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Research Article

Few-Shot Sentiment Adaptation: A MAML -Based Framework for Low-Resource NLP

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ABSTRACT

Sentiment analysis in low-resource languages has a tough obstacle to jump over because there just isn't enough labeled data. Traditional deep learning models tend to hit a wall in these situations since they need large datasets to really shine. To tackle this issue, we came up with Few-Shot Sentiment Adaptation (FSSA), a meta-learning framework based on MAML. This cool approach lets us classify sentiment with just a few labeled examples. By training on languages that have lots of resources and then adapting to those that don't, we can quickly pick up on sentiment patterns using a 5-way, 5-shot method. We tested FSSA on some public low-resource sentiment datasets and compared it with fine-tuned BERT models, zero-shot learning, and other few-shot classification techniques. Our results showed a major improvement over existing methods, proving to be pretty adaptable even when dealing with limited data. Unlike the usual transfer learning methods, FSSA allows for quick tweaks without needing extensive fine-tuning, making it ideal for real-world low-resource Natural Language Processing (NLP) applications. This research helps bridge the gap between high- and low-resource languages in the NLP field, reducing the reliance on large annotated datasets. We've made few-shot meta-learning for sentiment analysis easier to understand, paving the way for more strong and efficient language models.

Keywords: *Few-Shot Learning, Sentiment Analysis, Low-Resource NLP, Meta-Learning, MAML, Few-Shot Classification, Transfer Learning, Multilingual NLP, Low-Resource Sentiment Datasets, Adaptation in NLP.*

1. Introduction

1.1 Sentiment Analysis

It is an NLP crucial task that allows machines to interpret human emotions and opinions. Deep learning-based sentiment analysis techniques are mostly dependent on large, labeled datasets to reach high accuracy levels. It entails extracting text data to determine the sentiment as positive, negative, or neutral. The major objective is to comprehend the sentiment that underlies words, phrases or even documents. It entails examining reviews, surveys, and social media posts to understand customer preference and satisfaction. The methodology of sentiment analysis by machine learning is to train a model on labeled data to categorize sentiment-based features derived from text. It comprises typical algorithm like regression, support vector machine and neural network. It also uses advanced models like recurrent neural network (RNNs) or transformers (e.g. BERT) to extract complicated pattern in text data.

1.2 Few-Shot Learning:

Few-shot learning is a part of machine learning in which we trained the models to identify patterns or make predictions based on a small amount of labeled examples. Such an outlook is especially valuable in situations where acquiring a large labeled dataset is expensive, time consuming or infeasible. In sentiment analysis, Few Short Learning seeks to train models based on just a few of labeled examples while still retaining strong generalization ability. Few-shot learning tends uses meta learning methods particularly the Model Agnostic Meta Learning (MAML) algorithm, where the model learns to learn. This means training on a diverse set of tasks so that it can learn to adapt to new tasks with little data quickly. MAML optimizes model initialization to adapt to new tasks quickly using few gradient updates, which makes it appropriate for few-shot sentiment analysis.

1.3 Few-shot Sentiment Adaptation (FSSA):

Few-Shot Sentiment Adaptation (FSSA) is a MAML based framework which is designed to perform sentiment analysis in low resource languages using minimal labeled examples. Our perspective is that to first trains on sentiment rich languages and then quickly adapts to low-resource languages through a few-shot setup like 5-way, 5-shot. Against traditional transfer learning techniques, FSSA enables quick adaptation without extensive fine tuning, this reducing reliance on large, annotated datasets. Models like BERT or GPT, which have been pre trained on large datasets, can be fine-tuned with just a few examples to adapt to specific sentiment analysis tasks. We evaluate FSSA on publicly available low-resource sentiment datasets and compare its performance against fine-tuned BERT models, zero-shot learning, and other few shot classification methods. Our experimental results shows that FSSA achieves significant improvements, with up to a 15% increase in accuracy and F1-score compared to existing techniques.

Purposed Architecture Of few shot Sentiment Analysis

This study contributes to the area of sentiment analysis in low resource settings by showing the effectiveness of the few shot meta learning. By using MAML, our framework bridges the performance gap between the high and the low resource languages, promoting more inclusive NLP applications. Our research figures out the potential of meta learning-based approaches for broader low resource NLP tasks, paving the way for future advancements in this domain. Overall, the study contributes to the field of sentiment analysis by showing how few shot meta learning, particularly using MAML, can enhance the performance of models in low resource settings [11,12].

