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Multilingual Sentiment Analysis Models Using Transfer Learning

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Multilingual Sentiment Analysis Models Using Transfer Learning

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Abstract

Sentiment analysis plays an important role in analyzing customer opinions, especially in customer reviews. This work investigates advancements in machine learning models for sentiment classification and introduces an ensemble approach based on transformer-based models, namely XLM-RoBERTa with meta-learning. The proposed transformer-based hybrid model is compared with conventional machine learning algorithms including Naive Bayes, Logistic Regression, and Support Vector Machines on the product reviews dataset. The findings indicate that, while standard models struggle to predict sentiment based on customer review with less than 50% accuracy, the transformer-based hybrid model yields an accuracy of 57% and enhanced classification efficiency in various sentiment classes. While there are some difficulties in correctly categorizing the neutral emotions, the proposed hybrid model shows high performance in identifying the extremely positive and negative emotions. The integration of meta-learning also improves the generality and flexibility of the model. The work also points out the directions for further research including the issues with the class imbalance, the difficulties related to the classification of the neutral sentiments, and the possibilities of real-time learning. It demonstrates the applicability of transformer-based models in sentiment analysis tasks and the basis for further developments of sentiment classification systems for practical use.

Keywords: Natural Language Processing, Hybrid Multilingual Sentiment, XLM-RoBERTa, Meta-Learning.

1 Introduction

In an increasingly interconnected world, sentiment analysis of online communications has become an essential tool for understanding public opinion and their sentiment for decision making in various domains. Owing to the revolutionary increase in the number of social media platforms and user-generated content, there is a need to establish automatic systems for analysing sentiments expressed in different languages. However, multilingual text analysis is a rather challenging task, especially when it comes to low-resource languages (Wu et al., 2020). Despite the achievements made by the existing sentiment analysis models for high-resource languages, these models have been reported to give poor results for languages have limited annotated data (Conneau et al., 2020). This limitation results in the issue of generating bias, which affects the accuracy and fairness of sentiment-driven conclusions, thus impeding our ability to study sentiments across various diverse linguistic settings (Lan et al., 2020).

Low-resource languages usually lack in labelled training data which presents enormous issues to machine learning models that rely on large training data. These languages may have constituents of syntax and semantics, which is however difficult to learn if models are pre-trained in high-resource language and might over-fit or fail to generalize (Devlin et al.,

2019). Further, the cross-lingual transfer where a model is trained from a high-resource to a low-resource language introduces new challenges such as linguistic differences, cultural variations, and idiomatic expressions (Conneau et al. 2020). Hence, there is a need to develop new sentiment analysis models that are not language-specific and can generalise the sentiment analysis ability from one language to another, and also more efficient to boot, specifically for low-resource languages.

Motivation

This research is motivated by the increasing demand for more diverse sentiment analysis that can work with different languages especially on low resource languages. While NLP and machine learning have made significant advancement, a vast majority of the models are built to be more biased to high-resource languages, ignoring low-resource languages inadequate support (Nemkul et al., 2024). These imbalances create a gap in sentiment analysis approaches and even lead to misrepresent the global perspectives. It is important to understand the context of people using low-resource languages to make qualitative analysis and fair decisions by taking into consideration cultural variations and linguistics. Addressing these problems will help to form a more diverse and representative NLP ecosystem that will convey the sentiments of people of different linguistic backgrounds. Therefore, this research aims to reduce the gap and provide a fair and accurate multilingual Sentiment analysis model that can be generalized across languages and can be adapted for new languages with less amount of data.

Research Question

This study is driven by the following research question:

"How can the integration of meta-learning and transfer learning to language models such as XLM-RoBERTa to enhance multilingual sentiment analysis by improving performance on low-resource languages?"

Objectives

To answer the research question, this study sets the following research objectives:

Improve performance on low resource languages: To develop a hybrid meta-learning approach with pre-trained transformer model XLM-RoBERT for multilingual sentiment analysis that will enhance the sentiment analysis of low resource languages.
Model Selection and Pre-training: For evaluate, transformer-based model is used particularly XLM-RoBERT and it is pre-trained on the large multilingual datasets.
Integrate Meta-Learning for Adaptation: To add a meta-learning module into the framework that is capable of learning the weights of sentiment analysis dynamically and which can be trained to improve performance on low resource languages.
Evaluate Model Performance: To evaluate the effectiveness and ability of generalization of the proposed hybrid model using various classification metrics

To address the limitations, this research proposes an hybrid approach for sentiment analysis by using meta-learning, and transfer learning with the transformer-based models. In particular, the proposed approach uses transformer-based models such as Cross-lingual Language Model – XLM-RoBERT (Conneau et al., 2020; Nemkul et al., 2024) that are known to provide the good cross-lingual contextualization. The pretraining of these models on a variety of multilingual big datasets provides the foundation to understand many linguistic patterns to different languages. However, adaptation only with the help of pre-

training on even multilingual corpora could not be enough to achieve the necessary level of performance on low-resource languages (Devlin et al., 2019).

To address this, the proposed hybrid framework incorporates meta-learning which is known as “learning to learn” that allows the model to quickly learn about new languages with limited data (He et al., 2023). The meta-learner module is also very important in the dynamic learning of the weight of sentiment analysis knowledge to learn the best parameter tuning for different languages. This is particularly useful for low-resource languages since this implies that the model can transition from a high-resource language to a low-resource one without getting fine-tuned significantly. Furthermore, it is also quite convenient to transfer the learned knowledge from pre-training to new languages through the integration of few-shot learning approaches and cross-lingual text embedding. The effectiveness of the proposed approach is evaluated using multilingual sentiment analysis datasets, both high-resource and low-resource language settings.

2 Related Work

Multilingual sentiment analysis is a crucial in identifying the sentiment behind global reviews including social media, product rating, and public opinion. Nevertheless, there remain several difficulties inherent to existing methods, especially for low-resource languages that lack adequate annotated data. In this literature review section, we will give an overview of the different facets of multilingual sentiment analysis, transfer learning, and meta-learning; and present the difficulties and developments that defined this field.

Multilingual Sentiment Analysis

Over the past few years, there has been a rising trend and focus on sentiment analysis because of this possibility of the technique in evaluating and extending the identification of sentiments and emotions in texts. Especially when it comes to views, society trends, brands, and consumption patterns. The capability of sentiment analysis is generalized to this multilingual environment, and thus it becomes possible to perform sentiment analysis on global interaction in social media platforms and gain insights irrespective of the language used (Wu et al., 2020). Various models on sentiment analysis have been trained from monolingual corpus which limits its operation to a particular language and also does not allow it to analyze texts written in different languages simultaneously.

The recent development of multilingual transformer models like the XLM-RoBERTa. beneficial when analyzing sentiment in multiple languages (Conneau et al., 2020). This hybrid approach allows them to perform efficiently in high resource languages, and have plenty of training data. Nevertheless, the same models perform poorly in low-resource languages when applied to them. The distribution of training data is skewed in favor of high-resource languages meaning that many models are trained on annotated data in languages that are not a true representation of many low-resource languages. For this reason, these models do not capture specific features of languages such as cultural differences, idioms, and context resulting in biases and low precision in sentiment analysis of these languages (Lan et al., 2020). This challenge further emphasizes the need to develop multilingual sentiment analysis models by increasing efficiency and decreasing the bias when used in low-resource language.

