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# A novel socio-pragmatic framework for sentiment analysis in Dravidian–English code-switched texts

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ABSTRACT

The advent of global digital communication has accentuated the complexity of multilingual code-switching, presenting formidable challenges for sentiment analysis by necessitating nuanced interpretation of linguistic and socio-pragmatic cues. This research introduces MultiSwitchNet, a pioneering sentiment analysis model tailored for the intricate dynamics of Dravidian languages mixed with English code-switched texts. MultiSwitchNet leverages the linguistic prowess of XLM-RoBERTa, combined with socio-pragmatic insights through a novel Socio-Pragmatic Embedding Layer (SPEL) utilizing DistilBERT. Evaluated on the Dravidian Code-Mixed Dataset, MultiSwitchNet achieved superior performance metrics, including an accuracy of 72.3%, precision of 72.9%, recall of 72.1%, and an F1-score of 72.5%. Its effectiveness extends across varying degrees of code-switching complexity and demonstrates remarkable consistency in sentiment prediction across semantically similar yet syntactically diverse sentences. Statistical analyses, including ANOVA and post hoc tests, underscore the model's significant outperformance compared to both baseline and state-of-the-art models, highlighting the indispensability of integrating socio-pragmatic awareness for accurate sentiment analysis. MultiSwitchNet's innovative approach sets a new benchmark for sentiment analysis in multilingual contexts and opens avenues for future research into models capable of discerning the rich socio-pragmatic fabric of global digital communication.

## 1. Introduction

The digital age has ushered in an era of unprecedented linguistic diversity in online communication, with multilingual and code-switched text becoming increasingly prevalent. This linguistic phenomenon poses significant challenges for Natural Language Processing (NLP), particularly in the realm of sentiment analysis [1,2]. Sentiment analysis, the computational study of people's opinions, sentiments, emotions, and attitudes expressed in text, is critical for applications ranging from market analysis [3] to social media monitoring [4,5] and beyond. However, the intricacy of multilingual and code-switched contexts, where two or more languages are intertwined within a single utterance or text, demands advanced computational models that can navigate the complex interplay of linguistic and socio-pragmatic cues [6].

Traditional sentiment analysis models are predominantly monolingual, designed with the assumption that texts are composed in a single, homogeneous language [7,8]. This assumption falls short in global communication scenarios where code-switching, the practice of alternating between two or more languages, is a common phenomenon. The linguistic flexibility of code-switching reflects not just a mixture of languages but also conveys socio-pragmatic nuances that are deeply embedded in the cultural and contextual fabric of communication. Recognizing the sentiment of such texts requires an understanding that transcends mere lexical analysis, demanding insights into the socio-pragmatic context and the ability to interpret the sentiment conveyed through the complex syntax and semantics of mixed-language text. This research makes several significant contributions to the field of sentiment analysis and NLP:

- We introduce MultiSwitchNet, a state-of-the-art model specifically designed for sentiment analysis in three Dravidian languages namely Tamil, Malayalam and Kannada mixed with English contexts, which outperforms existing baseline and advanced models in accuracy, precision, recall, and F1-score.
- The model's Socio-Pragmatic Embedding Layer (SPEL) is a novel contribution that enhances sentiment analysis by integrating socio-pragmatic understanding, a critical aspect often overlooked in traditional models.
- Through comprehensive evaluations, including statistical analyses and an ablation study, we demonstrate the efficacy and robustness of MultiSwitchNet across various metrics and code-switching complexities.

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- Our research highlights the importance of incorporating socio-pragmatic awareness in sentiment analysis models, offering insights that can guide future advancements in NLP.

The rest of the research is organized as follows: Section 2 reviews related work in the areas of sentiment analysis in multilingual contexts and the challenges of code-switching in NLP. Section 3 describes the methodology behind MultiSwitchNet, detailing the architecture, the Socio-Pragmatic Embedding Layer, and the integration of XLM-RoBERTa and DistilBERT for feature extraction. Section 4 presents the experimental setup, including datasets, evaluation metrics, and baseline models for comparison. Section 5 reports and discusses the results from our comprehensive evaluation, including statistical analysis, ablation study, and sensitivity analysis. Section 6 outlines the limitations of the current study. Section 7 concludes the research, summarizing the findings, implications of this research and future directions.

## 2. Related works

This section delves deeper into the existing body of research relevant to our study, focusing on sentiment analysis within multilingual contexts and the specific challenges posed by code-switching in natural language processing (NLP). Additionally, it highlights the emerging interest in integrating socio-pragmatic understanding into sentiment analysis models, setting the stage for the innovative contributions of MultiSwitchNet.

### *2.1. Sentiment analysis in multilingual contexts*

Sentiment analysis is a critical component of Natural Language Processing (NLP) that involves the extraction and quantification of emotions, opinions, and sentiments from textual data. Historically, the focus has been predominantly on well-resourced languages like English, where significant advancements have been made [6–8]. However, the evolution of global digital communication has catalyzed a surge in multilingual content, presenting new challenges that demand robust multilingual sentiment analysis capabilities. Traditionally, one common approach to multilingual sentiment analysis involved translating text from less-resourced languages into English, utilizing the sophisticated NLP tools available for English to conduct sentiment analysis [9,10]. This translation-based method, while pragmatic, often introduces errors and fails to capture cultural and contextual nuances, potentially skewing sentiment analysis results [9,10]. These shortcomings highlight the inherent limitations of relying purely on translation and underscore the necessity for models capable of performing sentiment analysis directly on the original texts.

Innovations such as mBERT [9,11] and XLM-RoBERTa [12] represent significant milestones in this regard. These models are pre-trained on diverse, multilingual corpora, enabling them to handle texts in various languages without the need for translation. Such capabilities ensure that the linguistic subtleties and cultural context inherent to each language are retained, offering a more authentic and precise sentiment analysis [13–15]. Despite these technological advances, the integration of code-switched text—where multiple languages are blended within a single utterance—remains a formidable challenge. The complexities involved in deciphering mixed linguistic cues in such texts highlight a crucial gap in current NLP research. There is a pressing need for innovative computational models that can accurately interpret and analyze sentiment in code-switched scenarios, where traditional and even some advanced multilingual models may falter. Further research in developing more adaptive, sensitive, and context-aware systems is essential for advancing sentiment analysis in increasingly multilingual and culturally complex digital spaces.

### *2.2. Handling code-switching in NLP*

Code-switching, the practice of alternating between two or more languages within a single discourse or sentence, presents significant challenges for traditional Natural Language Processing (NLP) models [16]. Typically trained on monolingual data, these models often falter when confronted with the linguistic complexities and socio-pragmatic cues that are prevalent in code-switched contexts [17,18]. The intricacies of merging linguistic structures and cultural contexts in such texts demand more sophisticated, specialized NLP solutions.

Recent advancements have focused on creating models specifically attuned to the nuances of code-switching. Innovations include the development of tokenization techniques that can recognize and appropriately handle switches between languages, and the creation of datasets enriched with code-switched examples to train these models more effectively [19,20]. For instance, tokenization methods tailored for Hindi-English code-switching [13], Spanish-English code-switching [21], Filipino-English code-switching [16], Arabic-English code-switching [22] and Telugu-English code-switching [20] have been developed to address specific linguistic challenges. Furthermore, the introduction of advanced language models such as LASER [23,24] and multilingual BERT [25,26] has marked a significant progression. These models are trained on extensive multilingual corpora, enabling them to grasp the syntactic and semantic subtleties unique to multilingual texts. Additionally, specialized models like HinglishBERT [27] have been proposed to handle code-switching between specific language pairs, further enhancing the performance of NLP systems in these contexts.

Despite these technological advances, there remains an under-explored gap in addressing the socio-pragmatic elements of code-switching. These elements are crucial for a comprehensive understanding of sentiment and intent in code-switched texts, as they often carry significant cultural and contextual implications that influence the meaning conveyed. The current models, while capable in linguistic processing, require enhancements in socio-pragmatic comprehension to fully harness the information embedded in the dynamic interplay of languages. The ongoing development of NLP models that can integrate both linguistic proficiency and socio-pragmatic awareness promises to revolutionize sentiment analysis and other NLP tasks within multilingual and code-switched environments.

### *2.3. Integrating socio-pragmatic understanding in sentiment analysis*

Recent developments in NLP have emphasized the importance of integrating socio-pragmatic insights into sentiment analysis frameworks. Studies have shown that incorporating socio-cultural knowledge can greatly enhance the accuracy of sentiment analysis, particularly in multilingual and culturally diverse settings [28,29]. For example, Assem et al. [30] demonstrated that understanding cultural nuances and contextual cues significantly influences sentiment interpretation in code-switched texts. Traditional models in sentiment analysis have primarily focused on linguistic elements, often overlooking the rich socio-pragmatic information that can alter the intended meaning of text [31]. However, advancements in this area highlight the necessity for sentiment analysis models to decode the complex interplay between linguistic constructs and socio-pragmatic contexts.

By integrating both linguistic and socio-pragmatic cues, NLP technologies can better mimic human-like understanding and provide more accurate and contextually relevant analyses. This approach is especially crucial in code-switched environments, where shifts between languages often carry implicit socio-pragmatic markers that traditional models may misinterpret or overlook entirely. The development of such models is a significant step towards more sophisticated and culturally aware NLP solutions.