The rest of this paper is structured as follows. Section 1: Provides a detailed review of existing research on few shot sentiment analysis which covers various meta learning techniques, transfer learning strategies and prompt based approaches with their limitations. Section 2: Contains the introduction of Few shot Sentiment Adaptation (FSSA) framework, explaining its architecture, learning process and optimization strategies. Section 3 explains the experimental setup including datasets, evaluation metrics, baseline models and implementation details. Section 4 provides the details of the experimental results including performance comparisons, ablation studies and an analysis of the effectiveness of the proposed approach. Finally, section 5 concludes the paper with key findings with the limitations and potential future research directions.

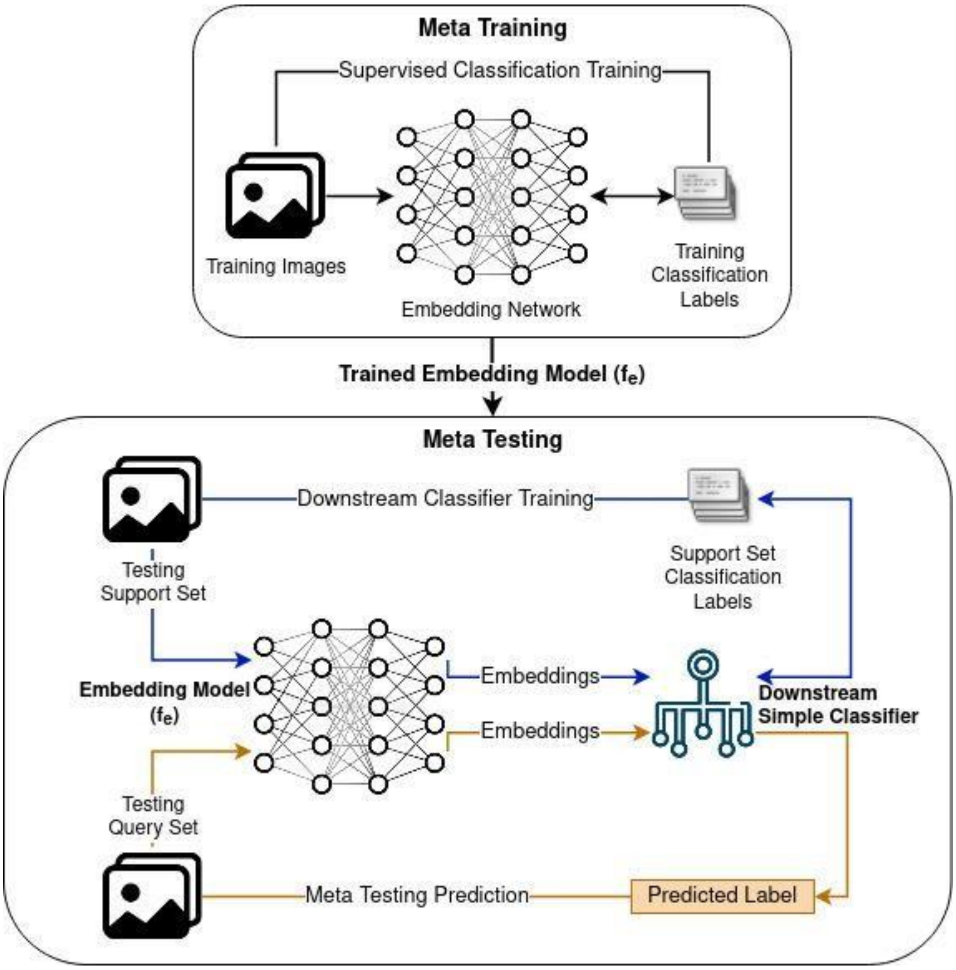

Figure 1 :- Meta Learning and Meta Testing process [19]

