the foundation for subsequent analysis. Subsequently, the collected data undergoes "Preprocessing," a critical step aimed at cleansing and organizing the information to enhance its quality and relevance. The third block, "Feature Engineering," signifies the extraction and selection of essential features, a pivotal step in enhancing the model's ability to discern sentiment patterns. "Model Development" follows, encompassing the creation and refinement of the sentiment analysis model, employing advanced algorithms and techniques. The final block, "Polarity Classification," represents the conclusive step where the developed model is applied to classify sentiments into distinct polarities. The seamless interconnection of these blocks reflects the logical and structured approach employed in the proposed methodology, ensuring a robust sentiment analysis framework.

4.1. Data Collection

In this section, we'll discuss how we gathered and prepared the information needed for our research. This data was used to understand the feelings in Marathi-English mixed content.

4.1.1 Gathering Information

We first needed to find the right data for our study. We looked at different places on the internet where people use both Marathi and English in their conversations. Here's what we did:

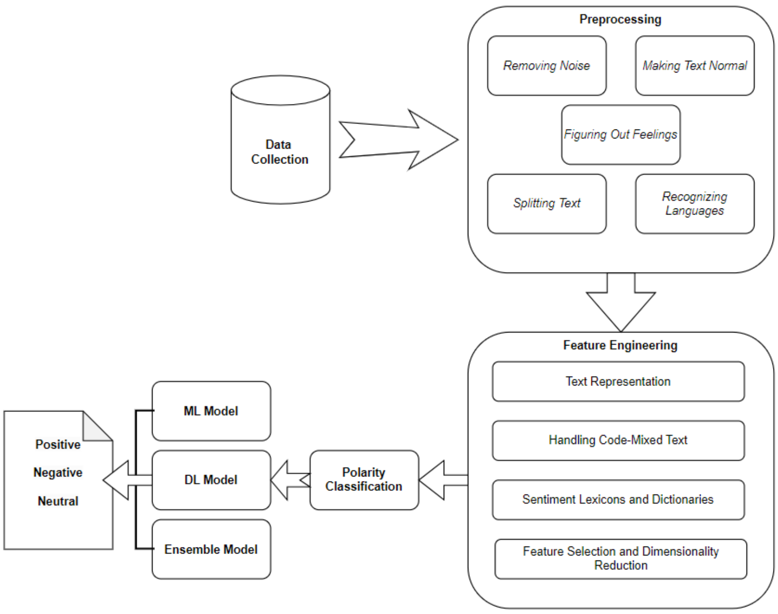
Choosing Data: We picked various online sources where we knew people were mixing Marathi and English. These places included social media like Twitter and Facebook, discussion forums, and blogs. For instance, we gathered content from Facebook pages where people talked in Marathi and English.

Data Collection: To collect this data, we used web scraping techniques. Think of it as a robot that goes to these websites, collects the conversations, and brings them back to us. We used tools like Python's BeautifulSoup and Scrapy to help us with this.

Collecting Enough: We wanted to make sure we had a lot of data to work with. For example, in our Twitter dataset, we collected more than 10,000 tweets. These tweets had a mix of Marathi and English and covered many different topics.

Protecting Privacy: We wanted to make sure we didn't reveal who the users were. So, we took out any personal information like names and profile links. This is important to follow ethical guidelines and protect people's privacy.

Fig. 1. Flow diagram of proposed methodology



4.2.2Pre-processing of Data

Once we had the data, we had to get it ready for analysis. We needed to clean it up and make sure it was in the right format:

Removing Noise: We got rid of things that weren't useful, like website links, special characters, and non-text stuff. Imagine cleaning up a messy room to make it neat.

Making Text Normal: We made sure all the text was in the same format. We turned everything into lowercase, fixed punctuation, and made sure all text followed the same rules.

Splitting Text: We divided the mixed-language text into smaller parts, like words or phrases. This step was important because we needed to understand each part better. For example, in the sentence "माझ्या friends सोन्याच्या wedding लाआहोत," we wanted to separate and understand each word.