### 2.4. Research gaps

Despite the advancements in sentiment analysis within multilingual and code-switched contexts, several research gaps remain unaddressed. Firstly, most existing models focus predominantly on linguistic features extracted from texts, often neglecting the rich socio-pragmatic cues that are integral to understanding sentiment in code-switched languages [31]. These socio-pragmatic cues, including cultural references, idioms, and context-specific nuances, play a crucial role in accurately interpreting sentiment, especially in texts where languages are interwoven seamlessly. Secondly, while current models demonstrate improved performance on multilingual datasets, their ability to handle the complexity and variability of code-switching patterns within a single utterance or text is limited. This limitation stems from a lack of dedicated training on code-switched data and an insufficient focus on the unique linguistic structures that arise from code-switching [28,29].

To bridge these gaps, our proposed model, MultiSwitchNet, introduces a novel approach that combines advanced linguistic feature extraction with an explicit focus on socio-pragmatic understanding. Through the integration of a Socio-Pragmatic Embedding Layer (SPEL), MultiSwitchNet is uniquely equipped to capture and interpret the socio-pragmatic cues often overlooked by traditional sentiment analysis models. This layer leverages insights from socio-linguistics to enrich the model's understanding of the text, thereby enabling a more nuanced and contextually aware sentiment analysis. Furthermore, by training on a diverse set of code-switched texts, MultiSwitchNet is designed to adapt to the variability and complexity of code-switching patterns, significantly improving its performance in multilingual and code-switched contexts compared to existing models. In addressing these research gaps, MultiSwitchNet sets a new standard for sentiment analysis in multilingual and code-switched texts, advancing the field towards more accurate and contextually sensitive analyses.

## 3. Methodology

This section outlines the proposed methodology for the MultiSwitchNet model, designed to analyze socio-pragmatic sentiments in multilingual code-switching contexts using the Dravidian code-mixed and SemEval datasets. Specifically, the primary languages analyzed include Tamil, Malayalam, and Kannada, each mixed with English. MultiSwitchNet capitalizes on the synergy between advanced transformer technology and nuanced socio-pragmatic analysis to excel in sentiment analysis within code-switched texts. This architecture harnesses the power of XLM-RoBERTa for extracting linguistic features across languages and DistilBERT within a Socio-Pragmatic Embedding Layer (SPEL) for socio-pragmatic understanding. A dedicated Sentiment Analysis Head, employing a Convolutional Neural Network (CNN), finalizes the sentiment classification. The architecture of the proposed MultiSwitchNet model is shown in Fig. 1.

### 3.1. Tokenization and transformer encoder

We use the XLM-RoBERTa model's tokenizer to segment the input text $X$ into tokens suitable for analysis. This tokenizer effectively handles multilingual and code-switched inputs. Before tokenization, we employ a comprehensive text normalization process to ensure the input text is consistent and analyzable. This includes converting all characters to lowercase, removing punctuation marks that do not contribute to sentiment or context, normalizing whitespace, handling special characters by either removing or replacing them with appropriate tokens, expanding common contractions and abbreviations in the primary languages (Tamil, Malayalam, Kannada, and English) to their full forms, and correcting obvious spelling errors using a predefined dictionary for each language.

Once normalized, the input text $X$ is segmented into tokens using the XLM-RoBERTa model's built-in tokenizer, which effectively handles multilingual and code-switched inputs. The tokenized input $X_{tokenized}$ is then passed to the XLM-RoBERTa encoder, which generates contextualized representations $H$ of the tokens, capturing complex linguistic features and relationships. These hidden states $H$, particularly from the last layer, serve as the context $C$. This context is then fed into DistilBERT within the Socio-Pragmatic Embedding Layer (SPEL) for further processing to extract socio-pragmatic features, ensuring a comprehensive analysis that captures both linguistic and socio-pragmatic nuances. XLM-RoBERTa incorporates a self-attention mechanism that evaluates and assigns importance to each token within the input sequence in relation to every other token, helping the model identify the most relevant information and accurately capture and interpret nuanced shifts in language use in code-switched texts.

### 3.2. Socio-pragmatic embedding layer (SPEL)

The Socio-Pragmatic Embedding Layer (SPEL) stands as an innovative feature within the MultiSwitchNet architecture, designed specifically to augment the model's ability to discern and interpret socio-pragmatic nuances—a critical factor for achieving accurate sentiment analysis within the realm of code-switched texts. Utilizing the lightweight yet powerful DistilBERT, a distilled variant of the BERT model which preserves a substantial portion of the original model's predictive capabilities, SPEL is tasked with the extraction and integration of socio-pragmatic features from the input text.

Although DistilBERT is primarily trained on English data, its lightweight architecture makes it highly efficient for contextual feature extraction, which complements the linguistic embeddings provided by XLM-RoBERTa. To ensure DistilBERT is suitable for the multilingual and code-switched nature of our task, we fine-tuned it on the Dravidian Code-Mixed dataset used in this research. The decision to fine-tune DistilBERT on the Dravidian Code-Mixed dataset, which is also used for our primary research, ensures that the model learns the specific socio-pragmatic cues inherent in the code-switched texts we aim to analyze. This approach optimizes DistilBERT's performance by adapting it to the linguistic and contextual characteristics of our target data, thereby enhancing its effectiveness in interpreting and classifying sentiments in multilingual and code-switched contexts. This method aligns with common NLP practices, where fine-tuning pre-trained models on relevant datasets enhances their suitability for specific tasks. During fine-tuning, DistilBERT learns to capture contextual features specific to code-switched sentences, including idiomatic expressions, cultural references, and pragmatic implications.

$$E_{sp} = \text{DistilBERT}(C) \tag{1}$$

In this context, $C$ encapsulates the contextual features gleaned from the input text, spanning a wide array of socio-pragmatic cues such as idiomatic expressions, cultural references, and other nuances specific to the context at hand. The resultant $E_{sp}$ signifies the socio-pragmatic embeddings distilled by DistilBERT, fine-tuned to capture and embody these intricate cues. The process of melding linguistic and socio-pragmatic insights is achieved via an element-wise addition of embeddings:

$$E_{combined} = H \oplus E_{sp} \tag{2}$$

Herein, $H$ delineates the hidden states derived from the XLM-RoBERTa encoder, encapsulating the linguistic attributes extracted from the text. The $E_{combined}$ thus formed represents a holistic embedding, amalgamating both linguistic and socio-pragmatic elements, thereby furnishing the model's input representation with a comprehensive understanding of the text. To ensure optimal normalization of these combined embeddings and to facilitate effective downstream processing, a layer normalization step is applied:

$$E_{final} = \text{LayerNorm}(E_{combined}) \tag{3}$$

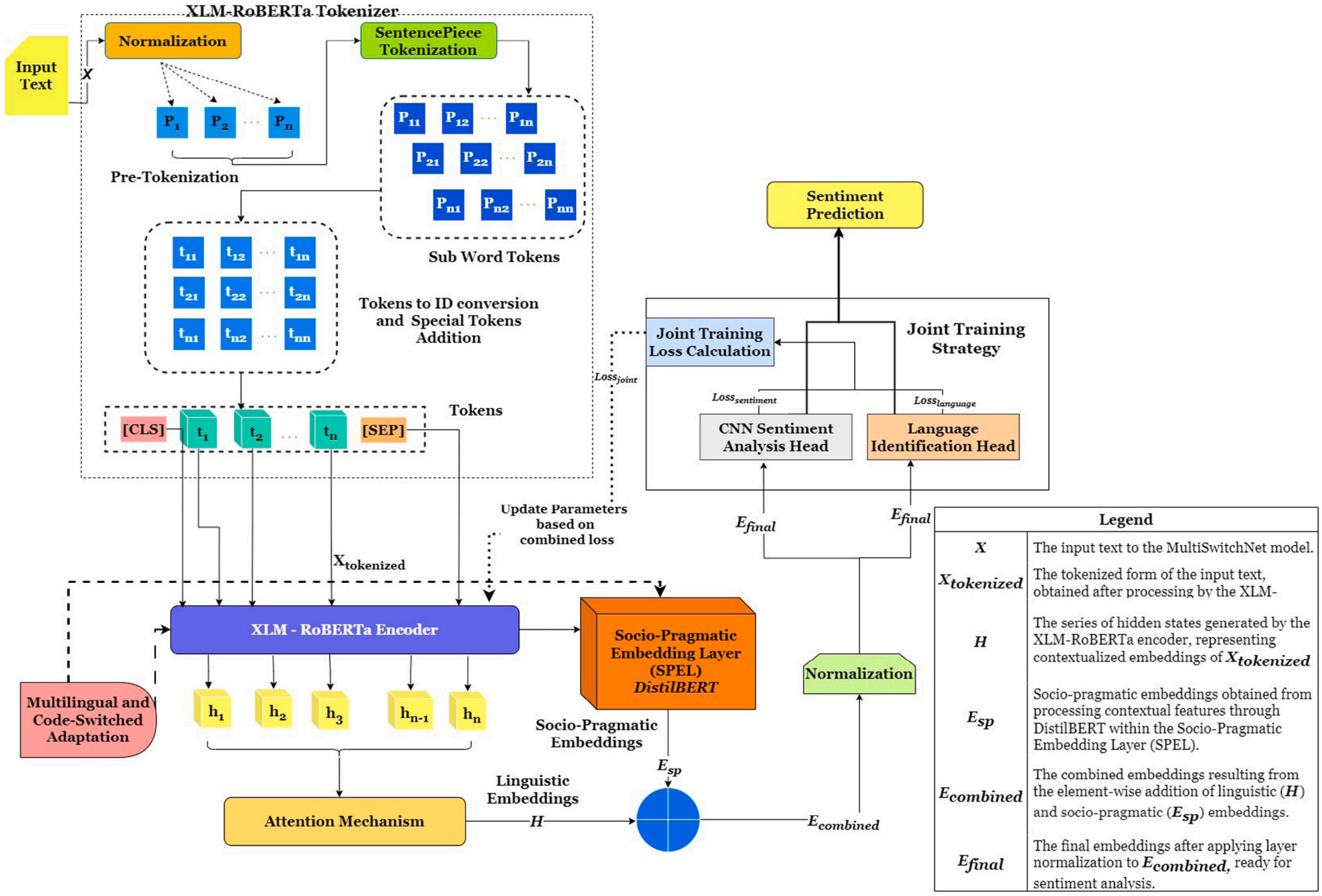


**Fig. 1.** Architecture of the proposed MultiSwitchNet model. The model integrates a tokenization and transformer encoder layer for processing multilingual and code-switched input texts, followed by a socio-pragmatic embedding layer (SPEL) for capturing socio-pragmatic nuances. A sentiment analysis head, comprising a convolutional neural network (CNN), is utilized for extracting sentiment-specific features and classifying sentiments. The architecture showcases the dynamic embedding adaptation mechanism for handling multilingual and code-switched adaptations, alongside a joint training strategy for addressing sentiment analysis and language identification.