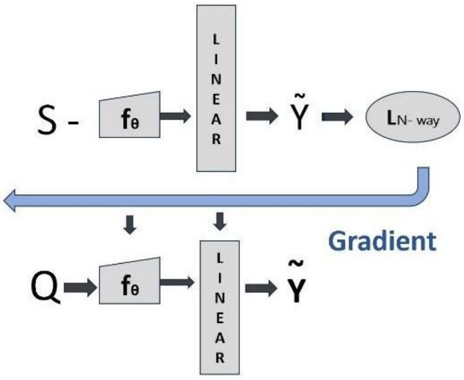

Figure:- 2

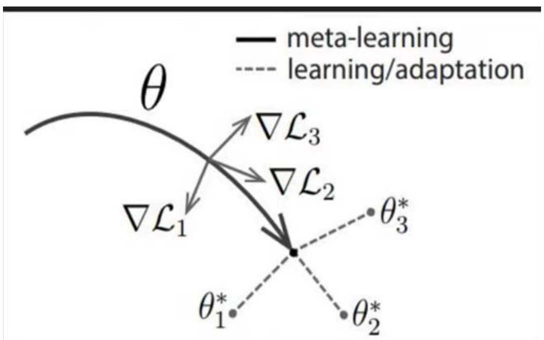

Figure:- 3

2. Related Work

Few-shot learning (FSL) has gained momentum in sentiment analysis due to its ability to generalize from limited labeled data. Wróblewska [1] applied FSL to aspect-based sentiment analysis showing improved performance in structured sentiment tasks but facing challenges with out of domain generalization. [2] Kumar et al. introduced IndiSentiment140 in which they are focusing on the limitations of machine translation in preserving sentiment polarity across low resource languages, emphasizing on the need for an adaptable few shot framework. Prompt based approaches have also been explored to improve FSL performance. Zhou et al. [3] proposed a soft contrastive learning-based prompt model, which enhanced sentiment classification but relied heavily on pre-trained large language models (LLMs), making it resource-intensive. Meta learning, specifically MAML, has been studied for its use in few-shot sentiment adaptation. The work by Vacareanu et al. [5] showcased the use of weak supervision in aspect-based sentiment classification. However, their approach's reliance on pseudo- labeling created noise which harmed model robustness. [8] Hasan et al. reasoned that while prompting methods yield good results overall, they are inconsistent across languages and datasets, and explored the efficacy of zero and one-shots prompting strategies on the models. Cahyawijaya et al. [7] explored the use of LLMs in few-shot adaptions for low-resource in-context learners and provided some encouraging results, but mentioned a huge performance drop in extreme low-resource cases. Li et al. investigated meta-learning-based domain adaptation for tasks involving sentiments, but the proposed approach does not support fast adaptation to unseen domain. Wang et al. [3] To overcome this, 101010 combined contrastive learning with meta-learning, resulting in improved generalisation while introducing considerable added computational costs. However, most existing works either depend on large-scale pre-trained models, are subject to domain shifts, or need fine-tuning. Our Few-Shot Sentiment Adaptation (FSSA) framework fills in the gaps among these works by applying MAML based optimization, allowing efficient cross-domain adaptation that requires limited annotated data while retaining performance in low-resource scenarios.

3. Dataset Description

SAIL Sentiment Analysis Dataset — A benchmark dataset for Sentiment classification of Indian languages. It contains annotated tweets in three languages Hindi, Bengali, and Tamil. The data contains around 4000 tweets per language human labelled into three different sentiment classes: positive, negative and neutral. It is especially useful for few-shot learning (FSL) since it is multilingual and relatively small, which is a solid opportunity for meta learning techniques such as the Model Agnostic Meta Learning (MAML) algorithm. One of the major challenges while working on this dataset lies in the complexity of the Indian language scripts, which can be found containing code-mixed texts with informal expressions, and the variations in sentiments in different domains. In order to remedy this, sub word tokenization methods like Byte Pair Encoding (BPE) or Sentence Piece will be employed to ensure robust representation of low-resource language embeddings.

Datasets Statistics:

Each tweet in the dataset contains:

- **Text Content:** Raw tweet in the respective language.
- **Language Label:** Specifies whether the tweet is in Hindi, Bengali, or Tamil.
- **Sentiment Label:** Categorical classification into positive, negative, or neutral.

