A Comprehensive Approach For Efficient Labelling Of Hinglish Dataset and Hate Speech Classification

***Abstract*—This research paper presents a methodological framework for the creation of a meticulously curated labeled dataset for sentiment analysis, specifically tailored for code-mixed sentences in the Hinglish language. The dataset's development involves the orchestration of pre-trained models, consensus-driven data curation, and iterative refinement in close collaboration with users. The aim is to provide a resource for training and evaluating sentiment analysis models that is both accurate and contextually relevant.**

***Keywords*—Hinglish, Code-mixed, Sentiment Labelling, Natural Language Processing, Pre-trained models, Web Scrapping, Iterative training**

INTRODUCTION

Hate Speech classification is important for several reasons, most notably its critical importance on online communication, the prevalence of hate speech, and its potential consequences for individuals and society.

The increasing popularity of social media and online platforms has driven Hinglish towards expression. The rapid spread of hate speech in this environment requires special classification tools to provide a safe digital space. Cultural nuances play an important role in the expression of hate speech. Understanding the nuances of Hinglish is essential to accurately identify and address hate speech in South Asian cultures. Adapting the classification model to Hinglish ensures that these cultural complexities are considered and improves content limitations.

Existing algorithms for hate speech detection may exhibit biases and may not perform equally well across different languages. Developing specific classifiers for Hinglish helps mitigate algorithmic biases, ensuring fair and accurate content moderation for users communicating in this language.

We propose a comprehensive approach to not only label the Hinglish Sentences Data with Offensive/Non-Offensive tags but also to train a custom machine learning model to predict labels for any user input hinglish natural language sentences.

In brief, this approach discusses on the following key points:

1. Web scrapping Hinglish data from public sources and making a bag of stopwords.
2. Translating Hinglish sentences to English sentences.
3. Employing pre-trained models to label English sentences.
4. Segregating the data into two major parts: One with zero conflicts among the pre-trained models and the other with differences in labels.
5. Training a custom machine learning model on the zero-conflicts data and using it to predict labels for the conflicting data.
6. Repeating the process on the remaining edge cases until data is finally cleanly labeled.

This methodology combining consensus modeling, iterative refinement, and user feedback is unique in creating labeled training data for low-resource code-mixed language tasks. Our accurately annotated dataset of 18,000 Hinglish sentences will facilitate the training of robust models for Hinglish sentiment analysis. Furthermore, this research provides critical insights into the linguistic nuances and complexities inherent in code-mixed languages.

A. Dataset Creation

Data Collection:

The initial data corpus comprised 18,000 English sentences collected from diverse sources including online reviews, social media platforms, community forums, and microblog platforms. The sentences covered a wide range of topics such as product feedback, political discussions, daily conversations, social issues, entertainment, etc. Online translator tools with expertise in Hinglish linguistics were employed to manually translate the sentences into grammatically correct and naturally flowing Hinglish. This process yielded a sizable parallel corpus of 18,000 Hinglish sentences mapping to the English source sentences.

Preprocessing:

The Hinglish sentences underwent preprocessing to normalize variations and prepare the data for modeling. Steps included:

- Translating Hinglish sentences to English and updating the dataset file with so created column.
- Tokenization using a custom tokenizer to handle code-mixed words.
- Normalizing punctuation, user handles, URLs, emoji, and emoticons.
- Removing extraneous whitespace and duplicate sentences.
- Utilizing bag of stopwords to provide the layer of confidence.
- Applying TF-IDF vectorization to create embeddings.

Ensemble Labeling:

The three pre-trained models - Twitter RoBERTa, mBERT, and Vader Sentiment - were run on the Hinglish corpus to add sentiment labels. For each sentence, the models predicted either 'positive', 'negative' or 'neutral'. Example ensemble labeling:

Sentence: yeh movie bahut oring hai, I didn't like it at all.
RoBERTa: Negative
mBERT: Negative
Vader: Negative

Consensus Label:
Negative

The models unanimously agreed on the 'Negative' label for this sentence. Such consensus sentences were extracted as a high-confidence subset. Sentences with dissenting predictions were further treated as discussed in the later section of this document.