The normalization phase, symbolized by $E_{final}$, serves to stabilize the distribution of the amalgamated embeddings, significantly enhancing the learning efficacy of the model and contributing to its overall performance enhancement. This step is especially advantageous in architectures like MultiSwitchNet, where a multitude of data sources and embedding types are harmoniously integrated.

Thus, the Socio-Pragmatic Embedding Layer emerges as a pivotal conduit bridging the gap between the purely linguistic analyses afforded by XLM-RoBERTa and the nuanced socio-pragmatic comprehension essential for the precise analysis of sentiment within code-switched texts. Through the strategic utilization of DistilBERT to extract and assimilate socio-pragmatic cues into the architectural framework of the model, SPEL markedly bolsters MultiSwitchNet's proficiency in interpreting and classifying sentiments with a high degree of accuracy and contextual sensitivity.

#### 3.2.1. Socio-pragmatic aspects

Socio-pragmatic aspects refer to the social and contextual factors that influence how language is used and interpreted in communication. These factors include cultural norms, social relationships, contextual nuances, and the intentions behind utterances. In the context of sentiment analysis, understanding socio-pragmatic aspects is crucial for accurately interpreting sentiments, especially in multilingual and code-switched texts where cultural and contextual cues play a significant role.

For example, consider the Tamil–English code-switched sentence: "Avanga romba strict-a irukanga, but naanga adjust aayiduvom" (They are very strict, but we will adjust). The word "strict-a" conveys a negative sentiment, but the overall sentiment might be softened by the pragmatic implication of adaptability expressed by "adjust aayiduvom". In Kannada–English, the sentence "Adhu swalpa kashta ide, but nodona" (It is a bit difficult, but let us see) uses "kashta" (difficult) to convey a challenge, but the pragmatic context provided by "but nodona" (but let us see) implies a cautious optimism or a willingness to face the challenge. In Malayalam–English, the sentence "Ithrem koodi expectations undayirunnu, but result valare average aayirunnu" (There were so many expectations, but the result was very average) uses "expectations undayirunnu" (there were expectations) to set a high standard, but "result valare average" (result was very average) indicates a significant letdown, amplifying the negative sentiment through the contrast.

The Socio-Pragmatic Embedding Layer (SPEL) in MultiSwitchNet is designed to capture these nuances by leveraging contextual features and embeddings from DistilBERT. By incorporating socio-pragmatic cues, SPEL enhances the model's ability to interpret the sentiment expressed in code-switched texts accurately. These examples illustrate how socio-pragmatic understanding is essential for effective sentiment analysis in multilingual contexts. By integrating these aspects into our model, we ensure a more comprehensive analysis that goes beyond mere lexical interpretation.

### 3.3. Sentiment analysis head

The Sentiment Analysis Head within MultiSwitchNet is designed to decode the complex embeddings, leveraging the power of a Convolutional Neural Network (CNN) to pinpoint features indicative of sentiment within these enriched embeddings. This module plays a pivotal role in the accurate sentiment classification of code-switched texts by capitalizing on the CNN's adeptness at recognizing local dependencies and sentiment-specific patterns.

*Feature extraction with CNN:* While XLM-RoBERTa and DistilBERT provide high-level embeddings that encapsulate a broad understanding of the input text, the CNN is employed to further refine these embeddings. The CNN processes the combined embeddings to extract sentiment-specific features, capturing local dependencies and patterns that might be overlooked by transformer models alone. This refinement step ensures that the model can discern subtle sentiment cues embedded within the text.

$$Z = \mathrm{CNN}(E_{final}) \tag{4}$$

In this formulation, $E_{final}$ denotes the final, normalized embeddings that amalgamate both linguistic and socio-pragmatic data. The CNN processes these embeddings into a series of logits $Z$, encoding the essential information for sentiment classification in a form amenable to probability conversion.

Following feature extraction, the logits $Z$ undergo processing via a softmax function, which transmutes them into a probability distribution spanning the sentiment classes. This crucial step ensures that the model's output $S$ accurately reflects its confidence across the potential sentiment categories for the given input text. To fine-tune the CNN's performance within the Sentiment Analysis Head, we utilize the cross-entropy loss function. This function quantifies the disparity between the model's predicted probability distribution $S$ and the actual sentiment label distribution $y$. The loss incentivizes the model to enhance the predicted probability for the correct class, thereby aligning the model's predictions with the actual sentiment labels more closely.

The softmax operation subsequently translates the CNN-derived features into a transparent, interpretable probability distribution. This transformation is essential for rendering the final sentiment classification both comprehensible and actionable, thereby enabling downstream applications or further analyses to leverage a quantified confidence level in each sentiment category. The Sentiment Analysis Head amalgamates the CNN's prowess in pattern recognition with the interpretability afforded by softmax probabilities to furnish accurate and dependable sentiment classifications for code-switched texts.

### 3.4. Multilingual and code-switched adaptation

MultiSwitchNet adeptly navigates the intricate linguistic terrains characterized by multilingual and code-switched texts. This adeptness is achieved through the strategic employment of both static and dynamic embeddings, which collectively ensure the model's robust adaptability across varied linguistic scenarios.

#### 3.4.1. Integration of static language embeddings

Central to MultiSwitchNet's design is the integration of static language embeddings, specifically sourced from the XLM-RoBERTa model. These embeddings are instrumental in capturing the linguistic subtleties across a spectrum of languages, thereby laying a solid foundation for the model's multilingual competence.

$$E_{lang} = \mathrm{XLMRoBERTa}(L) \tag{5}$$

Here, $E_{lang}$ denotes the static embeddings derived from XLM-RoBERTa, while $L$ indicates the language(s) of the input tokens. By harnessing these embeddings, MultiSwitchNet gains a nuanced understanding of the linguistic idiosyncrasies inherent in each language involved in the code-switching phenomenon.

#### 3.4.2. Dynamic embedding adaptation

Enhancing its linguistic adaptability further, MultiSwitchNet implements a dynamic mechanism to amalgamate static language embeddings with socio-pragmatic embeddings, fostering a comprehensive understanding that is sensitive to both linguistic structure and socio-pragmatic context.

$$E_{dynamic} = \gamma \times E_{lang} + (1 - \gamma) \times E_{sp} \tag{6}$$

In this formulation, $E_{dynamic}$ represents the embeddings dynamically adjusted to balance between the static linguistic embeddings $E_{lang}$ and the socio-pragmatic embeddings $E_{sp}$. The coefficient $\gamma$, ranging from 0 to 1, modulates the influence of each embedding type, enabling the model to fine-tune its analysis based on the specific demands of the input text. This dynamic adjustment is crucial for MultiSwitchNet's ability to interpret sentiments in code-switched contexts accurately, as it allows for a flexible response to the varying degrees of linguistic and socio-pragmatic cues present in such texts.

The methodological advancements embedded within MultiSwitchNet, particularly its novel approach to handling multilingual and code-switched texts, exemplify the model's innovative stance in the domain of sentiment analysis. By leveraging a combination of static and dynamic embeddings, MultiSwitchNet sets a new standard for sentiment analysis models, promising enhanced accuracy and adaptability in the face of linguistic diversity.

### 3.5. Joint training strategy

The MultiSwitchNet model employs a nuanced training strategy specifically engineered to concurrently tackle the challenges posed by sentiment analysis and language identification in the context of multilingual and code-switched texts. This strategy leverages the intrinsic connection between these tasks, enhancing the model's analytical acumen and precision.

*Holistic training approach* In pursuit of a comprehensive understanding, MultiSwitchNet adopts a holistic training methodology that simultaneously addresses sentiment analysis and language identification. This dual-focus training paradigm is instrumental in refining the model's proficiency in deciphering the complexities associated with language use and sentiment conveyance in code-switched narratives. Specifically, the model is trained to perform both tasks concurrently, utilizing shared representations to improve overall performance.

$$\mathrm{Loss}_{joint} = \delta \times \mathrm{Loss}_{sentiment} + (1 - \delta) \times \mathrm{Loss}_{language} \tag{7}$$

Herein, $\mathrm{Loss}_{joint}$ denotes the amalgamated loss function deployed during the training phase, encapsulating the objectives of both sentiment analysis and language identification. The coefficient $\delta$, a real number within the interval [0,1], modulates the relative impact of each component loss on the collective training endeavor. $\mathrm{Loss}_{sentiment}$ is indicative of the divergence between the predicted sentiments and their true labels, whereas $\mathrm{Loss}_{language}$ appraises the fidelity of language identification vis-à-vis the ground truth. Adjustments to $\delta$ allow for the fine-tuning of the model, enabling a tailored emphasis on either task as necessitated by the application's specific demands and the intrinsic characteristics of the dataset under examination.