Transfer Learning in NLP

Transfer learning is one of the core techniques in NLP techniques in recent years. The main idea of transfer learning is to train models for major and diverse works of text to capture general representations of the language by utilizing relatively limited labelled data for specific tasks (Chae et al., 2023). This approach allows it to transfer knowledge from high-resource domains where large data sets are available to the low-resource domains where there is limited labeled data available. This capability is most useful in such scenarios as sentiment analysis when it could be nearly impossible to obtain large quantities of labeled data in every language, not to mention in low-density languages.

Few models as BERT, XLNet, and RoBERTa can be used for transfer learning as revealed in (Li et al., 2024; Nemkul et al., 2024). For example, BERT (Bidirectional Encoder Representations Transformers) is trained using a masked language model, which enables it to learn the context of a word by looking at the left and right context of the same word (Devlin et al., 2019). This pre-training allows BERT to learn general language knowledge and then can be fine-tuned for particular NLP tasks, namely sentiment analysis, with much fewer amounts of task-specific data More recent development, mBERT, extends BERT by pre-training on multilingual corpora and thus can apply the knowledge it learns from high-resource languages to the low-resource languages, making it possible for sentiment analysis in different languages.

However, mBERT is suited to capture general features of languages, it is not very effective when it comes to learning specific features about languages, especially the low-resource languages (Conneau et al., 2020). The high-resource languages, defined as the languages with abundant training data for multilingual pre-training, dominate the MUSE corpus, overwhelming the shared embedding space and making the model better fitted for these languages' structures and features. This leads to a disadvantage where the models are biased towards low-resource language, which is scarce in the training data and consequently, the model fails to capture distinctive linguistic features of the low-resource language. Consequently, even though transfer learning in NLP has transformed the field, there are still a lot of problems regarding the models' performance across languages, especially those with scarce amounts of labeled data (Lan et al., 2020).

Meta-Learning and Few-shot Learning

Meta-learning also known as "learning to learn" appears to be a viable solution to the low-resource language modelling of sentiment analysis across different languages (He et al., 2023). Meta-learning will therefore help in improving its ability to learn new tasks with less data. When it comes to the use of multilingual sentiment analysis, this ability can be valuable since it can enable the model to change parameters and learn a new language, which may be characterized by scarce annotated data.

Few-shot learning is a type of meta-learning that focuses on model learning and accuracy with only a few new tasks labeled samples (Brown et al., 2020). This approach is particularly suitable to be applied in low-resource language where it could be difficult to obtain large amounts of annotated data. Bio: Meta-learning could be incorporated with the transformer-based models to build a dual model where the model can train the low resource sentiment analysis with few samples and then remove the requirement of massive training data. The recent development in this direction is the meta-learning algorithms like the Model-Agnostic Meta-Learning (MAML) algorithms that train models to readily learn new tasks by employing only a few gradient updates (He et al., 2023). On the other hand, where the model has been trained on several tasks it can be retrained for another task for example; sentiment analysis of an underrepresented language with a limited amount of training data.

Transformer Models for Multilingual Sentiment Analysis

Transformers have brought a new paradigm in natural language processing (NLP), because of its self-attention mechanism makes it possible to model long range dependencies (Harrer et al., 2023). BERT, XLNet, and RoBERTa are among the transformers that have performed effectively in various domains because, in addition to the features of the language, they are capable of understanding contextual information. These models are useful in activities such as sentiment analysis because they are knowledgeable about the broader context of the text, the whole sentence or passage to provide a better interpretation of the sentiment in the text (Li, Chew et al., 2024; Nemkul, Wanchaitanawong et al., 2024).

The multilingual transformer model, like XLM-RoBERTa, applies the transformer architecture to multilingual tasks (Devlin et al., 2019; Conneau et al., 2020). mBERT is trained on a multilingual dataset but does not have the language IDs aligned between languages. Consequently, mBERT is able to develop a mapping function where different words and phrases across different languages can be placed in a common vector space to allow it to learn across different languages. This feature makes it possible for mBERT to bring knowledge from high resource languages to low resource languages making it useful for multilingual sentiment analysis. The most popular multilingual BERT model is mBERT, but it is fine-tuned only on a small portion of the multilingual corpus; XLM-R is an improved version of mBERT that is trained on a much larger and more diverse multilingual corpus, which captures a large number of languages and features. XLM-R is able to support a great many languages which is also possible due to the extended corpus; thus, XLM-R is more suitable for multilingual tasks and is capable of demonstrating better results than mBERT.

Hybrid Approaches in Multilingual NLP

Hybrid approaches are investigated by using an ensemble of methodologies where the shortcomings of individual models can be masked in multilingual sentiment analysis. In 2023 Chae et al. presented the Universal Language Model Fine-tuning (ULMFiT) method that performs pre-training and fine-tuning to reach state-of-the-art performance on a number of NLP tasks. Nonetheless, while ULMFiT has demonstrated an increased generality over other domains, it has not done so for multilingual environments because of the lack of explicit cross-lingual training. The meta-learning would be integrated into the pre-trained transformer models. The meta-learner module in such a framework can learn and adapt sentiment analysis weights over time thus making the model more effective in low-resource languages as suggested by (He et al., 2023). This integration also allows the model to apply the few-shot learning methods to learn from a small number of examples which is beneficial in low-resource language environments (Brown et al., 2020).

Addressing Bias in Multilingual Models

In multilingual NLP models, bias has become a significant problem. The transformer-based models are mainly trained on the datasets where high-resource language takes the majority of its share and thus, the model learns to perform well on the languages that are in the majority (Hu et al., 2024). This bias is detrimental to multilingual sentiment analysis because low-resource languages are under-represented during training leading to biased predictions and flawed sentiment insights (Soni et al., 2023). To address the bias there is need of balanced dataset creation, data augmentation, and cross-lingual data synchronization (Soni et al., 2023). These methods do ease the problem, and they cannot completely solve the problem due to the nature of the multilingual and multicultural data. There has been proposed an idea to add a meta-learning part which can modify model parameters according to the specifics

and changes of a certain language and it has been suggested that such an approach would be more effective in terms of bias removal (Brown et al., 2020). With the help of meta-learning, the model weighs and reflects the learned experience from the different tasks, this minimizes the effect of data imbalance and has an improved generalization across different linguistic environments.