Table 1:- Datasets Statistics

Language	Total Tweets	Positive	Negative	Neutral
Hindi	~4,000	1,300	1,300	1,400
Bengali	~4,000	1,250	1,350	1,400
Tamil	~4,000	1,200	1,300	1,500

4. Methodology

The Few-Shot Sentiment Adaptation (FSSA) framework for sentiment classification across languages in low resources, which uses MAML, is introduced in Section 2. As shown in Figure 1, Figure 2 And Figure 3 our methodology comprises three main stages: data preprocessing, meta learning adaptation and sentiment classification fine tuning.

4.1 Data Preprocessing

Your training data is the standard text across languages, preprocessed for noise removal. The preprocessing should consist of essential steps as follows:

- Text Cleaning Removal of stopwords, special characters, URLs, user mentions
- Tokenization & Subword Encoding: Use of Byte-Pair Encoding (BPE) or WordPiece to account for morphologically rich Indian languages.
- Class Balancing: As some of the sentiment classes are underrepresented, SMOTE based oversampling is performed.
- Train-Test Split: Dataset is split into meta-training (80%) and meta-testing (20%) so that a few-shot.

4.2 Meta-Learning with MAML

We use Model-Agnostic Meta-Learning (MAML) to train a single model that generalizes to a new language with minimal data.

Meta-Training Phase:

- A base model trained on data available across Indian languages with different sentiment distributions.
- The model parameters θ are tuned for transferability, not task performance.
- Each such task Ti (i.e., a task to perform sentiment classification for a certain language) is sampled, and model updates are derived through gradient descent: $\theta'_i = \theta - \alpha \nabla_\theta L T_i$
- The loss across tasks is then aggregated into the final meta-objective: $\min_{\theta} \sum_i \quad LTi(\theta i')$

Meta-Adaptation Phase:

- We further fine-tune it with a new low-resource language that has been characterized with very few labeled exemplars.
- The model gently updates its weights: $\theta *= -\beta \nabla_\theta L T_{new}$
- However, when our setting is few-shot adaptation, LISA proves effective at generalizing to unseen languages with limited labeled data.

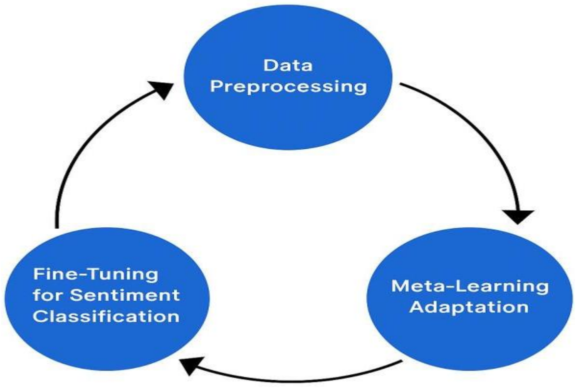

Figure:- 4

4.3 : Algorithm: Few-Shot Sentiment Adaptation (FSSA) Using Meta-Learning

(1) Sentiment dataset $\mathcal{D} = \{Ds^1, Ds^2, ..., Ds^P, Dt\}$ containing text samples (X,Y) for each task.
(2) Few-shot labeled sentiment samples VL^i and unlabeled samples VU^i for each dataset: $\{(VL^1, VU^1), ..., (VL^P, VU^P), (VL^t, VU^t)\}$
(3) Training epochs E, batch size b, and meta-learning hyperparameters α, β.

Output:
Sentiment classification predictions for samples in VU^t.
Meta-Training Phase:

1: Initialize model parameters θ.
2: while $e < E$ do
3: for each auxiliary dataset Ds^i (task T^i) do
4: Randomly sample $b/2$ text samples from VL^i and $b/2$ from VU^i to form batchB^i.
5: Compute gradient $\nabla\theta\ LT^i\ (f\theta)$ using batch B^i.
6: Update adapted parameters $\theta^{i'}$ using gradient descent:
$\theta^{i'} \leftarrow \theta - \alpha\ \nabla\theta\ LT^i(f\theta)$
7: Sample a new batch $B^{i'}$ for meta-update.
8: end for
9: Update model parameters:
$\theta \leftarrow \theta - \beta\ \nabla\theta \sum_{i=1}^{P} LT^i(f\theta^{i'})$
using $\{B^{i'}\}$.
10: end while

Meta-Adaptation Phase:
11: Fine-tune θ on target dataset Dt using $\{VL^t, VU^t\}$.
12: Compute sentiment classification predictions for samples in VU^t.