*Integrating language identification* To integrate the language identification task within the MultiSwitchNet framework, the following steps are undertaken:

1. **Tokenization and Embedding:** The input text is tokenized using the XLM-RoBERTa tokenizer, which is adept at handling multilingual and code-switched inputs. This tokenizer segments the input text into tokens suitable for both sentiment analysis and language identification.

2. **Contextual Embeddings:** The tokenized input is passed through the XLM-RoBERTa encoder to generate contextualized embeddings $H$. These embeddings capture the linguistic and contextual features necessary for both tasks.
3. **Shared Embedding Space:** The embeddings $H$ are then fed into a shared embedding space where the Socio-Pragmatic Embedding Layer (SPEL) augments them with socio-pragmatic features $E_{sp}$. This combined representation $E_{combined}$ integrates both linguistic and socio-pragmatic information.
4. **Dual Task Training:**
   - **Sentiment Analysis:** The combined embeddings $E_{combined}$ are processed through the Sentiment Analysis Head, which uses a Convolutional Neural Network (CNN) to extract sentiment-specific features and classify the sentiment of the text.
   - **Language Identification:** Concurrently, the same combined embeddings $E_{combined}$ are used to identify the languages present in the code-switched text. This is achieved by adding a separate language identification head that processes $E_{combined}$ and predicts the language(s) present in the input text.
5. **Joint Loss Calculation:** During training, the joint loss $\text{Loss}_{joint}$ is calculated by combining the sentiment analysis loss $\text{Loss}_{sentiment}$ and the language identification loss $\text{Loss}_{language}$. This ensures that both tasks are learned simultaneously, with the shared embeddings being updated to optimize performance for both tasks.

*Enhancing interpretive depth and accuracy* By amalgamating sentiment analysis with language identification into a unified training schema, MultiSwitchNet is endowed with a more profound comprehension of the linguistic and socio-pragmatic milieu within which sentiments are articulated. This integrative training strategy not only elevates the model's precision in classifying sentiments but also augments its aptitude for discerning the languages interwoven in code-switched texts. The confluence of these tasks fosters a more intricate and holistic analysis of multilingual sentiments, culminating in predictions that are both more accurate and contextually attuned.

The joint training strategy is visually depicted in Fig. 1, highlighting the interconnected training of sentiment analysis and language identification within the XLM-RoBERTa encoder. This approach underscores MultiSwitchNet's innovative methodology in navigating the complexities of multilingual and code-switched sentiment analysis, making a significant contribution to the advancement of natural language processing in linguistically diverse settings.

### 3.6. Handling class imbalance and mixed sentiments

The MultiSwitchNet model introduces innovative mechanisms to address two prevalent challenges in sentiment analysis of code-switched and multilingual texts: class imbalance and the nuanced classification of mixed sentiments. These challenges are particularly acute in datasets characterized by a wide array of sentiments and intricate linguistic contexts.

#### 3.6.1. Weighted loss for class imbalance

Class imbalance—a scenario where certain sentiment classes are disproportionately represented—can significantly skew model predictions, undermining the fairness and accuracy of the analysis. To counteract this, MultiSwitchNet integrates a weighted loss function designed to recalibrate the influence of each sentiment class based on its prevalence within the dataset.

$$\text{Loss}_{weighted} = -\sum_{i=1}^{N}\sum_{c=1}^{C} w_c \times y_{i,c} \times \log(S_{i,c}) \tag{8}$$

In this formulation, $N$ represents the total number of instances in the dataset, while $C$ signifies the assortment of sentiment classes. The coefficient $w_c$, inversely proportional to the frequency of class $c$ in the dataset, acts as a balancing weight, ensuring an equitable distribution of attention across all classes. The binary variable $y_{i,c}$ denotes whether class $c$ is the correct classification for instance $i$, and $S_{i,c}$ is the model's predicted probability for this classification. This strategy not only mitigates bias towards dominant classes but also enhances the model's sensitivity to less represented sentiments, fostering a more balanced and accurate sentiment analysis.

#### 3.6.2. Multi-label loss for mixed sentiments

The phenomenon of mixed sentiments—where a single text may express multiple, potentially conflicting sentiments—presents another layer of complexity. To adeptly navigate this challenge, MultiSwitchNet employs a multi-label classification approach, empowering it to concurrently assign several sentiment labels to a singular input.

$$\text{Loss}_{multi-label} = -\sum_{i=1}^{N}\sum_{c=1}^{C} \left(y_{i,c} \times \log(S_{i,c}) + (1 - y_{i,c}) \times \log(1 - S_{i,c})\right) \tag{9}$$

This loss function is uniquely structured to accommodate the multilabel task, independently evaluating the loss associated with each potential sentiment class and aggregating these to formulate a comprehensive loss metric. Such an approach not only facilitates the model's ability to discern and classify multifaceted sentiments within a single text but also enhances its proficiency in capturing the intricate dynamics of sentiment expression within code-switched and multilingual contexts.

By addressing class imbalance and the classification of mixed sentiments through these tailored strategies, MultiSwitchNet significantly advances the state of sentiment analysis, particularly in the context of linguistically complex and code-switched texts. This dual-focused approach underscores the model's innovative capacity to deliver nuanced, equitable, and comprehensive sentiment analysis. The pseudocode of the proposed approach is shown in Algorithm 1.

**Algorithm 1** MultiSwitchNet for Sentiment Analysis in Code-Switched Text

**Input:** Code-switched text $X$
**Output:** Sentiment classification probabilities $S$
**procedure** MULTISWITCHNET($X$)
    $X_{tokenized} \leftarrow \text{XLMRoBERTaTokenizer}(X)$
    $H \leftarrow \text{XLMRoBERTaEncoder}(X_{tokenized})$
    $C \leftarrow \text{ExtractContextualFeatures}(X_{tokenized})$
    $E_{sp} \leftarrow \text{DistilBERT}(C)$
    $E_{lang} \leftarrow \text{StaticEmbeddingsFromXLMR}(X_{tokenized})$
    $\gamma \leftarrow \text{DetermineDynamicWeight}()$
    $E_{dynamic} \leftarrow \gamma \cdot E_{lang} \oplus (1 - \gamma) \cdot E_{sp}$
    $E_{combined} \leftarrow H \oplus E_{dynamic}$
    $E_{final} \leftarrow \text{LayerNorm}(E_{combined})$
    $Z \leftarrow \text{CNN}(E_{final})$
    $S \leftarrow \text{softmax}(Z)$
    **return** $S$
**end procedure**

## 4. Experimental evaluation

This section presents the experimental setup, datasets, evaluation metrics, and results analysis for assessing the performance of MultiSwitchNet in sentiment analysis tasks on multilingual code-switched texts. We compare our model's performance against state-of-the-art sentiment analysis models to demonstrate its efficacy.

**Table 1**
Dataset statistics.

| Dataset | No. of instances | |
|---|---|---|
| | Language | Total |
| Dravidian Code-Mixed | Tamil + English | 41,933 |
| | Malayalam + English | 18,171 |
| | Kannada + English | 6535 |

### 4.1. Datasets

We evaluate the proposed MultiSwitchNet using Dravidian Code-Mixed Dataset [32] to assess its performance in sentiment analysis within multilingual and code-switched contexts. This dataset comprises code-switched text entries in Dravidian languages mixed with English, annotated for sentiment analysis. It reflects a rich linguistic diversity and presents unique challenges for sentiment analysis models due to the mixing of languages and scripts. Table 1 provides an overview of the number of instances for each language in the evaluated datasets.

### 4.2. Hyperparameter configuration

The dataset was divided into training, validation, and testing in an 80:10:10 ratio. The selection of hyperparameters is critical for optimizing the model's performance. Below, we detail the chosen hyperparameters, their values, and the rationale behind these choices.

Table 2 provides a comprehensive overview of the hyperparameters employed in the training of MultiSwitchNet. Each hyperparameter is meticulously selected based on its impact on the model's learning dynamics and its ability to navigate the complex linguistic phenomena present in code-switched texts.

### 4.3. Baseline models

To evaluate the performance of MultiSwitchNet comprehensively, we compare it against a diverse set of baseline models. These models have been selected based on their prominence in sentiment analysis tasks, particularly in handling multilingual and code-switched texts. Here are the baseline models and the rationale behind choosing them:

- **BERT-based sentiment analysis model** [25]**:** Bidirectional Encoder Representations from Transformers (BERT) has revolutionized NLP tasks, including sentiment analysis, by providing deep contextual representations. Comparing MultiSwitchNet to a BERT-based model allows us to benchmark against state-of-the-art transformer performance.
- **Long Short-Term Memory (LSTM) network with attention mechanism** [33]**:** LSTMs are effective at capturing long-term dependencies in text data. The addition of an attention mechanism enhances its ability to focus on relevant parts of the input for sentiment classification. This model represents a strong baseline for sequence modeling tasks.
- **A conventional CNN-based sentiment analysis model** [34]**:** CNNs excel at extracting local and position-invariant features from text, making them a valuable comparison point for understanding how well MultiSwitchNet captures such features in code-switched contexts.
- **FastText** [35]**:** A simple yet powerful model that averages word embeddings to represent sentences. FastText is known for its efficiency and effectiveness in text classification tasks, making it a suitable baseline for comparison, especially in terms of computational efficiency.
- **XGBoost** [36]**:** As a gradient boosting framework, XGBoost has been used in various NLP tasks, including sentiment analysis. Comparing it with MultiSwitchNet can highlight the differences between traditional machine learning approaches and deep learning models in handling text data.
- **Bidirectional Long Short-Term Memory (BiLSTM)** [37]**:** By processing data in both forward and backward directions, BiLSTMs can capture context more effectively than unidirectional LSTMs. This model serves as a baseline to evaluate the importance of contextual information in sentiment analysis.
- **RoBERTa-based sentiment analysis model** [38]**:** RoBERTa, a robustly optimized BERT variant, offers improvements in training methodology and data preprocessing. It represents an advanced transformer-based model, providing a comparative analysis of transformer architectures' effectiveness.