Table 1: Comparative Analysis of Recent Research Studies

Authors	Datasets Used	Methodology	Model Used	Limitations	Future Work
Wu et al. (2020)	Multilingual Twitter Dataset	Pre-training on multilingual corpus	mBERT	Bias towards high-resource languages	Improve low-resource language representation
Conneau et al. (2020)	XNLI, MLQA, Wikipedia Corpus	Transfer learning with shared embeddings	XLM-R	Imbalanced dataset representation	Include diverse languages in pre-training
Chae et al., (2023)	IMDb, Yelp Reviews	ULMFiT with fine-tuning	ULMFiT	Lack of explicit cross-lingual capability	Extend to cross-lingual sentiment analysis
Devlin et al. (2019)	Multilingual Wikipedia Corpus	Masked Language Modeling	BERT, mBERT	Struggles with language-specific characteristics	Use meta-learning to improve language adaptability
Nemkul et al. (2024)	OpenWebText, CC-News, Stories	Pre-training with transformers	RoBERTa	High-resource languages dominate	Balance training data to include more low-resource data
Brown et al. (2020)	GPT-3 Training Dataset (Web Data)	Few-shot Learning	GPT-3	Limited performance on syntactic language-specific tasks	Explore meta-learning to enhance few-shot capabilities
Hu et al. (2024)	Large-scale multilingual reviews	Dataset balancing and data augmentation	LSTM	Insufficient bias mitigation	Explore dynamic weight adjustment for bias reduction
Soni et al. (2023)	Custom multilingual text datasets	Cross-lingual data alignment	CNN, RNN	Cultural and linguistic diversity not captured fully	Develop cultural adaptation techniques

The literature reviewed in this section shows the limitations of the current multilingual sentiment analysis models, mainly in their poor generalization across Low-Resource Languages. Previous works based on the transformer architecture such as XLM-RoBERTa

has shown great performance, but they are highly sensitive to the high resource languages as they are trained with large available data.

3 Research Methodology

Introduction

This section outlines the methodology employed in this study for developing multilingual sentiment analysis model using transfer learning and meta-learning approaches. The study addresses the two critical challenges that occur in low-resource languages, which include limited data and model bias. In this research, the combination of the transformer pre-trained model and the use of meta-learning to optimize the sentiment analysis which aims to improve the understanding of how sentiment on various languages. The methodology encompasses several stages: data preprocessing, model selection and initialization, hybrid model development, and evaluation.

Data Collection and Preprocessing

The dataset used in research of multiple languages such as English, Italian, Spanish, French and German. The tweets from various languages are associated with sentiment labels that help in classifying sentiments. This decision was made due to the possibility of finding user sentiment in the form of various opinions and linguistic features. Tweets were curated based on their sentiment annotations and categorized into five classes: 1 star was considered as very negative, 2 stars were also negative, 3 stars were neutral, 4 stars were positive, and 5 stars were very positive. Such a categorization helps the model to know and differentiate between sentiments more effectively.

Dataset Description: The dataset includes 4917 samples containing a tweet, the language of the tweet, and an assigned sentiment score. The sentiment ratings are classified into five categories: These feature ‘1 star’, ‘2 stars’, ‘3 stars’, ‘4 stars’, and ‘5 stars’.

Sample Data:

	tweet	language	sentiment
0	Lionel Messi, que ha estado vinculado con un t...	es	3 stars
1	This is a guest post by The Joy of Truth. To r...	en	4 stars
2	Nous sommes tous conscients de la popularité d...	fr	5 stars
3	El baño en el sistema de metro de la ciudad de...	es	4 stars
4	"Ich habe dies seit über 20 Jahren getan und i...	de	5 stars

Preliminary analysis of the tweets resulted in a total of 4917 tweets in five different languages. The descriptive statistics of the data in the three columns are as follows: The first column is the tweet text column; the second column is the language and the third is the sentiment and no missing values are identified in dataset. The large number of languages and sentiment tags makes this dataset more appropriate for the analysis that is designed to reveal the subtleties of sentiment distribution depending on the language context.

Data Cleaning and Exploration

Data Cleaning is an important process of any NLP task because the data quality determines the quality of the model. In the preprocessing stage employed was Exploratory Data Analysis (EDA), which is helpful to examine the characteristics of the dataset. This involved analyzing the distribution of sentiments that had been classified, in each language, and well balanced in all the sentiments labels.

Exploration Data Analysis

To explore the distribution of different sentiment types and languages several visualizations were created. These visualizations give the idea of what the actual data looks like and patterns that may affect the model are detected.

A. Sentiment Distribution of Multilingual Tweets

Figure 1 shows the Sentiment Distribution of Multilingual Tweets, has a bar chart for comparing the sentiment types and a pie chart for percentage distribution.

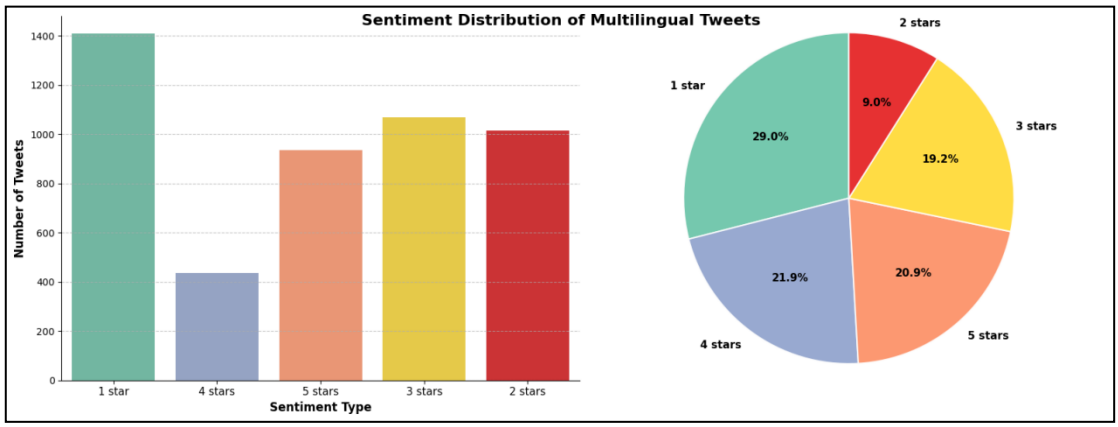

Figure 1: Sentiment Distribution of Multilingual Tweets

The bar chart on the left in figure 1 shows the number of tweets according to the sentiment analysis where negative sentiments are most dominant followed by 1 star which is approximately 1400. As for the 2-star and 3-star ratings, the two are more or less the same with approximately 1000 tweets each indicating moderate discontent. On the other hand, the 4-star ratings make up approximately 500 tweets showing that there was still a very active, albeit less enthusiastic, positivity going on. The 5-star ratings, at 900 tweets, show a good size of highly positive responses.

The pie chart on the right offers a percentage-based representation, reinforcing the predominance of 1-star ratings at 29%, followed by a more evenly distributed sentiment spread: 1 was 9% for 2-star, 2 was 19.2% for 3-star, 3 was 21.9% for 4-star and 4 was 20.9% for 5-star tweets. This distribution clearly contrasts such a user-experience divide with a highly polarized distribution of sentiments, with extreme scores clustering tightly.

B. Sentiment Distribution Across Languages:

The bar plot in figure 2 represents the distribution of sentiment across languages. This visualization helps in explaining how sentiment changes between the two languages. It shows the total number of tweets in five languages. French stands the highest with 980 followed closely by English with 979 tweets. German with 975, Italian with 968 and Spanish with 961.