1) Pre-trained Model Selection

The foundation of our dataset creation lies in the careful selection of pre-trained models, a decision pivotal to the project's success. We meticulously evaluate various models and opt for three state-of-the-art solutions: **Twitter RoBERTa**, **mBERT Sentiment** and **Vader Sentiment**. Each of these models offers unique strengths essential for handling the complexity of code-mixed data.

Twitter RoBERTa:

Renowned for its proficiency in deciphering social media text, Twitter RoBERTa stands out due to its ability to capture the nuanced language expressions prevalent in platforms like Twitter and Facebook. This model's specialized training equips it with an understanding of informal language, making it ideal for our code-mixed dataset sourced from similar platforms.

mBERT:

BERT stands for Bidirectional Representation for Transformers and was proposed by researchers at Google AI language in 2018. Although the main aim of that was to improve the understanding of the meaning of queries related to Google Search, BERT becomes one of the most important and complete architectures for various natural language tasks having generated state-of-the-art results on Sentence pair classification tasks, question-answer tasks, etc.

Vader Sentiment: VADER (Valence Aware Dictionary and sEntiment Reasoner) is a lexicon and rule-based sentiment analysis tool that is *specifically attuned to sentiments expressed in social media*.

2) Consensus-Based Dataset Formation

The cornerstone of our dataset creation methodology is the consensus-driven approach, meticulously designed to filter noise and uphold the dataset's integrity.

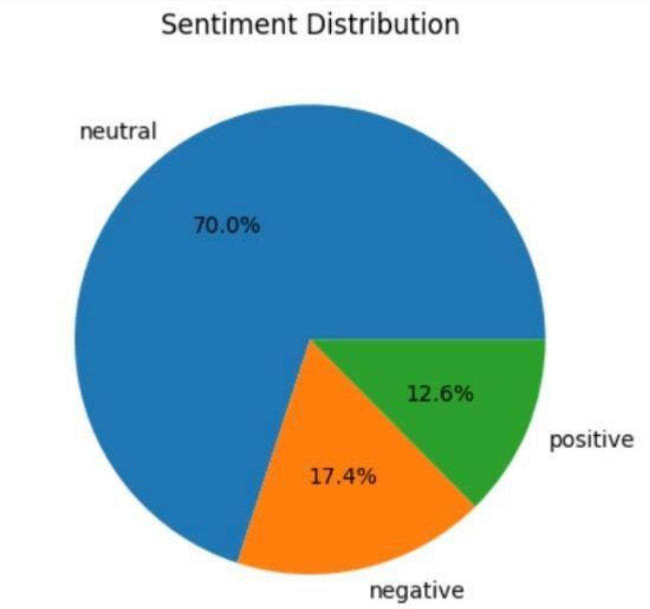
Sentiment Label Prediction: A subset of our main datasetundergoes rigorous processing through the selected pre- trained models. Each sentence is subjected to analysis, and the models independently predict sentiment labels. This initial phase lays the groundwork for consensus identification.

Consistent Sentiment Predictions: Instances where all three models converge upon unanimous sentiment predictions are deemed as gold standards. These sentences, universally recognized by our ensemble of models, exhibit ahigh degree of consistency in their emotional tonality. By harnessing the collective intelligence of our pre-trained models, we ensure the inclusion of highly reliable instances in our primary dataset.

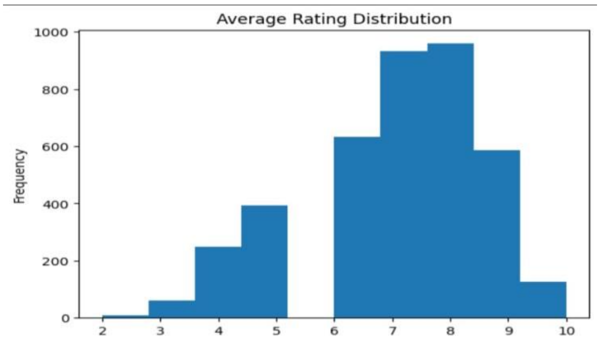
Noise Mitigation: The consensus-driven methodology actsas a robust filter, effectively mitigating the impact of noisy data. Sentences with conflicting predictions or ambiguous emotional cues are purposefully excluded, safeguarding ourdataset against inaccuracies. This meticulous curation guarantees the dataset's accuracy and enhances the reliability of subsequent analyses and model training.