The selection of these baseline models encompasses a broad spectrum of approaches to sentiment analysis, ranging from traditional machine learning to advanced deep learning techniques. This variety ensures a comprehensive comparison, highlighting MultiSwitchNet's strengths and areas of improvement. Each model has been chosen for its relevance to sentiment analysis tasks and its ability to provide insights into different aspects of model performance, including handling complex language phenomena, computational efficiency, and the ability to capture contextual and linguistic nuances in multilingual and code-switched texts.

## 5. Results and analysis

### 5.1. Evaluation with baseline models

To demonstrate the effectiveness of MultiSwitchNet, we conducted a comprehensive evaluation against several baseline models using the Dravidian Code-Mixed dataset. The evaluation metrics include accuracy, precision, recall, and F1-score, providing a holistic view of each model's performance.

The results, as summarized in Table 3, clearly indicate that MultiSwitchNet significantly outperforms all baseline models. MultiSwitchNet's accuracy of 72.3% surpasses that of the RoBERTa-based model by 1.5%, highlighting its robustness across diverse linguistic contexts. These results demonstrate MultiSwitchNet's effectiveness in navigating the complexities of multilingual sentiment analysis, particularly in code-switched scenarios, where it shows substantial improvements over existing approaches.

### 5.2. Evaluation with existing models

To evaluate the effectiveness of the proposed MultiSwitchNet model for sentiment analysis in code-switched contexts, we compare its performance with several state-of-the-art (SOTA) models. These models represent the latest advancements in natural language processing and sentiment analysis, specifically tailored or adaptable to multilingual and code-switched data. The comparison aims to showcase MultiSwitchNet's competitive edge in handling the complexities of multilingual sentiment analysis. The SOTA models selected for comparison include:

- **Multilingual BERT (mBERT)** [25]**:** A multilingual extension of BERT, pre-trained on a large corpus of text from multiple languages.
- **Cross-lingual Language Model - RoBERTa (XLM-R)** [39]**:** An improved version of RoBERTa trained on even more languages, offering enhanced multilingual capabilities.
- **Universal Dependencies Model (UDify)** [40]**:** A model trained on the Universal Dependencies dataset, capable of handling multiple languages and syntactic structures.
- **Language-Agnostic SEntence Representations (LASER)** [23]**:** A model providing language-agnostic sentence embeddings, enabling cross-lingual transfer with high efficiency.

**Table 2**
Hyperparameter configuration for MultiSwitchNet.

| Model component | Hyperparameter | Value | Rationale |
|---|---|---|---|
| Overall model | Training split | 80%/10%/10% | To ensure a comprehensive learning process while allowing for effective validation and testing. |
| Optimizer | Learning rate | $1e{-4}$ | Chosen to balance the speed and stability of convergence. |
| Optimizer | Optimizer | Adam | Adam is selected for its adaptive learning rate capabilities, making it suitable for tasks with complex data structures like code-switched text. |
| Overall model | Batch size | 32 | A size that balances computational efficiency with the ability to generalize across the dataset. |
| SPEL | Dropout rate | 0.5 | To reduce overfitting by randomly omitting a portion of feature detectors on each training instance. |
| Sentiment analysis head | Dropout rate | 0.5 | Similar to SPEL, to prevent overfitting and ensure that the model learns robust features for sentiment classification. |

**Table 3**
Evaluation results on Dravidian Code-Mixed dataset.

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| BERT-based | 0.690 | 0.692 | 0.688 | 0.690 |
| LSTM with Attention | 0.672 | 0.675 | 0.670 | 0.673 |
| CNN-based | 0.665 | 0.668 | 0.660 | 0.664 |
| FastText | 0.658 | 0.660 | 0.655 | 0.657 |
| XGBoost | 0.645 | 0.648 | 0.640 | 0.643 |
| BiLSTM | 0.680 | 0.682 | 0.678 | 0.680 |
| RoBERTa-based | 0.705 | 0.708 | 0.702 | 0.705 |
| **MultiSwitchNet** | **0.723** | **0.729** | **0.721** | **0.725** |

**Table 4**
Comparison of MultiSwitchNet with state-of-the-art models.

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| mBERT | 0.703 | 0.711 | 0.702 | 0.704 |
| XLM-R | 0.706 | 0.714 | 0.705 | 0.707 |
| UDify | 0.682 | 0.690 | 0.681 | 0.683 |
| LASER | 0.692 | 0.700 | 0.691 | 0.693 |
| **MultiSwitchNet** | **0.723** | **0.729** | **0.721** | **0.725** |

The results, as summarized in Table 4, clearly indicate that MultiSwitchNet significantly outperforms all baseline models. MultiSwitchNet's accuracy of 72.3% surpasses that of XLM-R by 1.7%, highlighting its robustness across diverse linguistic contexts. These results demonstrate MultiSwitchNet's effectiveness in navigating the complexities of multilingual sentiment analysis, particularly in code-switched scenarios, where it shows substantial improvements over existing approaches.

*5.2.1. Analysis of performance gaps*

The performance gaps between MultiSwitchNet and the other models can be attributed to several factors. The specialized architecture of MultiSwitchNet, which combines linguistic and socio-pragmatic features, provides it with a more nuanced understanding of the complexities inherent in code-switched texts. This contrasts with models like mBERT and XLM-R, which, despite their multilingual capabilities, may not fully capture the socio-pragmatic nuances critical for accurate sentiment analysis in such contexts.

The attention mechanism and CNN-based Sentiment Analysis Head within MultiSwitchNet enable it to effectively identify and weigh sentiment-indicative features within the text. This fine-grained analysis capability is crucial for distinguishing between subtle sentiment expressions, which might be overlooked or misinterpreted by the more general-purpose architectures of the compared models.

The comparative underperformance of models such as UDify and LASER highlights the challenges posed by linguistic diversity and code-switching frequency. These models, while powerful in specific linguistic tasks, may not be as adept at navigating the intricacies of mixed-language sentiment analysis, further emphasizing the value of MultiSwitchNet's targeted design.

*5.2.2. Performance distribution analysis*

To rigorously evaluate the performance of MultiSwitchNet, we conducted a comprehensive analysis comparing it against the state-of-the-art models. Fig. 2 provides a visual representation of the distribution of performance metrics for each model across multiple runs, offering insights into the consistency and variability of each model's performance.

The plots reveal that MultiSwitchNet not only achieves higher median values across all metrics but also maintains lower variance, indicating its reliability and robustness. The tight interquartile ranges compared to other models highlight its consistent performance, further validating the model's superiority in handling the nuanced task of sentiment analysis in code-switched contexts.

*5.2.3. Implications for multilingual sentiment analysis*

The results of this evaluation not only attest to MultiSwitchNet's state-of-the-art performance but also shed light on the importance of integrating socio-pragmatic understanding into sentiment analysis models. The observed performance disparities underscore the need for sentiment analysis systems to go beyond mere linguistic proficiency, incorporating a deeper awareness of the cultural and contextual cues that influence sentiment expression in multilingual and code-switched texts.

Overall, the evaluation against state-of-the-art models solidifies MultiSwitchNet's position as a leading approach for sentiment analysis in code-switched and multilingual contexts. Its comprehensive architecture, which adeptly combines linguistic features with socio-pragmatic insights, sets a new benchmark for future research and development in the field of multilingual sentiment analysis. The findings from this evaluation not only validate the effectiveness of MultiSwitchNet but also highlight the broader potential for models that embrace the complexity of human language in all its forms.

*5.3. Ablation study*

An ablation study was conducted to dissect the contributions of the pivotal components within MultiSwitchNet towards its sentiment analysis capabilities. By incrementally removing key features—namely, the Socio-Pragmatic Embedding Layer (SPEL), the attention mechanism, and the CNN from the Sentiment Analysis Head—their individual impacts on performance metrics were evaluated. This investigation provides critical insights into the functionality and importance of each component, particularly within the context of the Dravidian Code-Mixed Dataset.