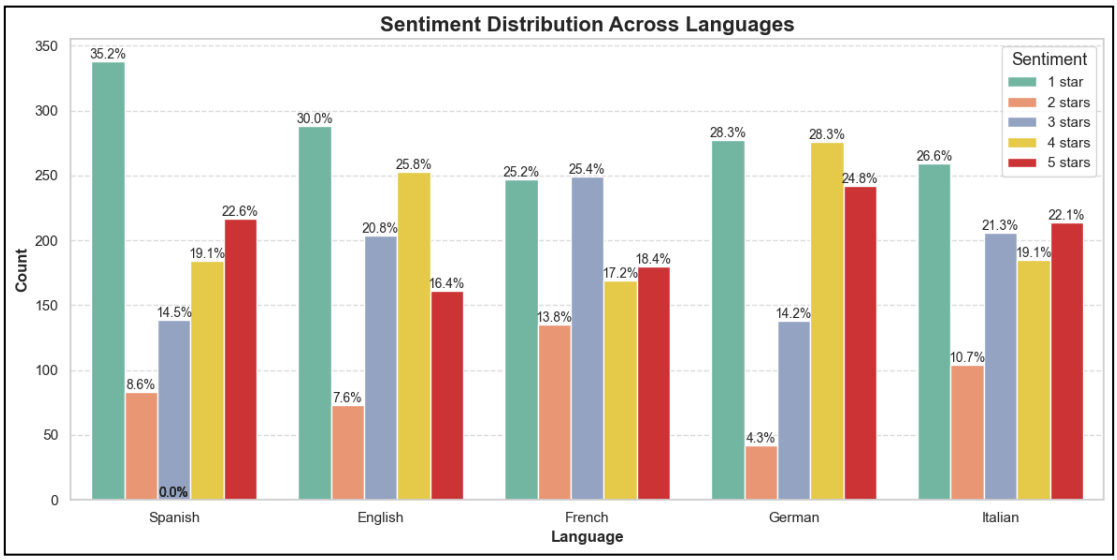

Figure 2: Sentiment Distribution Across Languages

From the above counts, it can be noted that the frequencies are fairly balanced for these five languages with French receiving slightly a higher tweet volume.

C. Length of Tweets:

The distribution of the number of characters and the number of words in the tweets were analyzed using histograms and Kernel Density Estimation plots. This analysis gives information on the general tweet length within the dataset used in this study.

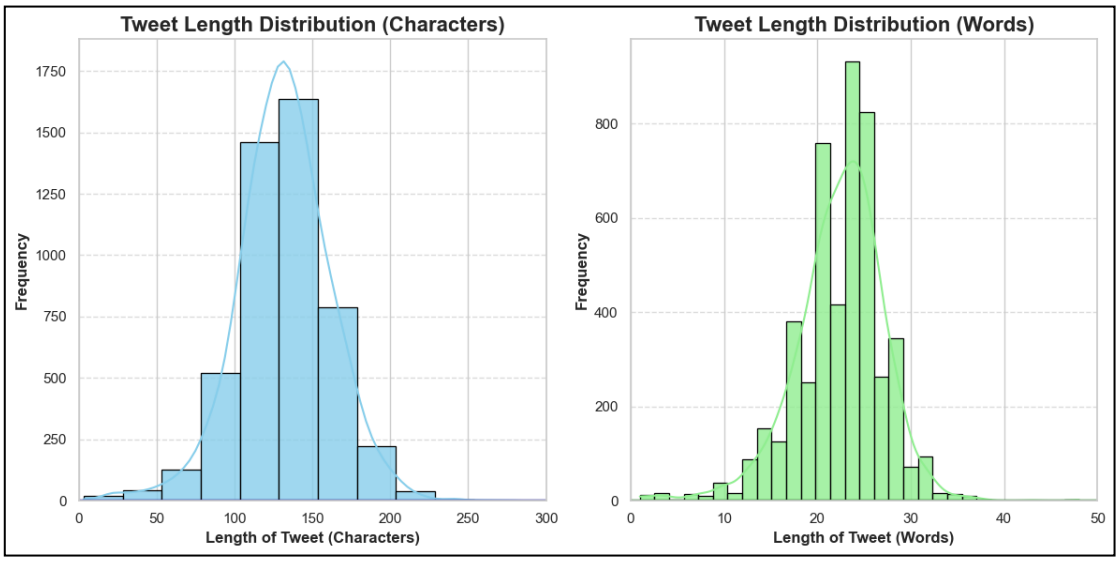

Figure 3: Distribution of Tweet Length Amongs Characters & Words

For character length, most tweets are concentrated around the mean of 140-character mark, with the majority the character length most of the tweets are between 100 and 180 characters long. The number of words varies between 10 and 30 words with a meaning of 23 words per tweet. This shows that tweets are normally brief, and a user is able to present his or her ideas concisely.

D. Word Cloud:

To compare the sentiments associated with the most commonly used words in the tweets, word cloud is used and shown in figure 4.

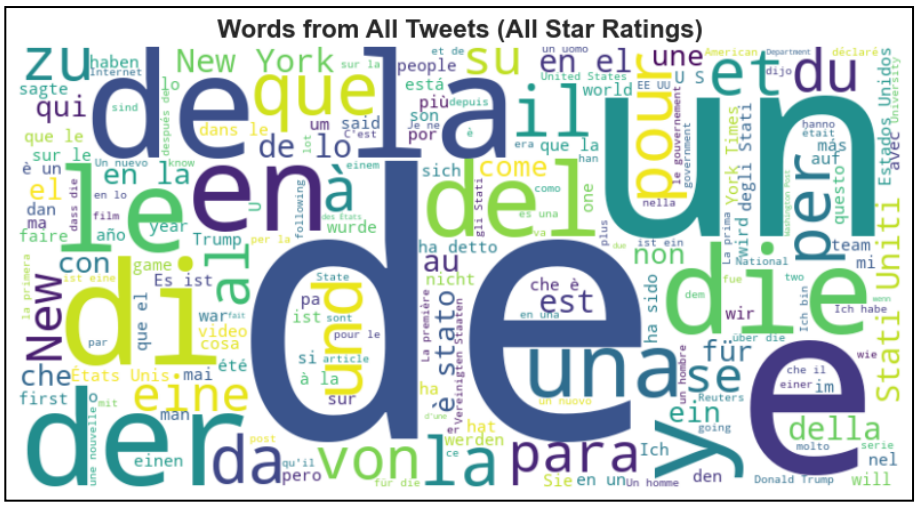

Figure 4: World Cloud Plot for All Star Ratings

Tweets Data Cleaning

Some of the main challenges of data analysis from social platforms include URL addresses, hashtags, mentions, and special symbols. To this end, text cleaning, which included the elimination of alpha numeric characters that may hinder the model from analyzing the text. This cleaning also involved standardizing punctuations in the datasets uniform across the dataset. As the dataset also contained the text in multiple languages, specific attention has been paid to the language-specific processing. Every single tweet was preprocessed by tokenization (splitting the input text into words/subwords) and excluding irrelevant features (hashtags, user mentions, etc.). Tokenization was vital to the feature extraction process since it divided a given tweet into comprehensible units of analysis, which is necessary when converting textual data into numerical form for use in machine learning.

Besides, the features with the sentiment labels were encoded using Label Encoding for the categorical labels. After cleaning and tokenizing the text, the data was split into training and testing sets, with different proportions (70:30, 75:25, and 80:20) to see results in various settings.