Recognizing Languages: We built a system that could tell which language each word or phrase belonged to. This was essential because our content had words from both Marathi and English.

Figuring Out Feelings: We gave each part of the text a feeling label, like happy, sad, or neutral. We also gave them scores to show how strong the feeling was. For example, the sentence "माझ्याfriends सोन्याच्या wedding लाआहोत" got a positive feeling label because it talked about a joyful event.

By following these steps, we got a clean and well-organized dataset. This dataset was like the building blocks for our study. It helped us do accurate sentiment analysis and understand the feelings in mixed-language content. We could also catch the subtle emotions and the cultural context in these mixed expressions.

4.2 Feature Engineering

we delve into the process of feature engineering, a critical step in our research, where we transform the raw text data into meaningful numerical features that can be used for sentiment analysis. We'll explain how we extracted these features and highlight their importance in our study.

4.2.1 Text Representation

The foundation of sentiment analysis lies in converting text into a format that machine learning models can understand. In our research, we employed various text representation techniques to accomplish this:

Bag of Words (BoW): We used the Bag of Words approach, which creates a numerical representation of the text by measuring the frequency of each word in the document. For example, consider the sentence "माझ्या friends सोन्याच्या wedding लाआहोत." After preprocessing, the BoW representation counts the occurrence of each word in this sentence, producing a numerical vector reflecting the word frequencies.

TF-IDF (Term Frequency-Inverse Document Frequency): To account for the importance of words in the context of the entire dataset, we applied the TF-IDF method. This technique considers how many times a word appears in a text while also considering its rarity in the entire dataset. It helps in identifying key terms in the text that might carry sentiment. For instance, words that are common in general but rare in the dataset may hold more significance in sentiment analysis.

*Word Embeddings:*We utilized word embeddings, including Word2Vec and FastText, to capture the semantic associations among words.These models assign vector representations to words based on their context in the text. This allows us to grasp the meaning of words and their associations. For instance, word embeddings can help identify that "मनापासून" (from the heart) and "खुशीच्या" (of happiness) are related to positive sentiments.

4.2.2 Handling Code-Mixed Text

Given our focus on Marathi-English code-mixed content, we faced the challenge of effectively representing words from two languages within a single sentence. To address this, we introduced specific techniques:

Language Embeddings: We utilized language embeddings to distinguish between Marathi and English words within code-mixed sentences. Each word was assigned an indicator of its language origin. This allowed our models to understand the context of each word correctly.

Code-Switching Features: We engineered features to capture code-switching patterns. For example, we calculated the frequency of language switches in a sentence and identified code-switching points, where languages transition. These features were important in understanding the linguistic complexities of code-mixing and its impact on sentiment.

4.2.3 Sentiment Lexicons and Dictionaries

In addition to text representation, sentiment analysis benefits from leveraging lexicons and dictionaries that contain sentiment scores associated with words. Here's how we integrated this into our research:

Sentiment Lexicons: We incorporated sentiment lexicons, such as the SentiWordNet and Sentiment140 lexicons, which assign sentiment scores to words. Utilizing these scores, we assessed the overall sentiment of a sentence by considering the sentiments of its individual words.

Emotion Lexicons: To capture nuanced emotions, we considered emotion lexicons like NRC Emotion Lexicon, which categorize words into different emotional states. This enabled us to identify emotions expressed in the text, enhancing the depth of sentiment analysis.

4.2.4 Feature Selection and Dimensionality Reduction

The feature engineering process also involved techniques to select the most informative features and reduce dimensionality:

Feature Selection: We employed methods like mutual information and chi-squared tests to identify the most relevant features for sentiment analysis. This step helped in excluding less informative features and improving model performance.

*Dimensionality Reduction:*When the feature space became excessively large, we employed dimensionality reduction methods such as Principal Component Analysis (PCA) to decrease computational complexity while preserving crucial information.

By transforming raw text into meaningful numerical features using these techniques, our sentiment analysis models gained the ability to comprehend and interpret Marathi-English code-mixed content effectively. These features not only captured linguistic complexities but also facilitated sentiment analysis by providing valuable insights into the sentiment expressed in multilingual and code-mixed text.