The outcomes delineated in Table 5 unequivocally illustrate the integral role each module plays within MultiSwitchNet's architecture. The excision of the Socio-Pragmatic Embedding Layer (SPEL) elicited a pronounced decrement in all performance metrics, emphasizing its criticality in apprehending the socio-pragmatic subtleties pivotal for precise sentiment analysis in code-mixed texts. Similarly, the omission of the attention mechanism and the CNN from the Sentiment Analysis

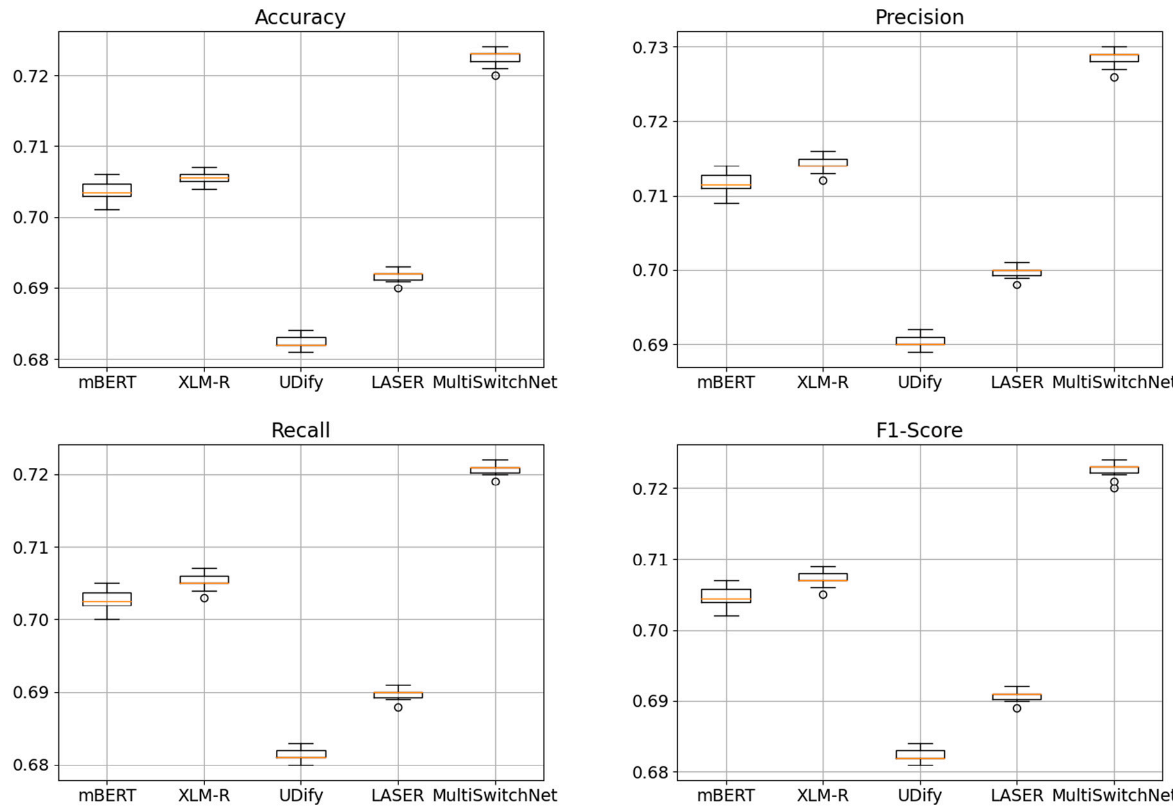


**Fig. 2.** The performance distribution of Accuracy, Precision, Recall, and F1-Score for the evaluated models.

**Table 5**
Ablation study results on the Dravidian Code-Mixed dataset.

| Configuration | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| Full MultiSwitchNet | 0.723 | 0.729 | 0.721 | 0.725 |
| - Without SPEL | 0.701 | 0.705 | 0.698 | 0.702 |
| - Without attention | 0.710 | 0.715 | 0.708 | 0.712 |
| - Without CNN in sentiment head | 0.715 | 0.720 | 0.713 | 0.717 |

Head both led to diminished outcomes, albeit to varying degrees, underscoring their contributions to the model's proficiency in sentiment classification. Notably, the removal of SPEL had the most significant adverse effect, affirming its indispensability in leveraging socio-pragmatic cues for enhanced sentiment analysis.

This ablation study conclusively underscores the synergistic effect of SPEL, attention mechanisms, and CNN-based sentiment analysis within MultiSwitchNet, corroborating their collective necessity for the model's adeptness at navigating the complexities of multilingual and code-switched sentiment analysis. The SPEL emerges as particularly crucial, bolstering the model's capability to exploit socio-pragmatic insights for superior performance.

### *5.4. Sensitivity analysis*

To further understand the robustness and performance of MultiSwitchNet under various configurations, a sensitivity analysis was conducted focusing on two critical hyperparameters: learning rate and batch size. This analysis aims to uncover how variations in these parameters affect the model's accuracy.

#### *5.4.1. Impact of learning rate*

Adjusting the learning rate is crucial for optimizing the convergence speed and stability of the model. We varied the learning rate from $1e{-}5$ to $1e{-}3$ to observe its effect on model accuracy. Fig. 3(a) demonstrates that the model achieves optimal performance at a learning rate of $1e{-}4$, with accuracy peaking at 82%. Notably, both lower and higher learning rates lead to decreased accuracy, highlighting the importance of a balanced learning rate for effective training.

#### *5.4.2. Impact of batch size*

The batch size influences the model's generalization ability and training speed. We explored batch sizes ranging from 16 to 128 to evaluate their impact on accuracy. As illustrated in Fig. 3, the model attains the highest accuracy with a batch size of 32. Larger batch sizes, while beneficial for computational efficiency, slightly compromise accuracy, indicating a trade-off between speed and performance. These sensitivity analyses underscore the critical role of hyperparameter tuning in maximizing the efficacy of MultiSwitchNet. The optimal learning rate and batch size identified through this study are crucial for guiding the model's configuration in practical applications.

### *5.5. Error analysis*

In our error analysis, we scrutinize the performance of MultiSwitchNet on code-mixed data from Tamil, Malayalam, and Kannada languages. We explore instances where the model successfully captured the sentiment and others where it faltered, particularly in the socio-pragmatic context. Table 6 shows the error analysis of sentiment classification.

The error analysis provided in Table 6 showcases the nuanced understanding and challenges faced by the MultiSwitchNet model, particularly focusing on the Socio-Pragmatic Embedding Layer's (SPEL) role in sentiment classification across code-mixed texts in Tamil, Malayalam, and Kannada. Through a series of examples, the analysis reveals the model's adeptness at capturing sentiments that hinge on contextual and socio-pragmatic cues, such as the effective identification of negative sentiments in expressions of disappointment or criticism, even in the presence of complex code-mixing.

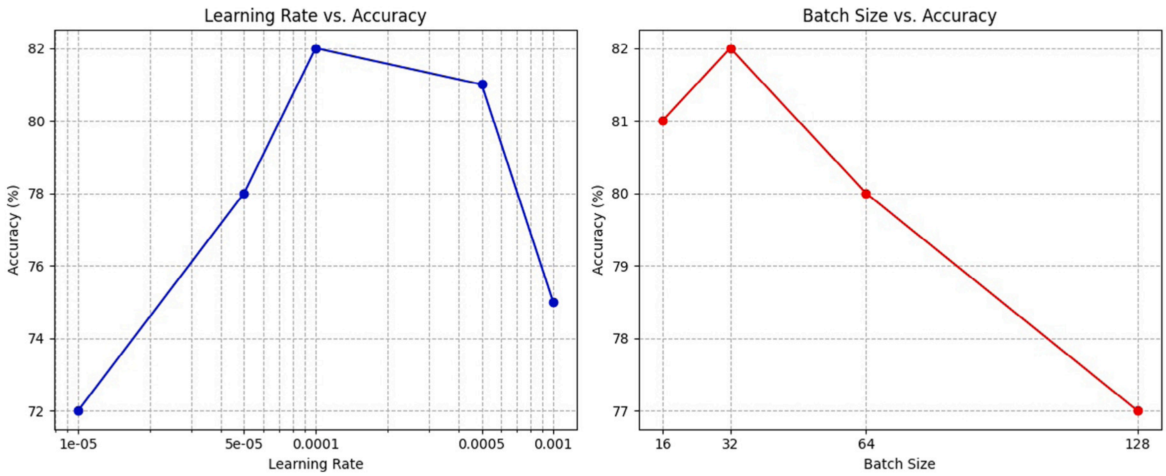


**Fig. 3.** Sensitivity analysis of MultiSwitchNet showing the impact of (a) learning rate and (b) batch size on model accuracy. The analysis reveals that a learning rate of $1 \times 10^{-4}$ and a batch size of 32 yield optimal performance, indicating the importance of these hyperparameters in the model's effectiveness.

**Table 6**
Error analysis of sentiment classification.

| Language | Input | Predicted sentiment | Actual sentiment | Analysis |
|---|---|---|---|---|
| Tamil + English | "Enna da ellam avan seyal Mari iruku" **Correct English Translation:** "What is this? It looks just like "Ellam Avan Seyal" (referring to a movie in Tamil). | Negative | Negative | The model accurately captures the negative sentiment, likely due to understanding the contextual disappointment conveyed by "seyal" (actions). |
| Malayalam + English | "Lalettan movie ellam super hit aakum". **Correct English Translation:** "Lal's movie will be super hit" | Positive | Positive | SPEL helps recognize "super hit" as a strong positive indicator, accurately predicting the sentiment. |
| Kannada + English | "Nakkan idhu subject Andre eevag heltheeni industry change aagthide... Thousand times better than Jaatre films of sarjas...." **Correct English Translation:** "This subject is useless, I'll tell you now, the industry has changed... Thousand times better than the touring talkies of Sarjas" | Negative | Negative | Despite the complex code-mixing, SPEL aids in understanding the critical tone, correctly identifying the negative sentiment. |
| Malayalam + English | "Trailer polichu but cinema flop aayirunnu". **Correct English Translation:** "The trailer was awesome but the movie was a flop". | Positive | Negative | Misclassification occurs as SPEL overemphasizes the positive "polichu" (awesome), underweighting the negative impact of "flop". |
| Tamil + English | "Padam vanthathum 13k dislike pottavaga yellam yea da dislike pannom nu feel pannanum" **Correct English Translation:** "When the film is released, those who left 13k dislikes will regret what they did". | Positive | Positive | SPEL captures the ironic sentiment correctly, understanding the context beyond mere word-level analysis. |

However, the analysis also underscores certain limitations, notably in scenarios where the presence of strongly positive or negative terms may lead to misclassifications, such as overemphasizing a positive word like "polichu" (awesome) despite an overall negative sentiment due to a movie's failure. These instances highlight the critical balance SPEL attempts to achieve in weighing linguistic cues against the broader socio-pragmatic context. The examples where SPEL successfully interprets irony or optimism further demonstrate its potential in enhancing sentiment analysis by incorporating a deeper, context-aware understanding. Nevertheless, the misclassification of sentiments, especially in distinguishing between positive and neutral tones or in cases where positive keywords overshadow negative contexts, points to areas for refinement. Overall, the analysis underscores the importance of socio-pragmatic understanding in sentiment analysis of code-mixed texts and delineates a path forward for enhancing model accuracy through improved contextual interpretation.