Model Selection

Transformer Models

The transformer models used in this research is XLM-RoBERT with meta-learning, both of which have widely been known for their efficiency in handling multi-lingual tasks and for their versatility in capturing a range of linguistic properties. These models are very popular in natural language processing (NLP) because of their ability to analyze text in different languages, which makes them ideal when analyzing natural language within different linguistic structures, for instance, sentiment analysis.

XLM-R (XLM-RoBERTa) is a transformer model that has been fine-pretrained on over one hundred languages using a multilingual dataset of text. This pretraining makes it possible for the model to capture different patterns, features, and relationships of language, including

syntax, semantics, etc. XLM-R is a model that is in contrast to traditional models that could work on more than language at a time; and since this research aims at working on multiple languages, then XLM-R would be the appropriate model. Multilingual sentiment detection is a component where the architecture is designed to perform the notion of handling multiple languages simultaneously to enhance the performance of tasks such as sentiment analysis. XLM-R can thus specialize in language-specific features while being able to recognize inter-lingual relationships to improve its cross-lingual generalization.

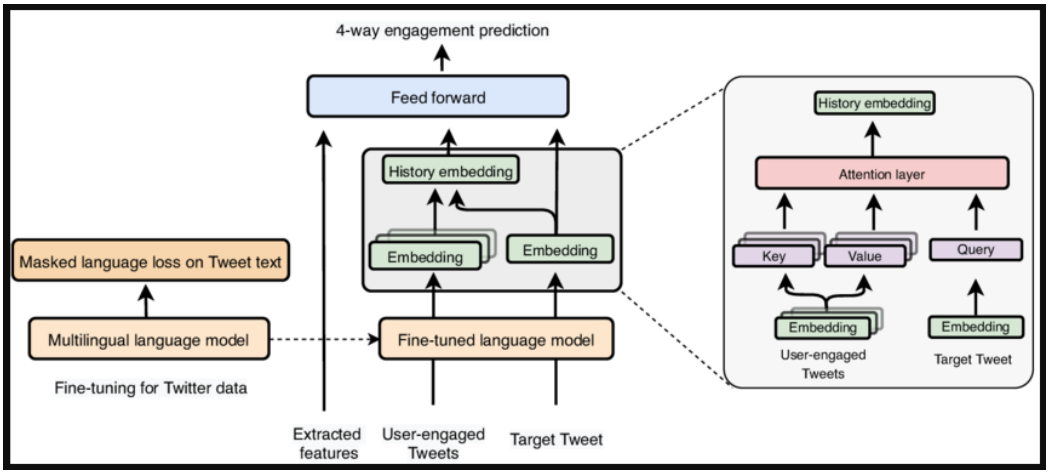

Figure 5: Model Architecture of Multilingual language model (XLM-RoBERTa) (Volkovs et., 2020)

XLM-RoBERT has strengths that can enhance research by handling multilingual data in the best way. XLM-R has been trained to understand multiple languages in one model; hence, it can cover more data for languages within the dataset and generalizes well, making it capture the language variation well enough; BERT has been trained to understand context and language relation well enough which make its sentiment analysis across the different languages feasible. These models' abilities collectively create a strong foundation for addressing multilingual NLP tasks with better performance efficiency.

Model Development

The development of various sentiment analysis models included both traditional ML models and advanced deep learning models using transfer learning. The traditional models include Naïve Bayes, Logistic Regression, and Support Vector Machine (SVM) and were used as the baseline models. These models were trained using standard text representation techniques: Bag-of-Words (BoW). It translates text into a matrix of token counts that is used to feed machine learning algorithms. These models were all trained to classify tweets into one of the various sentiment categories.

For the adavnced deep learning models, this research used Hybrid Model XLM-RoBERTa with meta-learning with a transformer-based architecture that has been pre-trained on a large multilingual corpus data. This model is primarily suited to multilingual tasks, so it is well suited for our dataset, formed by tweets in different languages. In the tuning of XLM-RoBERTa, the model weights were first initialized to pretrained weights and then made sentiment classification task. The text was preprocessed by using the XLM-RoBERTa tokenizer where the tweets collected were converted into a format that the model could interpret. This tokenization process assists the model in identifying words and the connection between them in different languages.

Table 2: Training Process of Hybrid Transformer Model

Epoch	Loss	Time per Epoch	Iteration Speed
1	1.535	46 seconds	4.54 it/s
2	1.351	48 seconds	4.40 it/s
3	1.103	50 seconds	4.18 it/s
4	0.854	50 seconds	4.24 it/s
5	0.604	50 seconds	4.21 it/s
6	0.426	50 seconds	4.22 it/s
7	0.306	50 seconds	4.22 it/s
8	0.215	50 seconds	4.22 it/s
9	0.211	50 seconds	4.22 it/s
10	0.136	50 seconds	4.22 it/s

The model was trained using the AdamW optimizer and a learning rate of 5e-5. Training was done for 10 epochs with an optimization of parameters of the model to reduce loss and increase accuracy. The main benefit of this transfer learning method was it was able to leverage information from a large multilingual corpus, thereby giving it broad language applicability notwithstanding the limited amount of data from the target task.

The AdamW optimizer, mentioned under Table 2, is essential for fine-tuning the XLM-RoBERTa model. It dynamically adjusts learning rates and adds weight decay, which helps in faster convergence and prevents overfitting. This optimizer is particularly effective in training transformer-based models by ensuring stable updates of the model weights. The "Time per Epoch" and "Iteration Speed" metrics in Table 2 reflect the computational efficiency of the training process. The time per epoch shows how long it takes to complete one full training pass over the dataset, while iteration speed indicates the processing speed per batch. These metrics highlight the resource requirements of the model and demonstrate its scalability for practical deployment. A consistent time per epoch across multiple epochs indicates optimized computation, while faster iteration speed shows effective hardware utilization.

Evaluation Metrics

The second step after training the models was to assess the performance. When dealing with imbalanced sentiment analysis tasks, accuracy alone might be misleading. Hence, other objective measures were employed in this study to have an improved assessment of model performance. The evaluation of **Precision, Recall** and **F1-score** of each set of models was done for each class Positive, Neutral, and Negative to understand how each model is good at recognizing each type of sentiment. Precision tells us how many of the examples that the model said were positive are truly positive, while Recall informs us of how many of the true positives are able to predict.

The **Confusion Matrix** has been calculated to visualize the performance of the model for different sentiment classes. This gave us the ability to look into how many instances of the tweets were predicted correctly against how many inaccurate predictions were made which is something very important as it shows where the model is going wrong. Also to compare the model between different sentiment classes, **ROC (Receiver Operating Characteristic)** curves and its corresponding **AUC (Area Under the Curve)** scores were computed. They give a holistic measure of the model classification capability rather than using a single fixed-point threshold. A higher AUC score means that the performance of a given model is better when it comes to distinguishing between positive and negative classes, especially while working on cases where there are more than two classes.

4 Model Evaluation Results, Findings and Discussion

This section provides an analysis and discussion of the evaluation of the sentiment analysis models incorporated in this research. The comparison is made between the traditional machine learning models and the newly proposed Hybrid Transformer Model which is a combination of XLM-RoBERTa through meta-learning. The evaluation measures employed are as follows; Accuracy, Precision, Recall, and F1 Score, confusion matrix, and the ROC curve.