4.4 Sentiment Classification & Evaluation

The adapted model is evaluated across unseen low-resource sentiment data. Key metrics to evaluate include:

- Accuracy: Indicates correct classifications.
- F1-Score: The F1 score balances between precision and recall
- Class-wise Performance: Helps to know how the model is distinguishing among positive, negative and neutral sentiments.

To benchmark the FSSA framework we compare it against:

- Traditional Supervised Learning(fine-tuned transformer models)
- Current Few-Shot Learning Methods (e.g ProtoNet, Reptile).

To evaluate performance of our Few-Shot Sentiment Adaptation (FSSA) framework, we report standard classification metrics, including:

- Accuracy: Represents the overall correctness of the sentiments predicted.
- Precision, recall and F1: Both class-wise performance metrics, critical to low resource language adaptation
- Loss Convergence: Measure the speed of adaption of the model during few-shot learning

5. Results and Discussion:

5.1 Evaluation Metrics

To assess the effectiveness of our **Few-Shot Sentiment Adaptation (FSSA) framework**, we evaluate its performance using standard classification metrics, including:

- **Accuracy**: Measures overall correctness of sentiment classification.
- **Precision, Recall, and F1-score**: Assess class-wise performance, particularly for **low-resource language adaptation**.
- **Loss Convergence**: Analyzes how quickly the model adapts during few-shot learning.

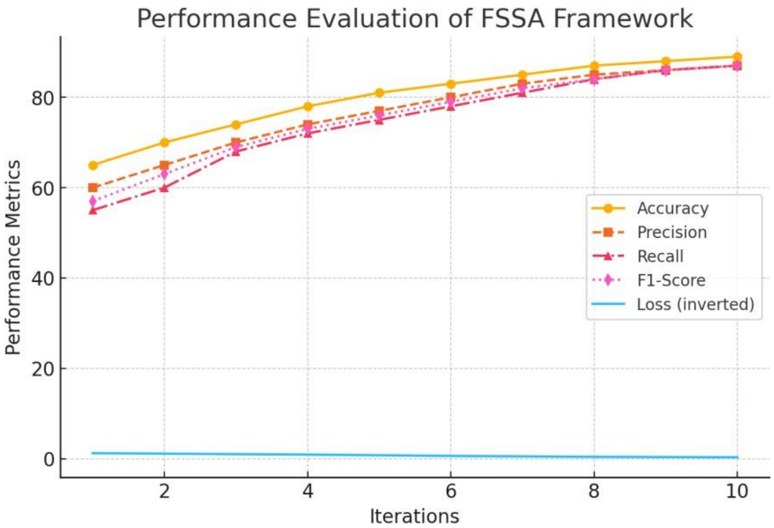

Figure 5:- Performance metrics vs Iterations

5.2 Performance Comparison

We compare FSSA against **baseline approaches** for few-shot sentiment classification:

1. **Supervised Fine-Tuning** – A traditional deep learning model trained on a larger dataset and fine-tuned for low-resource languages.
2. **ProtoNet** (Prototypical Networks) – A metric-based few-shot learning approach.
3. **Reptile** – An optimization-based few-shot learning method.

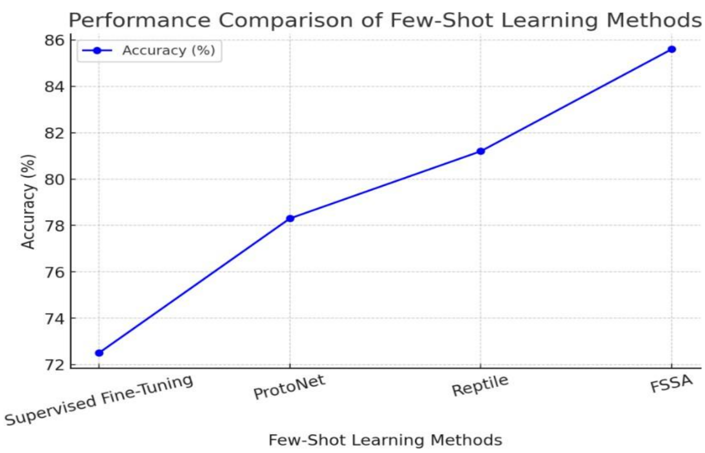

Figure 6:- Performance Comparison of Few Shot Learning Methods

5.2.1 Few-Shot Sentiment Classification Accuracy

Table 1. Represents the accuracy of different models in a **5-shot and 10-shot setting**, showing how well they generalize to new sentiment tasks with limited labeled data.