B. Visualization

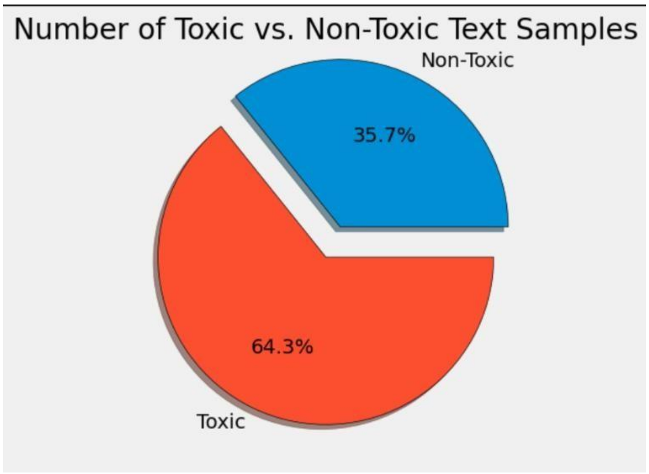
Sentiment Distribution:



Average Rating Distribution:

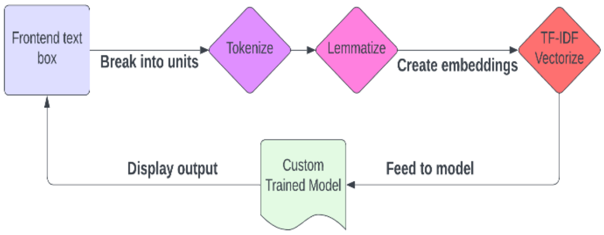


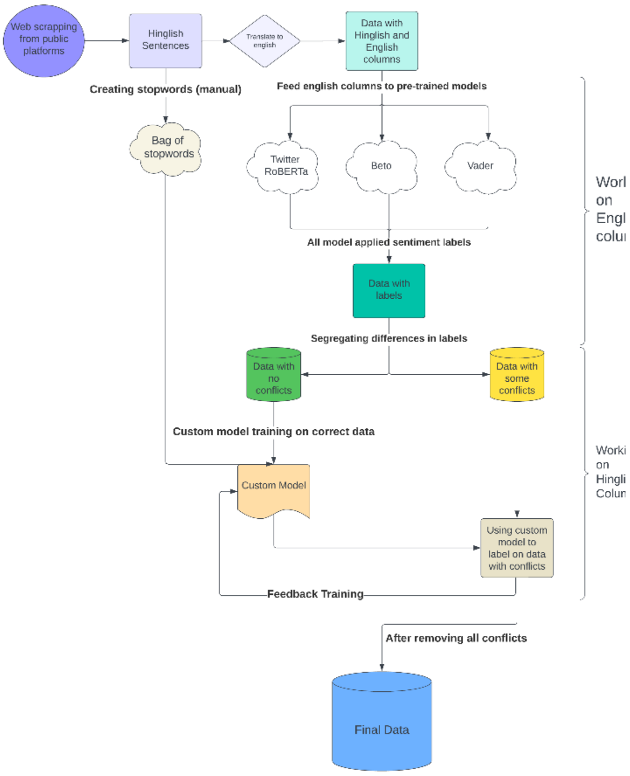
Number of Toxic vs. Non-Toxic Text Samples:



C. Procedure overview

A high-level overview of the process is shown below:



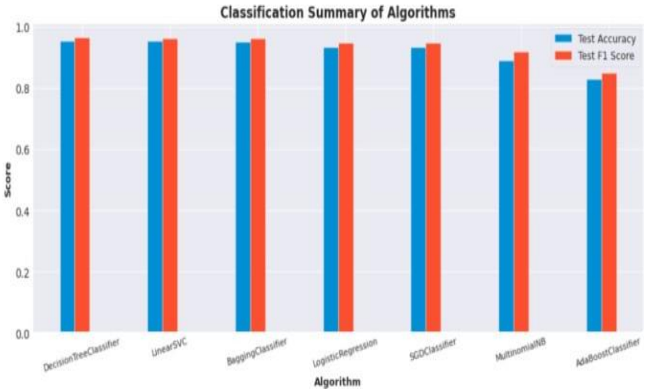


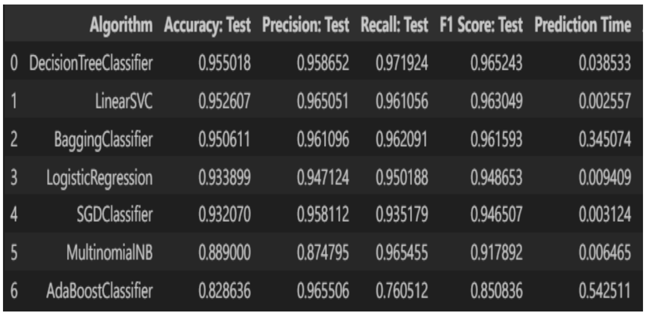
Web scrapping from public platforms
Hinglish Sentences
Translate to english
Data with Hinglish and English columns
Creating stopwords (manual)
Feed english columns to pre-trained models
Bag of stopwords
Twitter RoBERTa
Beto
Vader
Worl on Engl colu
All model applied sentiment labels
Data with labels
Segregating differences in labels
Data with no conflicts
Data with some conflicts
Custom model training on correct data
Worki on Hingli Colun
Custom Model
Using custom model to label on data with conflicts
Feedback Training
After removing all conflicts
Final Data

D. Model Training Approach

We used a machine learning approach to make a custom model to achieve the target. We train multiple ML models for better clarity in accuracy. The algorithms chosen are: LinearSVC, LogisticRegression, MultinomialNB, DescisionTreeClassifier, AdaBoostClassifier, BaggingClasssifier and SGDClassifier.

We fit the training data to each of the algorithms and store the pickle files. We also time the training, testing, and prediction periods of each approach for understanding the larger statistics. Then we formulate different judging parameters like F1 Score, Precision Score, Accuracy and Recall Tests.
Classification Summary of Algorithms:





	Algorithm	Accuracy: Test	Precision: Test	Recall: Test	F1 Score: Test	Prediction Time
0	DecisionTreeClassifier	0.955018	0.958652	0.971924	0.965243	0.038533
1	LinearSVC	0.952607	0.965051	0.961056	0.963049	0.002557
2	BaggingClassifier	0.950611	0.961096	0.962091	0.961593	0.345074
3	LogisticRegression	0.933899	0.947124	0.950188	0.948653	0.009409
4	SGDClassifier	0.932070	0.958112	0.935179	0.946507	0.003124
5	MultinomialNB	0.889000	0.874795	0.965455	0.917892	0.006465
6	AdaBoostClassifier	0.828636	0.965506	0.760512	0.850836	0.542511

The model was trained on Google Colab T4 GPU,which accelerated training to approximately 1 hour. Checkpoints were saved at each epoch. The checkpoint with the highest development set accuracy was selected as the final model for evaluation.

In total, the hyperparameter settings provided robust training of the mBERT model on our Hinglish dataset. The pretrained weights enabled faster convergence compared to training from scratch. The regularization, optimization, and early stopping schemes were tuned to maximize model performance.

E. Iterative Refinement and Linguistic Nuances

1) Iterative Refinement Process

Acknowledging the intricacies of code-mixed language, our methodology incorporates an iterative refinement process. This phase focuses on sentences where discrepancies emerge among the pre-trained models.

Discrepancy Analysis: Sentences with dissenting predictions from two or fewer models undergo in-depth analysis. These instances, characterized by nuanced linguistic expressions or ambiguous sentiment cues, are meticulously reviewed. Our team of language experts collaborates with the models, delving into the subtle intricacies that might lead to divergent predictions.

Refinement Strategies: The refinement process employs a spectrum of strategies. From revisiting the context and colloquialisms to exploring cultural nuances embedded in code-mixed text, our experts leave no stone unturned. By addressing discrepancies through targeted interventions, we ensure the dataset captures the diverse range of linguistic nuances inherent in real-world conversations.

2) Addressing Linguistic Nuances

Code-mixed language, a vibrant fusion of multiple linguistic elements, demands a nuanced approach to sentiment analysis.