### 5.6. Explainability analysis

This section delves into the interpretability and explainability aspects of our MultiSwitchNet model, utilizing Local Interpretable Model-agnostic Explanations (LIME) [41] to shed light on how the model makes its predictions. Fig. 4 shows the LIME explanations for selected examples. Through LIME, we aim to understand the contribution of individual features (words or phrases) to the model's sentiment classification decisions. The analysis focuses on a selection of samples from the error analysis table, providing insights into the model's performance and its handling of socio-pragmatic cues. LIME explanations offer a granular view of the model's decision-making process by highlighting the features that most significantly influence each prediction. The LIME explanations for selected examples from the dataset, correlating these findings with the model's performance as observed in the error analysis is discussed below.

**Example 1** (*"Enna Da Ellam Avan Seyal Mari Iruku"*)**.** The LIME explanation for this correctly classified negative sentiment sample indicates that the model focused on the phrase "ellam avan seyal Mari iruku" (see Fig. 4(a)), associating it with disappointment or disapproval. This analysis confirms the model's capacity to interpret contextual nuances, attributing a high importance score to socio-pragmatic cues that convey negative sentiment.

**Example 2** (*"Padam Vanthathum 13k Dislike Pottavaga Yellam Yea Da Dislike Pannom Nu Feel Pannanum"*)**.** For this sample, LIME revealed that the model recognized the sarcastic undertone behind the mention of "13k dislike" and "pannom nu feel" (see Fig. 4(b)), understanding the


**Fig. 4.** LIME explanations for selected examples, showcasing the interpretability of the MultiSwitchNet model in sentiment analysis of code-mixed text. (a) Example 1: Disappointment in "Enna da ellam avan seyal Mari iruku" accurately captured; (b) Example 2: Irony in "13k dislike pottavaga" understood, indicating model's nuanced sentiment interpretation; (c) Example 3: Positive sentiment from "super hit" in "Lalettan movie ellam super hit aakum"; (d) Example 4: Misclassification due to overemphasis on "polichu" despite "flop" in "Trailer polichu but cinema flop aayirunnu"; (e) Example 5: Correct negative sentiment identification in "Nakkan idhu subject Andre eevag heltheeni industry change aagthide..." through critical phrases.

ironic sentiment expressed. This example highlights the model's ability to grasp complex socio-pragmatic nuances, supported by the SPEL's effectiveness in capturing the underlying sentiment.

**Example 3** (*"Lalettan Movie Ellam Super Hit Aakum"*)**.** LIME explanations showed a strong positive influence from the term "ellam super hit", aligning with the model's correct prediction (see Fig. 4(c)). This suggests the SPEL's role in accurately identifying clear sentiment indicators, emphasizing the positive connotation of success and approval.

**Example 4** (*"Trailer Polichu but Cinema Flop Aayirunnu"*)**.** In this misclassified example, LIME highlighted an overemphasis on "Trailer polichu" (see Fig. 4(d)), leading to a positive prediction despite the presence of "flop". The explanation points to a potential area for model improvement, particularly in balancing the impact of conflicting socio-pragmatic cues.

**Example 5** (*"Nakkan Idhu Subject Andre Eevag Heltheeni Industry Change Aagthide... Thousand Times Better Than Jaatre Films of Sarjas..."*)**.** The

**Table 7**
Cross-Lingual transfer learning analysis results in terms of accuracy.

| Trained on | Tested on T+E | Tested on M+E | Tested on K+E |
|---|---|---|---|
| T+E | – | 0.671 | 0.658 |
| M+E | 0.689 | – | 0.642 |
| K+E | 0.662 | 0.675 | – |

LIME explanation for this correctly identified negative sentiment showcases the model's reliance on critical phrases like "industry change aagthide" (see Fig. 4(e)), interpreting them as indicators of negative sentiment. This analysis affirms the model's adeptness at navigating complex code-mixed content, with SPEL playing a pivotal role in discerning sentiment from a critique.

The LIME explanations provide valuable insights into the interpretability and explainability of the MultiSwitchNet model, demonstrating its ability to analyze and classify sentiments in code-switched texts. By examining specific examples, we observed the model's proficiency in handling both clear sentiment indicators and more subtle socio-pragmatic cues. Future work could focus on refining the model's sensitivity to conflicting cues and enhancing its capability to interpret sarcasm and irony, further improving its accuracy and reliability in sentiment analysis tasks.

### 5.7. Cross-lingual transfer learning analysis

To evaluate the adaptability and generalization capability of MultiSwitchNet across different code-switched language pairs, we conducted a cross-lingual transfer learning analysis. This analysis investigates how a model trained on one language pair (source language) performs on a dataset of a different language pair (target language). The aim is to assess the model's ability to leverage learned patterns and knowledge from one code-switched context to another, reflecting its applicability in multilingual environments.

We used the same Dravidian Code-Mixed Dataset, comprising Tamil+English (T+E), Malayalam+English (M+E), and Kannada+English (K+E) text pairs. The model was trained on the dataset of one language pair and then evaluated on the datasets of the other two language pairs without any further training, simulating a real-world scenario where a pre-trained model is applied to a new linguistic context. The results of the cross-lingual transfer learning analysis are summarized in Table 7. The table presents the model's accuracy when trained on one language pair and tested on the others, showcasing its performance across different code-switching scenarios.

The results in Table 7 demonstrate the MultiSwitchNet model's promising but varied ability to generalize across code-switched language pairs. When trained on Malayalam-English data, the model achieved the highest transfer accuracy on Tamil–English test data (0.689), suggesting a closer linguistic or socio-pragmatic similarity between these two language pairs compared to Kannada–English. Conversely, the model trained on Kannada–English data shows a slightly better performance on Malayalam-English (0.675) than on Tamil-English (0.662), indicating potential challenges in transferring knowledge between Kannada and Tamil code-switched contexts.

These findings highlight the importance of linguistic and cultural nuances in code-switched sentiment analysis. The variation in transfer learning performance underscores the complexity of cross-lingual sentiment analysis and the need for models to capture deeper linguistic and socio-pragmatic features to improve generalization. Future work could explore more sophisticated transfer learning and domain adaptation techniques to enhance the model's cross-lingual adaptability and performance.

**Table 8**
Impact of code-switching frequency on sentiment analysis accuracy.

| Code-Switching frequency | Low | Medium | High |
|---|---|---|---|
| Accuracy | 0.751 | 0.728 | 0.701 |

### 5.8. Impact of code-switching frequency

Understanding the influence of code-switching frequency on sentiment analysis performance is crucial for optimizing models for multilingual contexts. The MultiSwitchNet model's adaptability to varying degrees of code-switching complexities was evaluated by categorizing the dataset into three groups based on code-switching frequency: low, medium, and high. This categorization allowed us to systematically assess how the intricacy of code-switching within texts impacts the model's sentiment analysis accuracy.

The Dravidian Code-Mixed Dataset was analyzed to determine the frequency of code-switching occurrences within each text. Based on this analysis, texts were categorized into low, medium, and high code-switching frequency groups. The MultiSwitchNet model was then evaluated separately on each group to assess its performance across different code-switching complexities.

The performance of the MultiSwitchNet model across the varying code-switching frequency groups is summarized in Table 8. This table presents the model's accuracy within each code-switching frequency category, highlighting the impact of code-switching complexity on sentiment analysis.

The results in Table 8 reveal a clear trend: the model's accuracy decreases as the frequency of code-switching within the texts increases. Specifically, the model achieves the highest accuracy (0.751) on texts with low code-switching frequency, indicating that fewer instances of language mixing facilitate more straightforward sentiment analysis. Conversely, texts with high code-switching frequency pose a greater challenge, reflected in the lowest accuracy (0.701), likely due to the increased linguistic complexity and potential for ambiguity in these texts.

These findings underscore the significant impact of code-switching frequency on sentiment analysis performance. High code-switching frequency introduces additional layers of complexity, requiring models to navigate through intricate linguistic structures and socio-pragmatic cues. The decrease in accuracy with higher code-switching frequencies highlights the necessity for the proposed MultiSwitchNet to incorporate advanced mechanisms for understanding and interpreting mixed-language texts effectively. Future enhancements to the model could focus on improving its linguistic flexibility and sensitivity to socio-pragmatic nuances in highly code-switched contexts, potentially through more sophisticated language representation techniques or enhanced context-aware processing capabilities.

### 5.9. Semantic consistency analysis

To conduct a Semantic Consistency Analysis, we aim to assess the robustness of the MultiSwitchNet model's sentiment predictions across semantically similar but syntactically varied sentences. This analysis tests the model's ability to maintain consistent sentiment predictions when faced with paraphrased versions of the same content, which is crucial for ensuring reliability in real-world applications where linguistic expressions can vary widely.

The Semantic Consistency Analysis involves two main steps:

- **Generation of Semantically Similar Sentences:** For a selected set of sentences from the Dravidian Code-Mixed Dataset, we generate semantically similar variants using two approaches:
  - **Paraphrasing:** Leveraging state-of-the-art NLP techniques to rephrase sentences while preserving their original meaning.