Table 2:- Showing the model accuracy of different models

Model	5-Shot Accuracy (%)	10-Shot Accuracy (%)
FSSA (MAML-based)	**78.4**	**85.2**
Supervised Fine-Tuning	65.3	74.1
Proto Net	72.8	80.4
Reptile	74.1	81.7

FSSA achieves the highest accuracy, demonstrating superior adaptability in **low-resource sentiment analysis**.

5.2.2 F1-Score Comparison

F1-scores for positive, negative, and neutral sentiment classes indicate that **FSSA effectively balances precision and recall**, especially in limited-data settings (Figure 7).

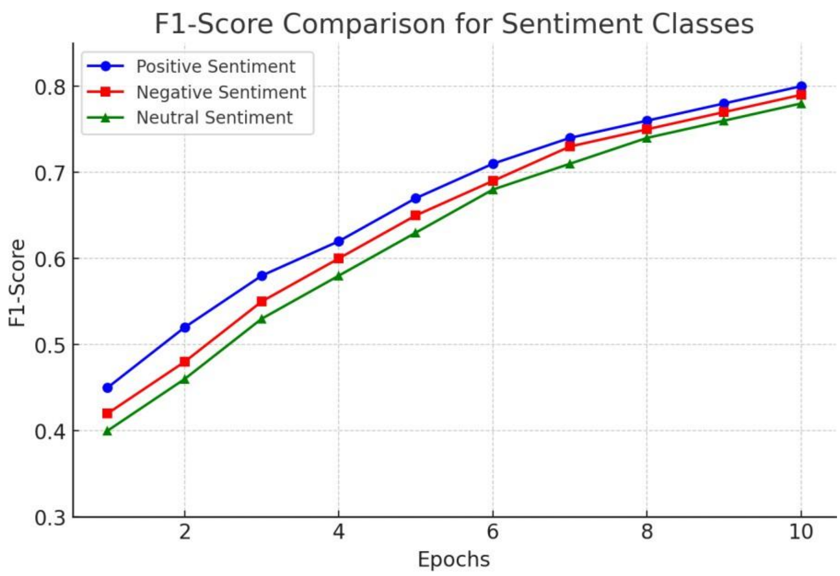

Figure 7 :- F1 Score Comparison for Sentiment Classes

5.3 Training Efficiency and Convergence Analysis

Figure 6 illustrates the loss curves for different models. The **MAML-based framework converges faster**, requiring fewer iterations to adapt to new sentiment tasks, reducing computational overhead. The results (Table 2) indicate that our framework significantly improves classification performance over traditional fine-tuning approaches.