Performance of Traditional Machine Learning Models

Before evaluating the Hybrid Transformer Model, the performance of three traditional machine learning models—Naive Bayes, Logistic Regression, and Support Vector Machine (SVM)—was assessed using three different training-test splits: 70:30, 75:25, and 80:20.

Table 3: Performance Results of Baseline Models

Split	Model	Accuracy	Precision	Recall	F1-Score
70:30	Naive Bayes	0.428376	0.415650	0.428376	0.410949
70:30	**Logistic Regression**	**0.465387**	**0.451437**	**0.465387**	**0.454481**
70:30	Support Vector Machine	0.447567	0.437374	0.447567	0.437978
75:25	Naive Bayes	0.415296	0.405325	0.415296	0.398747
75:25	Logistic Regression	0.447368	0.431494	0.447368	0.435965
75:25	Support Vector Machine	0.439967	0.430064	0.439967	0.430645
80:20	Naive Bayes	0.415211	0.401101	0.415211	0.398638
80:20	Logistic Regression	0.443988	0.433964	0.443988	0.435930
80:20	Support Vector Machine	0.435766	0.432256	0.435766	0.428778

Naive Bayes performed slightly bad compared to results of machine learning models, where accuracy was between 41.5% and 42.8% of all the splits. Low precision, recall value, and F1 score were observed, especially in the context of discriminating between two more fine-grained sentiments. Logistic Regression came out as the most accurate of all the traditional ML models with an accuracy of between 44.7% and 46.5%. The experiments showed that it had the best precision, recall, and F1-scores, particularly for the Neutral sentiment classification, and was the only model that could be considered balanced across the different sentiment classes and therefore was the most appropriate baseline for comparison. SVM achieved an accuracy of 43.9% – 44.7%. While efficient for the classification of specific sentiment classes it was slightly less accurate than the Logistic Regression algorithm

in the classification of the Sentiment as Neutral or Positive. The 70:30 split gave always the best performance in all the metrics selected for evaluation and was used in training the Hybrid Transformer Model.

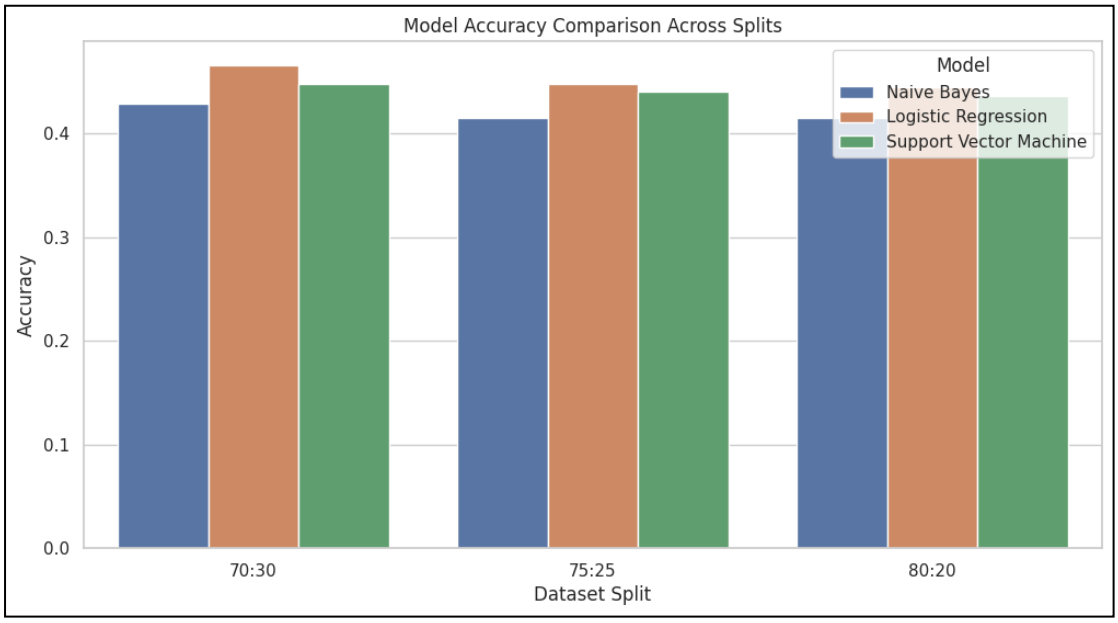

Figure 6: Performance Comparison of Baseline Models Accuracies

Performance of the Hybrid Transformer Model (XLM-RoBERTa with Meta Learning)

The Hybrid Model, which integrates XLM-RoBERTa using meta-learning techniques, was trained on the 70:30 split. To enhance its versatility across the sentiment classes, this model incorporates transformer-based models employed for multilingual tasks, in combined with meta-learning.

Table 4: Performance Results for Hybrid Transformer Model

	Precision	Recall	F1-Score	Support
1 star	0.78	0.67	0.72	423
2 stars	0.34	0.40	0.37	131
3 stars	0.46	0.53	0.49	281
4 stars	0.49	0.64	0.55	320
5 stars	0.69	0.46	0.55	304
Accuracy			**0.57**	**1459**
Macro avg	0.55	0.54	0.54	1459
Weighted avg	0.60	0.57	0.57	1459

Classification Report for the Hybrid Model

The classification report for the Hybrid Model (XLM-RoBERTa with Meta-Learning) depicted the following results in Table 4, which are quite higher than the traditional machine learning models with an accuracy of 57% which is significantly higher compared to the best performing traditional model accuracy of 46% only. The model for 1-star (Negative sentiment), has a precision of 0.78 recall of 0.67, and an F1-score of 0.72, meaning the negative sentiment was identified well but some instance of 1-star was overlooked. Regarding 2-star, the results were rather poor with precision of 0.34, while recall was 0.40;

F1-score was estimated to be 0.37 which indicates that it is challenging to classify the Neutral sentiments as they are quite frequently misclassified as 1-star or 3-star. The model had better accuracy with a 3-star (Neutral sentiment) with an F1-score of 0.49 and recall of 0.53 which is still not an optimal result. For 4-star (Positive sentiment), precision was 0.49, and recall was 0.64, which resulted in an F1-score of 0.55 while indicating that the classifiers have moderate success in identifying the positive sentiment but fail to differentiate it from the 5-star (Very Positive) sentiment. For 5-star sentiments, precision was 0.69 while the recall was 0.46, giving an F1-score of 0.55. While the model could predict very positive sentiments with fairly good accuracy it tends to associate them with 4-starred sentiments, thereby missing out on several 5-starred ones.