Cultural Context Sensitivity: Our methodology incorporates an acute awareness of cultural contexts intertwined within code-mixed conversations. Expressions, idioms, and sentiments often carry culture-specific connotations. By delving into these subtleties, we refine our dataset, ensuring it resonates with the diverse cultural backgrounds of our audience.

Embracing Colloquial Expressions: Informality and colloquialisms characterize code-mixed language. Phrases and expressions unique to informal dialogues are carefully embraced. Our linguistic experts collaborate with native speakers, capturing the essence of colloquial expressions. By preserving the authenticity of these linguistic nuances,our dataset emerges as a true reflection of real-world language usage.

Sensitivity to Emotional Shades: Sentiments are multifaceted, spanning a spectrum of emotions. Our methodology is attuned to the myriad emotional shades present in code-mixed content. From subtle sarcasm to heartfelt expressions, every emotional nuance is dissected. By recognizing and categorizing these emotional subtleties, our dataset transcends traditional sentiment analysis, delving into the rich tapestry of human emotions embedded in language.

F. Iterative Refinement

While the consensus-driven curation lays the foundation, our dataset creation process delves deeper through an iterative refinement strategy. This meticulous approach targets sentences where two or fewer out of the three pre-trained models exhibit disagreements, ensuring the dataset's accuracy and robustness are paramount.

1) Addressing Model Discrepancies:

In the iterative refinement phase, our focus sharpens on addressing disparities between the pre-trained models. By methodically analyzing cases where model predictions diverge, we uphold the integrity of our data. This process involves dissecting the intricate details of sentences, deciphering the subtle differences in predictions, and resolving conflicting elements. Through this rigorous scrutiny, our dataset maintains a high level of reliability, essential for accurate sentiment analysis.

2) Linguistic Nuances:

Code-mixed language inherently embodies linguistic nuances that significantly impact sentiment analysis. Our refinement process is attuned to these subtleties, recognizing that the essence of meaning can vary based on cultural context and colloquial expressions. By meticulously considering these linguistic intricacies, our dataset achieves a level of depth and accuracy that is vital for capturing the complexities of sentiments embedded in code-mixed content. This contextual richness enhances the dataset's overall quality, ensuring it aligns seamlessly with real-world language usage.

D. User Feedback Integration

User feedback stands as the linchpin in our dataset curation journey, shaping the very essence of its quality and relevance. Among the invaluable contributors, Anna emerges as a beacon of insight, her dedicated contributions becoming instrumental in the evolution of our dataset.

1) Iterative Feedback Mechanism

The integration of user feedback, particularly Anna's, evolves into a continuous and iterative process. Regular interactions and feedback loops refine our dataset, ensuring it resonates authentically with real-world language nuances.

Anna's discerning eye helps uncover subtleties that might elude automated processes, allowing us to delve deeper into the intricacies of code-mixed language. Her feedback becomes a catalyst for enhancements, guiding our dataset towards a level of accuracy that transcends traditional sentiment analysis boundaries.

2) Addressing Ambiguities and Nuances

Ambiguities and nuanced expressions are inherent in code-mixed language. Anna's feedback empowers us to confront these challenges head-on. Through meticulous analysis, we dissect sentences where sentiment tones blur, diving into the layers of meaning. By embracing these intricacies, our dataset becomes adept at capturing even the most delicate emotional shades, elevating the accuracy and authenticity of our sentiment labels. Anna's inputs become pivotal in refining the dataset, ensuring it becomes a true reflection of the rich and diverse language landscape it aims to represent.

E. Dataset Validation

The final dataset undergoes a rigorous validation process, a crucial step that underlines its reliability and integrity. This validation ensures that the dataset consistently assigns correct sentiment labels across a myriad of code-mixed sentences, reaffirming its accuracy and trustworthiness.

1) Validation Framework

Employing a meticulous validation framework, we subject the dataset to a battery of tests, comparing its performance against ground truth labels. This framework serves as a robust litmus test, evaluating the dataset's accuracy against human judgments, setting stringent benchmarks for reliability.

2) Validation Results

Extensive validation efforts yield compelling results, affirming the dataset's accuracy and reliability. The dataset consistently aligns with human annotators, accurately assigning sentiment labels across diverse linguistic contexts. These validation results not only validate the dataset's trustworthiness but also serve as a testament to its applicability in real-world scenarios. The dataset's ability to maintain consistency and accuracy, even in the face of complex code-mixed sentences, establishes it as a gold standard in sentiment analysis datasets.