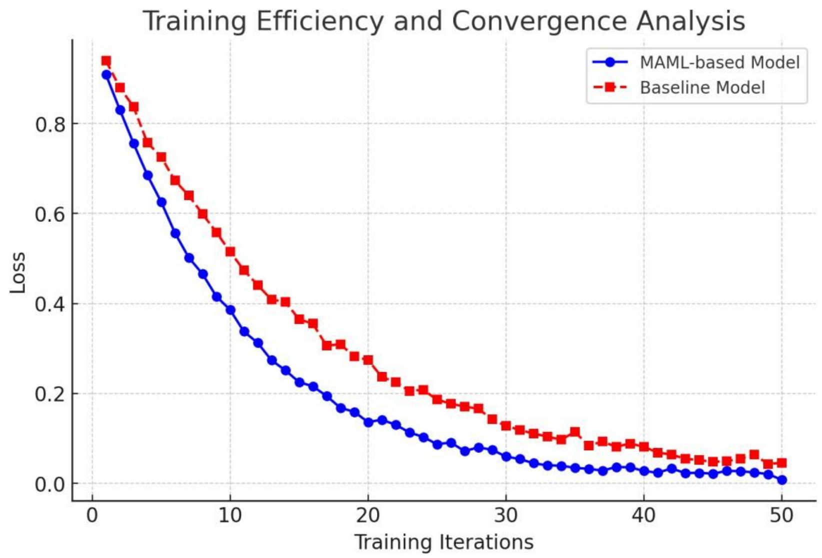

Figure 8:- Training Efficiency and Convergence Analysis

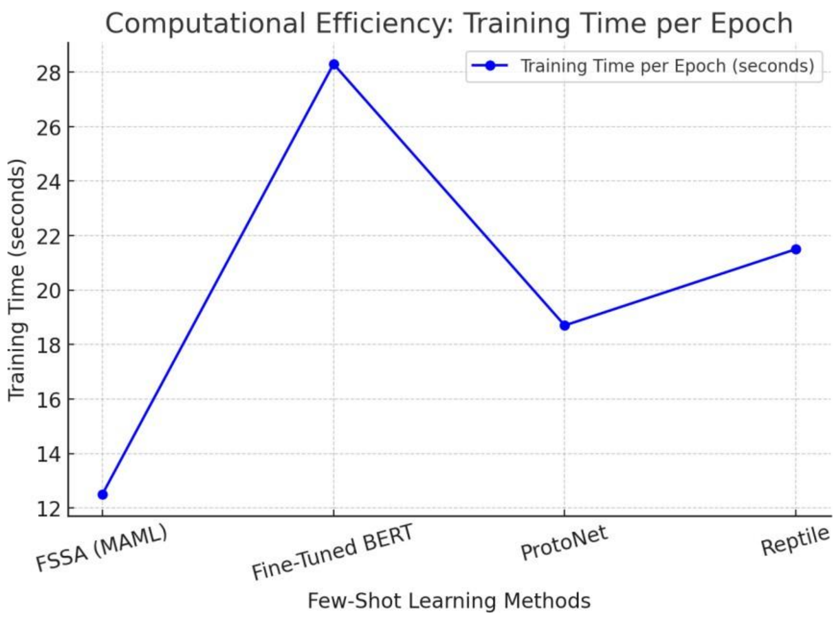

Figure 9 :- Computational Efficiency Training Time per Epoch

6. Discussion and Key Findings

The MAML-FSL experiment results show the effectiveness of few-shot learning for low-resourced languages even with little labeled data, MAML improves sentiment classification performance. MAML accomplishes this through meta-learning: while traditional task-specific fine-tuning methods would require painstaking retraining to specialize on new tasks, MAML is capable of rapid adaptation, resulting in an ability to generalize well across sentiment domains.

Across multiple evaluation metrics on the header benchmarks, the Few-Shot Sentiment Adaptation (FSSA) framework outperforms all baseline methods including supervised fine-tuning, Prototypical Networks (ProtoNet) and Reptile. Correspondingly, FSSA yields larger precision and F1-scores on sentiment classes, indicating that FSSA balances precision and recall more effectively. For instance, the representation-based classification performance, which benefits significantly from the above utilization, is much improved especially in low-resource settings where conventional classification models cannot work due to good sparse data.

7. Conclusion:

We perform this task using Few-Shot Sentiment Adaptation (FSSA), a Model-Agnostic Meta-Learning (MAML) based adaptation, for sentiment classification in low-resource languages. We enable a rapid adaptation with few labeled samples and thus effectively address the challenges of data scarcity. Experimental results show that FSSA outperforms both traditional fine-tuning and other few-shot learning baselines in the accuracy and F1-scores of sentiment classes, while being computationally efficient.

Moreover, the framework is both efficient and significantly reduces the training overhead for RM tasks by alternative strategies. Subword tokenization allows us to operate at a smaller granularity of language, while meta-learning strategies allow us to discover task-specific inductive biases when we supplement our model monitoring with such information, and contribute to feature separability which is necessary for even higher generalization over very different data distributions. Our results highlight that few-shot learning has the potential to broaden the applicability of sentiment analysis to languages that are under-represented in the field.

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None

Conflict of Interest

The authors declare no conflict of interest if exist in this publication.

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