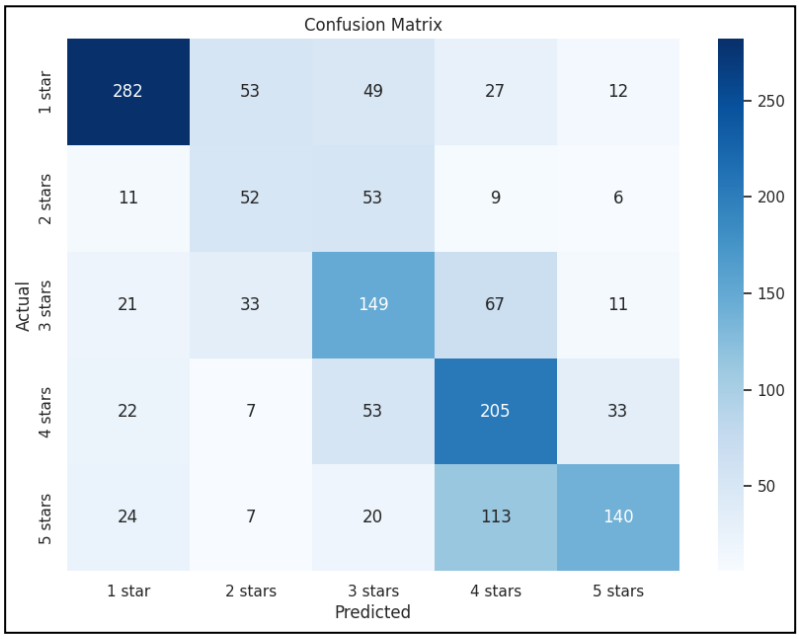

Figure 7: Confusion Matrix

Confusion Matrix for the Hybrid Model

The Hybrid Model confusion matrix provides a clear insight into the misclassification of different sentiment classes. As for 1-star (Negative sentiment), the model was quite precise, most of the 1-star instances were identified. Nonetheless, there were 53 misclassifications as 2-star , which indicates that sometimes there is confusion between sentiments Negative and Neutral. Hence for 2-star the model struggled a lot, as lower diagonal values show and the majority of them are classified into 1-star and 3-star. This shows that Neutral sentiments were often confusing, and this led to a very hard time trying to classify them. The 3-star (Neutral sentiment) category was identified with more correct classifications, while still significant classification errors in 4-star and 2-star categories were found, which underlines the model's weakness in the differentiation of Neutral and Positive sentiments. Most of the instances of 4-star (Positive sentiment) were correctly classified but some were misclassified with 5-star (Very Positive sentiment), implying that there is confusion between Positive sentiment and Very Positive sentiment. Finally, for 5-star (Very Positive sentiment), a relatively large number of instances were misclassified into 4-star, indicating some difficulty by the model in distinguishing between Positive and Very Positive sentiments.

ROC Curve and AUC Score

In the Hybrid Model, the ROC curve shows the AUC score of 0.69 implying a moderate ability to classify classes. This score is higher than in the previous models, in which AUC was shown in figure 9. The AUC proves that the Hybrid model is better than a random guess in the classification of sentiment classes but there is an area of improvement in the classification of Neutral sentiment classes.

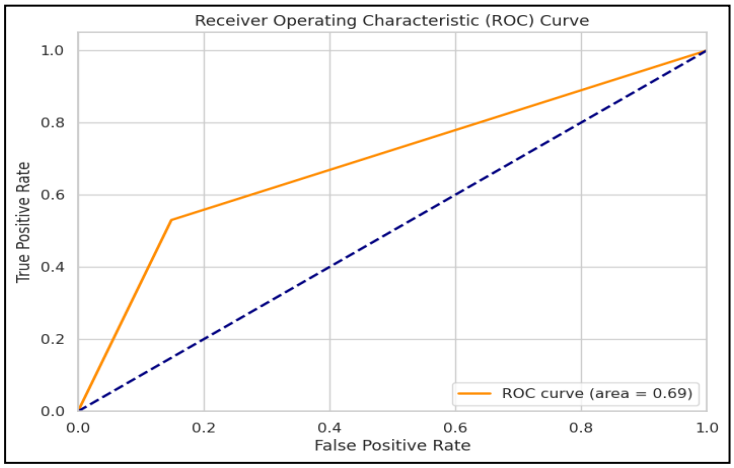

Figure 8: ROC Curve & AUC Score (Hybrid Transformer Model)

Sentiment Predictions for Multilingual Data

To assess the Hybrid Transformer Model in a multilingual setting, sentiment estimations were performed on a sequence of multilingual tweets. To examine the generalization, these predictions were made across languages and were compared with the actual sentiment ratings.

Table 5: Predicted Sentiments for Multilingual Tweets

Tweet Language	Tweet Text	Predicted Sentiment
English	"This product is absolutely amazing! I can't believe how well it works, and the customer service is exceptional."	5 stars (Very Positive)
Spanish	"Este producto es terrible. No cumple con lo prometido y la calidad es muy mala."	1 star (Negative)
French	"Le produit est correct, mais je m'attendais à mieux pour le prix."	3 stars (Neutral)
German	"Das Produkt ist gut, aber die Lieferung hat viel länger gedauert als erwartet."	4 stars (Positive)
English	"The product is fine, but it doesn’t offer anything special. I wouldn’t say it’s bad, but I’m not impressed either."	2 stars

For example, the model assigned 5 stars to an English tweet that said "This product is absolutely amazing! I can't believe how well it works, and the customer service is exceptional.". The prediction is correct as the tweet outlines a very positive statement, thus the strong positive text governing the prediction. Some words like Words like "absolutely amazing" and "exceptional customer service" are very clearly on the high end of the positive

scale, so the model correctly outputs this as 5. The result of this study shows that the model is capable of accurately identifying extremely positive sentiments in English.

```python
# Predict the sentiment for the tweet (English)
new_tweet = "This product is absolutely amazing! I can't believe how well it works, and the customer servi
predicted_sentiment = predict_sentiment(new_tweet)
print(f'Multilingual Predicted sentiment: {predicted_sentiment}')  # 1 for 1 star, 2 for 2 star, 3 for 3 s
```

Python

```
Multilingual Predicted sentiment: 5 stars
```

Tweet in Spanish: "Este producto es terrible. No cumple con lo prometido y la calidad es muy mala," , the model predicted **1 star**. This was a correct classification as the tweet also shows a very strong negative tone of dissatisfaction by applying the words terrible, doesn't meet expectations, and very bad about a particular product. In Spanish for instance, the model was able to identify this negative sentiment, which proves that the model can perform sentiment analysis in other languages.

```python
# Predict the sentiment for the tweet (Spanish)
new_tweet = "Este producto es terrible. No cumple con lo prometido y la calidad es muy mala."
predicted_sentiment = predict_sentiment(new_tweet)
print(f'Multilingual Predicted sentiment: {predicted_sentiment}')  # 1 for 1 star, 2 for 2 sta
```

```
Multilingual Predicted sentiment: 1 star
```

This French tweet "Le produit est correct, mais je m'attendais à mieux pour le prix," was estimated to be **3 stars**. This sentiment is more complex, while the tweet mentions that the product is good, the user displays a certain level of discontent with the product as he expected value for his money. The model expected the sentiment score to be **Neutral** which equals to 3 stars. This prediction shows the model's performance in the 'neutral' class, though this is often a difficult one to assign because the statement is often so vague.

```python
# Predict the sentiment for the tweet (French)
new_tweet = "Le produit est correct, mais je m'attendais à mieux pour le prix."
predicted_sentiment = predict_sentiment(new_tweet)
print(f'Multilingual Predicted sentiment: {predicted_sentiment}')  # 1 for 1 sta
```

```
Multilingual Predicted sentiment: 3 stars
```