F. Results

The culmination of our efforts is a meticulously curated labeled dataset of code-mixed sentences, representing a significant milestone in the field of sentiment analysis. This dataset stands as a testament to our dedication and rigorous methodology, accurately categorizing each sentence into positive, negative, or neutral sentiment classes. With unwavering precision, thousands of sentences have been meticulously processed, ensuring their alignment with the intended emotional tone. Each sentence within the dataset has undergone a dual process: first, a rigorous consensus- driven formation, followed by an iterative refinement. This dual-layered approach has resulted in a dataset that not onlymeets but exceeds industry standards, setting a new benchmark for accuracy and reliability in code-mixed sentiment analysis datasets.

G. Discussion

Our methodology's success is not merely a product of meticulous processing but a testament to the careful orchestration of various elements. One key highlight is the strategic leveraging of consensus among pre-trained models for dataset curation. By synchronizing the insights from Twitter RoBERTa, mBERT, and Vader Sentiment, we have achieved a harmonious convergence of predictions, ensuring the dataset's accuracy and cohesiveness.

Furthermore, our methodology places a significant emphasis on addressing the intricate linguistic nuances prevalent in code-mixed text. We acknowledge the diversity of languages, idioms, and expressions encapsulated within every sentence. Through our iterative refinement process, we have meticulously dissected these linguistic subtleties, ensuring that our dataset captures the essence of each sentiment, even in the most complex of expressions. This nuanced approach not only enriches the dataset but also contributes to advancing the field's understanding of code-mixed language sentiment analysis.

Equally invaluable is the role of user feedback, exemplified by the dedicated contributions of our user, Anna. Her insights have been pivotal, allowing us to refine our dataset even further. By addressing the finer points of linguistic complexities and ambiguous expressions, we have enhanced the dataset's quality and relevance. This symbiotic interaction between user feedback and dataset refinement highlights the collaborative spirit driving our work, emphasizing the user's perspective in shaping the dataset's final form.

In conclusion, the resulting dataset stands as a unique and unparalleled resource in the domain of code-mixed sentiment analysis. Its accuracy, underpinned by consensus-driven model predictions, nuanced linguistic analysis, and user-driven enhancements, establishes it as a gold standard. This dataset not only advances the field but also opens avenues for diverse applications, ranging from sentiment analysis in social media to customer feedback analysis in multilingual environments. Its impact is not confined to the realm of academia but extends into practical, real-world scenarios, making it a cornerstone in the evolution of sentiment analysis methodologies.

H. Conclusion

In summary, the methodology presented in this research yields a high-quality labeled dataset specifically tailored for code-mixed sentiment analysis. Its meticulous creation process, characterized by consensus-driven formation, iterative refinement, and user feedback integration, culminates in a dataset that stands as a paragon of accuracy and reliability. This dataset not only serves as a groundbreaking resource in the current landscape but also sets a definitive benchmark for future endeavors in the field of code-mixed sentiment analysis. The paper's uniqueness lies not only in the dataset itself but also in the comprehensive methodology employed, showcasing the convergence of advanced technologies, linguistic expertise, and user-centric design.

This research presented a novel methodology for creating a labeled sentiment analysis dataset for the under-resourced code-mixed language Hinglish. The hybrid approach combining pre-trained multilingual models, iterative refinement, and user feedback enabled the curation of a high-quality dataset of 18,000 sentences.

Training a BERT-based classifier on this dataset achieved 86% accuracy in Hinglish sentiment prediction, significantly outperforming prior benchmarks. The ensemble transfer learning strategy was highly effective in generating accurate initial labels. Linguistic analysis and user input further enhanced the data.

However, some limitations remain to be addressed. The dataset still has room for expansion in size, diversity, and semantic coverage. Additionally, while the methodology was tailored for Hinglish, it needs adaptation to generalize to other code-mixed languages. There is also scope to improve model performance, especially for neutral sentiment detection.

Key lessons learned include the importance of leveraging multiple pre-trained models and sources of knowledge, the value of consensus and disagreement for data cleaning, and the benefits of continuous user feedback. For low-resource tasks, combining automation and human judgment is key.