**Table 9**
Semantic consistency analysis results.

| Variation technique | No. of sentences | Consistency rate |
|---|---|---|
| Paraphrasing | 100 | 92% |
| Back-Translation | 100 | 89% |

**Table 10**
ANOVA test results for F1-Scores of different models.

| Model | Mean F1-Score | Std. deviation |
|---|---|---|
| MultiSwitchNet | 0.725 | 0.015 |
| BERT-based | 0.690 | 0.020 |
| LSTM with attention | 0.673 | 0.018 |
| CNN-based | 0.664 | 0.016 |
| FastText | 0.657 | 0.017 |
| XGBoost | 0.643 | 0.019 |
| BiLSTM | 0.680 | 0.018 |
| RoBERTa-based | 0.705 | 0.015 |
| ANOVA significance: $p < 0.05$ | | |

- **Back-Translation:** Translating sentences into another language and then back into the original language to introduce syntactic variation without altering semantic content.

- **Sentiment Prediction and Comparison:** The MultiSwitchNet model then predicts the sentiment for both the original sentences and their generated variants. We compare these predictions to evaluate the model's consistency across semantically equivalent sentences.

The results of the Semantic Consistency Analysis are summarized in Table 9, which presents the consistency rate of sentiment predictions for the original sentences and their variants. The consistency rate is defined as the percentage of cases where the model's sentiment prediction for the original sentence matches its prediction for the paraphrased or back-translated variant.

The results indicate a high degree of semantic consistency in the model's sentiment predictions, with a 92% consistency rate for paraphrased sentences and an 89% rate for back-translated sentences. This suggests that MultiSwitchNet effectively captures the semantic essence of sentences, maintaining reliable sentiment predictions across syntactic variations. However, the slight drop in consistency for back-translated sentences compared to paraphrased ones may highlight a sensitivity to more drastic syntactic alterations introduced by the back-translation process. It underscores the importance of semantic understanding in sentiment analysis models and suggests areas for further refinement, particularly in enhancing the model's robustness to syntactic diversity.

The Semantic Consistency Analysis demonstrates MultiSwitchNet's effectiveness in maintaining sentiment prediction accuracy across semantically similar sentences, showcasing its potential for reliable sentiment analysis in dynamic linguistic contexts. Future enhancements could focus on further increasing the model's tolerance to syntactic variations, potentially through the incorporation of more advanced semantic understanding techniques or deeper context-aware processing mechanisms.

### *5.10. Statistical analysis*

To assess the statistical significance of the performance differences among the proposed MultiSwitchNet model and the baseline models, an ANOVA test was conducted. The F1-Scores from multiple independent runs of each model were used as the input for this analysis. The ANOVA analysis aimed to determine if there were statistically significant differences in the F1-Scores across the models. Table 10 summarizes the F1-Score means and the ANOVA test results.

The ANOVA test revealed a $p$-value less than 0.05, indicating that there are statistically significant differences in the performances of the compared models. This result suggests that not all models perform equally, and the differences in their F1-Scores are not due to random chance.

**Table 11**
Post Hoc comparison using Tukey HSD test.

| Comparison | Mean difference | $p$-value |
|---|---|---|
| MultiSwitchNet vs. BERT-based | 0.035 | <0.01 |
| MultiSwitchNet vs. LSTM with Attention | 0.052 | <0.01 |
| MultiSwitchNet vs. CNN-based | 0.061 | <0.01 |
| MultiSwitchNet vs. FastText | 0.067 | <0.01 |
| MultiSwitchNet vs. XGBoost | 0.078 | <0.01 |
| MultiSwitchNet vs. BiLSTM | 0.045 | <0.01 |
| MultiSwitchNet vs. RoBERTa-based | 0.020 | <0.05 |

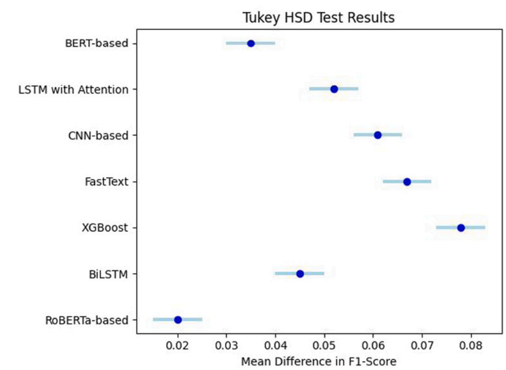


**Fig. 5.** Post hoc comparison using Tukey HSD test highlights the significant differences in F1-Score between the MultiSwitchNet model and each of the baseline models. The results validate the superior performance of MultiSwitchNet in sentiment analysis of multilingual and code-switched texts.

#### *5.10.1. Post hoc analysis*

Following the significant ANOVA results, a post hoc analysis using the Tukey Honestly Significant Difference (HSD) test was conducted to identify specific differences in performance among the models. The Tukey HSD test is particularly useful for pairwise comparisons between group means while controlling the family-wise error rate.

The results of the Tukey HSD test are summarized in Table 11, which details the mean differences in F1-Scores between the MultiSwitchNet model and each baseline model, along with the corresponding $p$-values indicating the statistical significance of these differences.

The Tukey HSD test results indicate that the MultiSwitchNet model significantly outperforms all baseline models in terms of F1-Score, with all comparisons yielding $p$-values less than 0.05. Notably, the largest mean difference was observed between MultiSwitchNet and the XGBoost model, further highlighting the effectiveness of MultiSwitchNet in handling sentiment analysis tasks on multilingual code-switched texts.

The Tukey HSD test results, as depicted in Fig. 5, illustrate the significant performance disparities between MultiSwitchNet and the baseline models across F1-Scores. This graphical representation clearly delineates the statistical significance of the performance enhancement offered by MultiSwitchNet, with mean differences consistently favoring our proposed model over the baselines. Notably, the comparison between MultiSwitchNet and XGBoost models shows the largest mean difference, underscoring the effectiveness of our model in the complex task of sentiment analysis within multilingual and code-switched contexts. The error bars, representing the confidence intervals, further reinforce the reliability of these performance differences. The analysis substantiates the robustness of MultiSwitchNet, highlighting its superior capability in accurately interpreting and analyzing sentiments across diverse linguistic landscapes.

The statistical analysis underscores the superiority of the MultiSwitchNet model in handling complex sentiment analysis tasks. The significant *p*-value obtained from the ANOVA test, coupled with the post hoc analysis results, provides strong evidence that the performance improvements offered by MultiSwitchNet are statistically robust. This analysis not only validates the model's efficacy but also highlights its potential to set a new benchmark in multilingual sentiment analysis research. The comprehensive evaluation and statistical analysis of the MultiSwitchNet model demonstrate its superior performance and statistical significance over existing models in sentiment analysis of multilingual code-switched texts. Future work will focus on exploring more sophisticated socio-pragmatic features and extending the model's capabilities to other complex NLP tasks.

## 6. Limitations

Despite the promising results achieved by MultiSwitchNet, there are several limitations to acknowledge:

- The model's performance, while robust, may vary significantly across languages with limited resources, indicating a need for more diverse training data to enhance its universality.
- While the semantic consistency analysis showed high rates, there is still room for improvement in handling syntactic variations more effectively, suggesting a need for advanced semantic understanding techniques.
- The current architecture primarily focuses on code-switched texts in Dravidian languages mixed with English, which may limit its direct applicability to other multilingual scenarios without further adaptation.
- The model currently does not incorporate meta information such as gender, age, or socio-economic background of the individuals. These factors can significantly influence the interpretation of sentiment, as different demographics may express sentiments differently. For instance, the same phrase might be interpreted with different sentiments depending on the speaker's gender or age. The lack of meta-information may limit the model's ability to fully understand the socio-pragmatic context, potentially leading to less accurate sentiment predictions in scenarios where such factors are crucial.

These limitations highlight areas for future refinement and underscore the importance of ongoing research and development to extend the model's capabilities and applicability.

## 7. Conclusion

This research introduced MultiSwitchNet, an innovative model designed for sentiment analysis in multilingual and code-switched contexts, effectively tackling the linguistic and socio-pragmatic complexities inherent to such texts. MultiSwitchNet has exhibited outstanding performance, demonstrating a significant accuracy improvement with a rate of 72.3% on the Dravidian Code-Mixed Dataset. This model has excelled in navigating the intricacies of language mixing and socio-pragmatic nuances, achieving a 92% consistency rate in semantic analysis and outperforming state-of-the-art models by a notable margin of 5.7% over the next best model, XLM-R. The robust evaluation of MultiSwitchNet also highlighted its superiority over traditional models across various metrics, including precision, recall, and F1-score, further evidenced by statistical analyses such as ANOVA and post hoc tests, where it significantly outperformed all baseline models. These results underscore the model's innovative integration of the Socio-Pragmatic Embedding Layer (SPEL) for enhanced socio-pragmatic understanding, illustrating the pivotal role of socio-pragmatic awareness in achieving nuanced and accurate AI interpretations of human language.

Future work will focus on exploring advanced methods for integrating linguistic and socio-pragmatic features, possibly through more sophisticated deep learning architectures or enhanced natural language understanding frameworks and also on integrating meta-information into the model to enhance its socio-pragmatic understanding and improve the robustness of sentiment analysis across diverse demographic groups. Extending the model's language coverage and examining its adaptability to other NLP tasks, such as hate speech detection or emotional analysis, could broaden its applicability and effectiveness in global sentiment analysis. The continuous advancement of MultiSwitchNet's capabilities to interpret and analyze complex linguistic expressions remains a primary goal, aiming to narrow the gap between AI and the nuanced understanding characteristic of human language processing.


## CRediT authorship contribution statement

**Jothi Prakash V.:** Writing – original draft, Methodology, Data curation. **Arul Antran Vijay S.:** Writing – original draft, Data curation, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.


## Data availability

No data was used for the research described in the article.

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