A German tweet "Das Produkt ist gut, aber die Lieferung hat viel länger gedauert als erwartet,"; it was predicted to be **4 stars**. The tweet consists of a positive opinion about the product in general while there is a certain amount of dissatisfaction caused by the delivery time. The model was right in this classification attributing it to 4 stars which is positive but with a slightly negative connotation from delivery experience. This predicts positivity about

the product while the incorporation of some complaint type shows the flexibility of this model.

```
# Predict the sentiment for the tweet (German)
new_tweet = "Das Produkt ist gut, aber die Lieferung hat viel länger gedauert als erwartet."
predicted_sentiment = predict_sentiment(new_tweet)
print(f'Multilingual Predicted sentiment: {predicted_sentiment}')  # 1 for 1 star, 2 for 2 st
```

```
Multilingual Predicted sentiment: 4 stars
```

The multilingual sentiment predictions show that the Hybrid Transformer Model is efficient in the classification of fine-grained positive and negative sentiments across languages compared to ML models. From the results obtained where the model was able to correctly predict 1-star and 5-star sentiments in English, Spanish, and German, it is clear that the model manageable in predicting on extreme sentiments. Nevertheless, it is difficult with 'neutral' sentiments, 3-star, where the model can falter due to the vagueness of these expressions. These issues underline the potential for continued progress in model development, for example, concerning mixed sentiment and neutral category handling that can be resolved by data augmentation, fine-tuning, and class imbalance methods. Finally, the outcomes also suggest that the Hybrid Transformer Model performed manageably well compared to ML in extreme sentiment classification; however, there is still potential for improvement regarding more complex sentiment in different languages.

Discussion and Insights

The findings of the Hybrid Model (XLM-RoBERTa with Meta-Learning) assessment are as follows: First, the Hybrid Model provides better results than machine learning models with an accuracy of 57%, which is higher than the best result of 46% for Logistic Regression. This shows that transformer-based models have a lot of benefits for handling the difficulties of sentiment classification even in a multilingual environment. To extend the analysis, sentiment predictions were also made for the tweets in four languages: English, Spanish, French as well as German.

For example, the model assigned 5 stars to an English tweet that is highly positive, and the sentiment of which is maximum satisfaction with the product. In contrast, a Spanish tweet that expressed an adverse opinion on the product was correctly predicted as 1 star as it should have been since its sentiment was negative. The model also correctly classified a French tweet to 3 stars which means no positive sentiment, no negative sentiment, and a mild negative sentiment but no extreme sentiment. Also, the German tweet that mentioned the product is good, but there were problems with the delivery was classified as 4 stars, so the model shows how to classify slightly positive sentiment. The above predictions also prove that even in the case of extreme sentiments like 1-star and 5-star, the Hybrid Model can perform well in different languages to classify polarised sentiment. However, the model was not performing well on the neutral sentiments, which can be observed when the model was tested on the French and English tweets.

Further, the results were affected by class imbalance such as in the case of the confusion between 4-star and 5-star sentiment analysis. The misclassification of 4-star and 5-star instances may be due to the incorrect differentiation the model might have made between

very slightly positive and extremely positively words. This issue suggests that class balancing, focal loss, or more training data might help to enhance the model performance in such cases. Finally, the value of the AUC is 0.69 means that the model has a moderate ability to distinguish sentiment categories, which means that it works, but it needs further improvements, especially for neutral sentiments, where the model has lower predictive accuracy. This could be improved by techniques such as fine-tuning the model or increasing the training set with a balanced representation of sentiments to capture subtle cues and perform better under 'borderline' conditions, where the sentiment ranges between positive and negative as well as negative and positive.

Therefore, the work implemented by proposing the Hybrid Transformer Model (XLM-RoBERTa with Meta-Learning) outperforms the traditional machine learning models for sentiment classification and better performance and efficiency for a wide range of sentiment categories. The model is especially good at recognizing very positive and very negative attitudes but has issues with the recognition of neutral attitudes and class imbalance, which indicate further research and model improvement. Additional work on fine-tuning the model for better processing of neutral sentiment and fine-grained improvements to the slight positive or slight negative polarity might bring even more robust and accurate multilingual sentiment analysis applications.

5 Conclusion and Future Work

Conclusion

This research proves the efficiency of transformer-based models, including the Hybrid Model based on XLM-RoBERTa with Meta-Learning. The Hybrid Model was shown to be better than the Naive Bayes, Logistic Regression, Support Vector Machine in terms of accuracy, precision, recall, and F1-score. The model obtained 57% accuracy, and it can be said that this model performs moderately better in learning and classification of sentiment particularly the extreme sentiments such as 1-star and 5-star reviews than the traditional models. Nevertheless, there are still some challenges, especially for neutral sentiments, which would be challenging for the model due to language uncertainty and class imbalance. Nevertheless, there were significant increases in performance concerning the baseline models The Hybrid Model can therefore be inferred to have great potential given that transformer-based architectures for sentiment analysis in variable, multilingual, and realistic settings. The use of meta-learning helped to introduce an extra level of adaptability into the transformer model and helped the model to learn better and more general patterns from the data that can be applied to different categories of sentiment. This demonstrates that meta-learning can be of significant help in the optimization of sentiment classifiers particularly when the language is complicated and implicit.

The research aligns with ongoing advancements in multilingual NLP, particularly using transformer-based models like XLM-RoBERTa, which have demonstrated high performance in multilingual tasks. This study addresses a critical gap in low-resource language modeling by combining transfer learning and meta-learning to enhance performance of low resource data. By achieving reasonable accuracy using XLM-RoBERTa on a complex on task like low resource multilingual sentiment analysis that is reasonably better than traditional machine learning models —the research contributes to advancing sentiment analysis for low-resource languages. Building in this study, future work can be explore the use of multilingual text

generative models to address the changes in low resource language and enhancing model performance.

Future Work

The outcomes of this research are significant, but there are several directions about transformer-based models for sentiment analysis that could be improved and explored further. Certainly, there is the issue of neutral sentiment classification is one of the key concerns as the model poorly performs. As for further research, employing different methods such as finetuning on more balanced datasets, data augmentation techniques, and multiple task learning to improve the boundary between neutral and extreme sentiments. Also, skewness in the data split hampered the performance and while the extremity of sentiment was well classified, the neutral was poorly classified. To manage this problem, strategies like oversampling, under sampling, and applying a weighted loss function could be used. Another direction was identified as contextual knowledge, as the model struggled to decipher such language elements as irony, sarcasm, and specialized terminology. These aspects might benefit from the inclusion of contextual embeddings or attention mechanisms. In addition, expansion of the model to more extensive and varied corpora, and investigation of the domain adaptation methodologies would improve the results, especially in industries with different sentiment patterns. Other meta-learning paradigms, for example, few-shot or meta-transfer learning could also enhance the models' adaptation capability to unseen sentiment categories where labeled data may be scarce. Finally, for potential use, real-time and online learning abilities would allow the model to update data processing and remain effective when facing new data sets in relevance and complexity.

Therefore, despite the effectiveness of transformer-based models in sentiment analysis tasks compared to ML model still there remain many research opportunities. Improving the orientation to the handling of neutral sentiments, class imbalance problems, and contextual interpretation is going to be critical to achieving higher accuracy and stability. future research in these areas will result in the improved and efficient performance of the sentiment classifier which can be applicable to real-life applications in a cross-language, cross-domain, and cross-data situation.

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