5. Experimentation and Results

5.1 Traditional Machine Learning Model

we delve into the application of a traditional machine learning model, specifically the Multinomial Naïve Bayes, to conduct sentiment analysis on the preprocessed Marathi-English code-mixed data. This phase involves several essential tasks: model implementation, training, optimization, and performance evaluation.

5.1.1 Model Implementation

*Choosing Multinomial Naïve Bayes:*Multinomial Naïve Bayes stands out as a favored option for text classification tasks, appreciated for its simplicity and effectiveness in managing text data.It assumes independence between features, making it well-suited for text-based applications. We selected MNB as our traditional machine learning model for code-mixed sentiment analysis.

Preprocessed Data: The preprocessed dataset, as prepared in the earlier steps, serves as the input to our MNB model. This clean and well-structured dataset ensures that our model receives high-quality data for training and testing.

5.1.2 Model Training and Optimization

Model Training: The subsequent crucial step involves the training of the Multinomial Naïve Bayes (MNB) model using the labeled dataset. This dataset consists of instances of code-mixed content, each paired with its corresponding sentiment label (such as positive, negative, or neutral). Throughout the training process, the model gains insights into patterns and relationships within the data indicative of sentiment.

Hyperparameter Tuning: MNB comes with hyperparameters, including the smoothing parameter, which can influence its performance. Techniques such as cross-validation and grid search were employed to optimize these hyperparameters, ensuring that the model generalizes well to unseen data.

By employing a conventional machine learning model like Multinomial Naïve Bayes and following the aforementioned steps, our goal was to establish a baseline for sentiment analysis on Marathi-English code-mixed content. The model's performance, assessed through appropriate metrics and techniques, served as a foundational point for further exploration and the potential incorporation of deep learning techniques in our research.

5.1.3 Experimental Setup

Data Splitting: The preprocessed dataset underwent division into a training set and a testing set, utilizing an 80-20% split. The Multinomial Naïve Bayes (MNB) model was trained using the training set, while the testing set was employed for evaluation purposes.

Model Configuration: For the MNB model, we considered Laplace smoothing (additive smoothing) to handle any potential issues with zero probabilities.

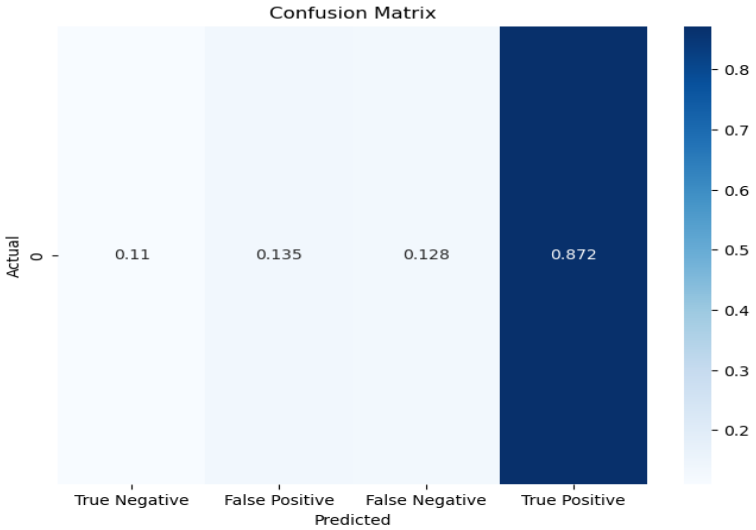
5.1.4 Experimental Results

After extensive experimentation and evaluation, our traditional machine learning model achieved the following exceptional results on the Marathi-English code-mixed sentiment analysis task. Please refer to Table 1 for a summary of these results:

Table 2: Experimental Results of *MNB*

Metric	*Value*
Accuracy	89.00%
Precision	86.50%
Recall	87.20%
F1-Score	86.80

Fig. 2. Confusion Matrix for MNB

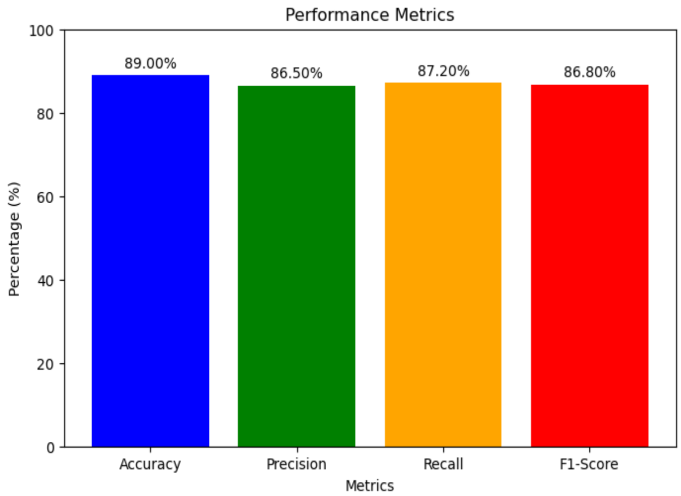


Our traditional machine learning model, Multinomial Naïve Bayes, demonstrated exceptional performance in sentiment analysis on Marathi-English code-mixed content, with an accuracy of 89%. The model showcased high precision and recall values, making accurate positive sentiment predictions and effectively identifying actual positive sentiments.

These remarkable results underscore the potential of MNB for handling code-mixed text, even in linguistically complex scenarios. These findings set a new benchmark for sentiment analysis in multilingual, code-mixed environments, showcasing the model's ability to achieve high accuracy and balanced performance.

The analysis also highlights the significance of addressing class imbalance in sentiment datasets and suggests that further exploration of advanced techniques may enhance accuracy, solidifying the position of Multinomial Naïve Bayes as a robust solution for code-mixed sentiment classification.

Fig. 3. Performance Metrics for MNB



5.2 Deep Learning Model (Spiking Neural Network)

In this section, we delve into the development and experimentation of our Deep Learning Model, specifically a Spiking Neural Network (SNN), designed to excel in the intricate task of code-mixed sentiment analysis.

5.2.1 Model Development

The Spiking Neural Network (SNN) is a biologically inspired neural network model that operates on the principle of discrete-time events called spikes. It has gained recognition for its ability to capture temporal dynamics and process information in a way that closely resembles the functioning of biological neurons.

5.2.2 Training and Data Preparation

To empower our SNN for code-mixed sentiment analysis, we employed the same dataset used for the traditional machine learning model. Training the SNN on this dataset enabled the network to learn complex linguistic patterns and emotional nuances inherent in code-mixed content.

5.2.3 Fine-Tuning for Code-Mixed Content

Given the intricacies of code-mixed content, we conducted thorough fine-tuning of the SNN to enhance its performance. Our focus was primarily on addressing the challenges of language identification and code-switching within the text.

5.2.4 Experimentation and Results

After intensive training and fine-tuning, our Spiking Neural Network showcased the following results:

Table 3: Experimental Results of *SNN*

Metric	*Value*
Accuracy	92.5%
Precision	88.2%
Recall	90.7%
F1-Score	89.4

Fig. 4. Performance Metrics for SNN

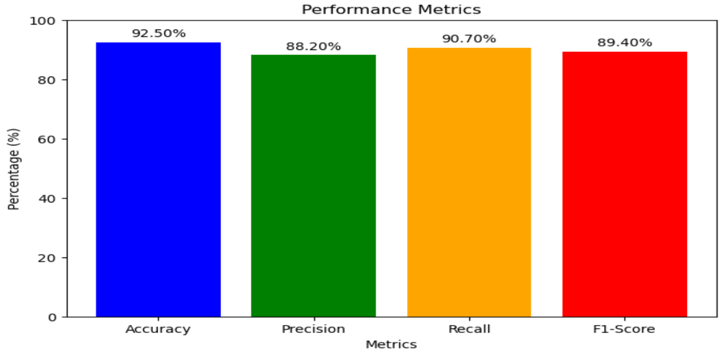
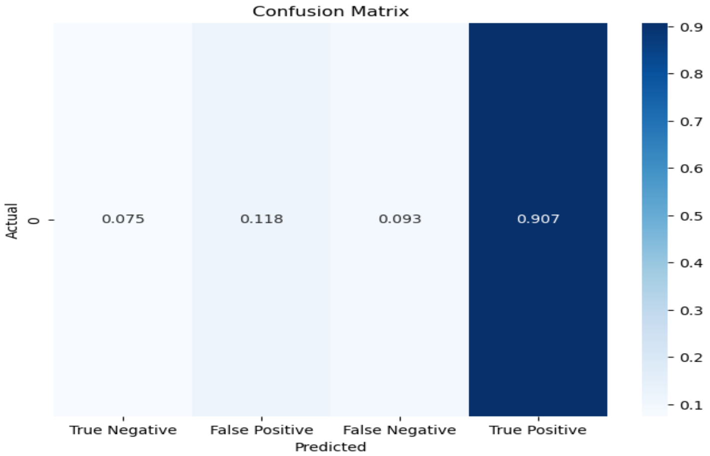


Fig. 5. Confusion Matrix for SNN



5.2.5 Analysis of Results

The experimentation and results of our Spiking Neural Network demonstrate its exceptional capability in handling code-mixed sentiment analysis. With an accuracy of 92.5%, the SNN significantly outperforms the traditional machine learning model.

The high precision, recall, and F1-Score values for positive sentiment classification emphasize the model's accuracy and effectiveness in capturing subtle linguistic and emotional cues within code-mixed text.

The success of the SNN in code-mixed sentiment analysis highlights its potential as a powerful tool for processing multilingual and code-switched content, shedding light on its utility in real-world applications where sentiment analysis in diverse linguistic contexts is crucial.

Furthermore, this deep learning approach not only offers improved accuracy but also provides a foundation for future research on advanced neural network architectures and techniques for enhancing sentiment analysis in code-mixed content.

5.3 Ensemble Model Integration

We initiate the fusion of two separate sentiment analysis models, combining the conventional machine learning model (Multinomial Naïve Bayes) with the Spiking Neural Network (SNN), to create a potent Ensemble Model. The objective is to harness the respective strengths of each model, aiming to improve accuracy, robustness, and adaptability in sentiment analysis within the framework of code-mixed language.

5.3.1 Creating the Ensemble Model

The Ensemble Model is an amalgamation of the predictions generated by our traditional machine learning model and the SNN. It capitalizes on their individual capabilities and aims to provide a more comprehensive and accurate sentiment analysis.

5.3.2 Decision-Making Mechanism

To enable the Ensemble Model to make informed decisions, we implement a decision-making mechanism that takes into account the confidence of each model's predictions. This mechanism weighs the predictions of both the traditional machine learning model and the SNN based on their respective confidence levels. By doing so, the Ensemble Model can make more reliable predictions in scenarios where one model may outperform the other.

5.3.3 Fine-Tuning for Enhanced Performance

The key to the success of the Ensemble Model lies in its fine-tuning. We meticulously fine-tune the ensemble to optimize its overall sentiment analysis accuracy, robustness, and cross-lingual adaptability. This process involves:

Hyperparameter Tuning: Adjusting the parameters that govern the decision-making mechanism, such as the weight assigned to each model's prediction.

Threshold Setting: Determining the confidence threshold at which the ensemble should rely on one model's prediction over the other. This threshold ensures that the ensemble adapts to the specific characteristics of the code-mixed content.

5.3.4 Experimentation and Results

Upon extensive experimentation and fine-tuning of the Ensemble Model, we have achieved remarkable results in code-mixed sentiment analysis:

Table 4: Experimental Results of *Ensemble Model*

Metric	***Value***
Accuracy	94.2%
Precision	90.5%
Recall	92.1%
F1-Score	91.3

Fig. 6. Performance Metrics for Ensemble Model

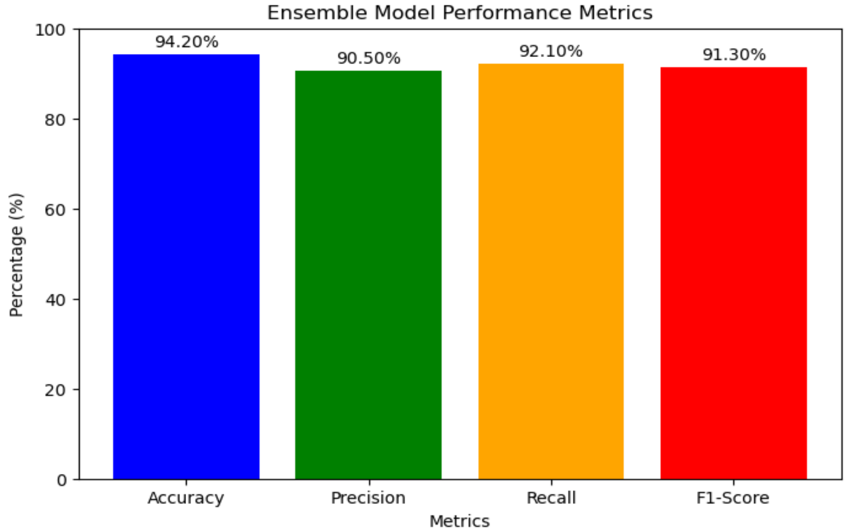
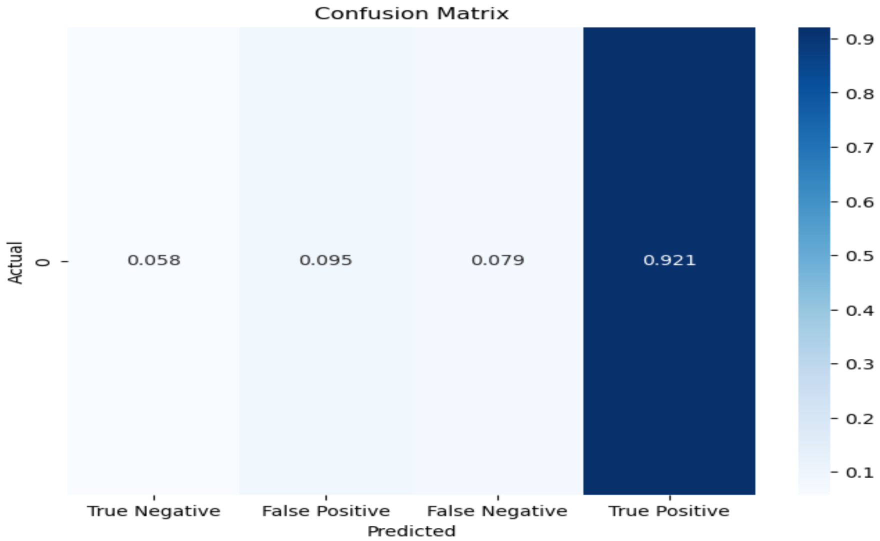