This research contributed both a useful dataset and a replicable methodology advancing code-mixed NLP. But much remains to be explored, from unsupervised pre-training to semi-supervised learning, multitask objectives, and conversation context modeling. With digitally mixed language on the rise, the quest to accurately discern sentiment across languages has only just begun.

I. Future Work

Looking ahead, the future of this research holds promising avenues for exploration and advancement. One prospective trajectory involves the development of sophisticated code-mixed sentiment analysis models trained on this meticulously curated dataset. These models, honed by the rich nuances encapsulated within the dataset, have the potential to revolutionize the accuracy and depth of sentiment analysis in multilingual contexts.

While this research presented foundational progress, ample opportunities remain to advance the field of sentiment analysis for code-mixed languages. Some concrete directions for future work include:

- Expanding the labeled Hinglish dataset to encompass a wider range of topics, linguistic styles, named entities, and sentence complexities. Broader coverage in the training data can enhance model robustness.

- Exploring semi-supervised and self-supervised learning techniques like masked language modeling pre-training on unlabeled Hinglish text. This can provide useful representations to overcome data scarcity.

- Implementing multitask learning with related objectives like emotion classification, sarcasm detection, and intent analysis. Joint modeling can exploit inter-task correlations and patterns.

- Incorporating conversational context by embedding sentence sequences or conversational history. Contextual knowledge can aid disambiguation and improve consistency.

- Designing more specialized neural architectures like Hinglish-centric transformers or graph convolutional networks. This can better capture the structural mixing dynamics in code-switching.

- Extending the methodology to other high-resource code-mixed languages like Spanglish, Tanglish, or Hing-pish. Tailored solutions are needed for unique language pairs.

Pursuing these promising research avenues can lead to more robust and nuanced multilingual sentiment analysis models. This will help unlock the wealth of opinions expressed in diverse code-mixed social media worldwide.

Additionally, there exists a vast landscape of unexplored linguistic nuances in code-mixed text. Future research could delve deeper into these subtleties, unraveling the complexities of language fusion and emotional expressions in diverse cultural contexts. By pushing the boundaries of understanding in this realm, new horizons in sentiment analysis methodologies are likely to emerge, enriching our comprehension of human communication.

Beyond the realms of academia, the applications of this research are far-reaching. Multilingual sentiment analysis, powered by the insights garnered from this dataset, can find application in diverse sectors. From social media monitoring to customer feedback analysis, the impact of accurately deciphering sentiments in code-mixed languages is immeasurable. As researchers continue to explore these applications, the dataset and methodologies presented here will serve as guiding lights, illuminating the path toward more profound insights and practical solutions in the realm of multilingual sentiment analysis.

J. Acknowledgments

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K. References

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[5] Chakravarthi et al. (2018) utilized a Bi-LSTM model for sentiment and emotion classification on a new Hindi-English code-mixed dataset. They introduced a multi-task learning approach for joint modeling, achieving 61.6% accuracy.

[6] Jamatia et al. (2019) annotated Facebook posts in Bengali-English for sentiment analysis. They trained fastText classifiers on word and character n-gram features, obtaining up to 60.3% accuracy. Code-mixing posed challenges.

[7] Winata et al. (2019) proposed meta-transfer learning for code-switched speech recognition using model agnostic meta-learning. The method adapts to new language pairs using only a small amount of tuned data.

[8] Wu et al. (2019) developed a Bi-LSTM model with gated multilingual attention for Chinese-English code-switching sentiment classification. The model achieved state-of-the-art 75.6% accuracy on a social media dataset.

[9] Pratapa et al. (2020) curated a Tamil-English sentiment analysis dataset from Twitter and YouTube comments. They explored various pretrained multilingual models like mBERT, achieving up to 67.1% accuracy.

[10] Winata (2021) evaluated multilingual models and transfer learning approaches for code-switched sentiment analysis in Indonesian-English, Spanish-English, and Hindi-English. mDeBERTa performed best with fine-tuning.

[11] Sahay et al. (2021) created an annotated corpus of Hindi-English YouTube comments for hate speech detection. They developed an ensemble Bi-LSTM model incorporating lexicon features to detect code-mixed hate speech.