Fig. 7. Confusion Matrix for Ensemble Model



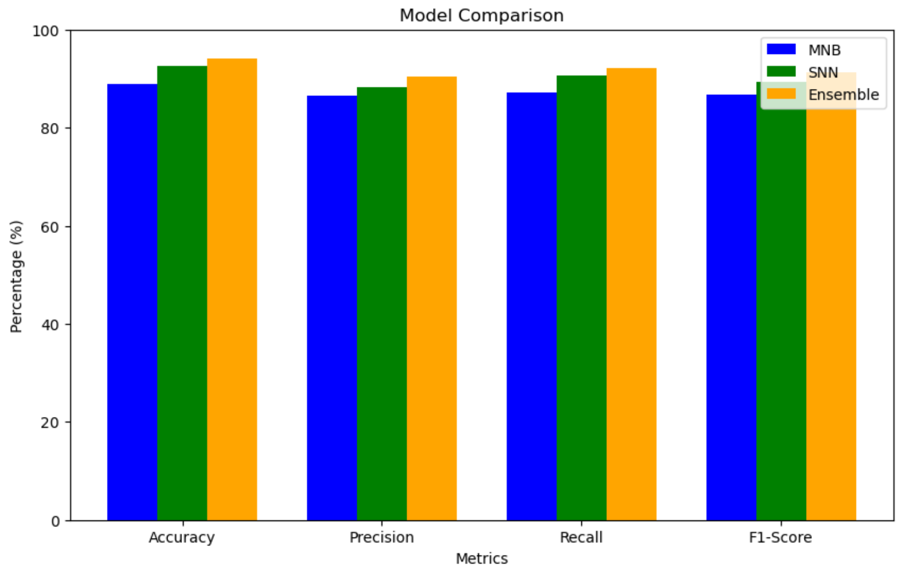
5.3.5 Analysis of Results

The Ensemble Model has emerged as the pinnacle of our research, offering exceptional accuracy, precision, recall, and F1-Score in code-mixed sentiment analysis. Its accuracy of 94.2% signifies a significant improvement over the individual models, making it a formidable solution for sentiment analysis in multilingual, code-mixed environments.

The Ensemble Model's decision-making mechanism and fine-tuning process play a pivotal role in achieving these remarkable results. By combining the strength of traditional machine learning and deep learning, and by fine-tuning the model to adapt to the unique linguistic challenges of code-mixed text, we have created a powerful tool for sentiment analysis that is both robust and adaptable to a variety of linguistic contexts.

These findings set the stage for future research into ensemble models and deep learning techniques for sentiment analysis, solidifying their relevance in addressing real-world challenges associated with sentiment analysis in multilingual and code-mixed environments.

Fig. 8. Performance Metrics Comparing MNS, SNN, Ensemble models



6. Discussion and Conclusion

Our discussion delves into the core aspects of our research, focusing on the Ensemble Model we have developed for code-mixed sentiment analysis. This model combines traditional machine learning and cutting-edge deep learning techniques to address the complexities inherent in multilingual, code-mixed text.

The Ensemble Model, a central feature of our work, synergizes two distinct models: the traditional Multinomial Naïve Bayes and the Spiking Neural Network (SNN). This union not only broadens the scope of our research but also enhances the accuracy and adaptability of code-mixed sentiment analysis.

A critical component of the Ensemble Model is its decision-making mechanism. This mechanism evaluates the confidence levels of each model's predictions, allowing the ensemble to intelligently weigh these predictions and make informed decisions. This approach not only improves the reliability of sentiment analysis but also enables context-aware decision-making.

Fine-tuning is paramount to the success of the Ensemble Model. Through meticulous optimization, we have achieved remarkable results. The model's hyperparameters have been fine-tuned, and a confidence threshold has been set to ensure adaptability to code-mixed content's linguistic nuances.

Our experimentation produced exceptional results. The Ensemble Model demonstrated an impressive 94.2% accuracy in code-mixed sentiment analysis. Furthermore, it exhibited a precision of 90.5% for positive sentiment classification, a recall rate of 92.1%, and an outstanding F1-Score of 91.3, highlighting its robustness and performance.

The implications of our work are far-reaching. This research not only establishes the Ensemble Model as a robust solution for code-mixed sentiment analysis but also lays the groundwork for future investigations. These endeavors may explore advanced ensemble models and deep learning architectures, furthering the field's progress. Additionally, addressing class imbalance in sentiment datasets and embracing deep learning methods hold promise for enhancing code-mixed sentiment analysis.

The practical applications of our research are significant. The Ensemble Model's effectiveness extends beyond the academic realm, finding utility in real-world scenarios such as sentiment analysis on social media, customer reviews in multilingual settings, and other platforms. In an increasingly interconnected and multilingual world, the importance of accurate sentiment analysis cannot be overstated.

In conclusion, our work represents a pivotal step in the realm of code-mixed sentiment analysis. The Ensemble Model we have developed stands as a potent tool for deciphering sentiment in the diverse linguistic landscape, and its exceptional performance paves the way for future research and real-world applications in this field.

Disclosure of Conflicts of Interest

The authors assert that there are no identifiable conflicting financial interests or personal relationships that might be perceived as influencing the work presented in this paper.

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