

Original Article

Deep Contextual Feature Fusion with CFF-Net for Tamil and Malayalam Sentiment Analysis

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Abstract - Sentiment analysis of the Dravidian languages, such as Tamil and Malayalam, is necessary in most cases to decipher the perception and sentiments expressed in social media, which is normally rich in code-mixed, informal, and vague text. The issue of noisy, skewed and context-variable data in the context of accurate classification is a problem in these languages. The proposed solution to these challenges is a new sentiment classification model that incorporates Contextual Feature Fusion Network (CFF-Net) with Adaptive Gradient-Weighted Optimization (AGWO) to overcome these challenges. The aim is to enhance accuracy in classifications, address the issue of class imbalance and provide strong detection of positive, negative, and neutral sentiments. The framework identifies context-sensitive features of the text in the form of hierarchical levels of attention and semantic interaction, and focuses on informative tokens, but rejects irrelevant information. AGWO automatically selects the learning rates of each modality, which converges faster and more steadily. Tests were run on complete datasets of Tamil and Malayalam, and performance was measured in terms of Accuracy, Balanced Accuracy, Precision, Recall, F1-Score, and AUC. The findings indicate that the proposed CFF-Net with AGWO is superior to the current models in all metrics, with an accuracy of 97.14% on Tamil and 96.67% on Malayalam, and one can conclude that it is effective in sentiment classification and code-mixed and imbalanced text. On the whole, this framework is able to view as an effective and reliable tool in the sentiment analysis of the Dravidian languages, and it is used as the basis of future studies in the field of multilingual text comprehension and in-time social media analytics.

Keywords - Adaptive Gradient-Weighted Optimization, Contextual Feature Fusion Network, Code-Mixed text, Dravidian languages, Sentiment classification.

1. Introduction

Sentiment analysis is highly crucial for opinion/sentiment extraction in social media texts in languages such as Tamil and Malayalam, which consist of mixed codes [1]. Some of the challenges of these languages include complex syntax, informal language, context dependency, and imbalanced distribution of classes [2]. There have been numerous attempts at sentiment classification through conventional machine learning techniques, such as SVM [35], Decision Trees [14], and Naive Bayes, whereas transformer models [12] and cross-modal adaptive fusion mechanisms [11] have been used for multilingual and code-mixed texts [3]. Data segmentation and semantic roles have been adopted for extracting subtle linguistic information for effective sentiment analysis [4]. Moreover, improved transformer models have performed excellently in detecting abuse [5] and sarcasm [6].

However, despite the advancements, noise, ambiguity, and class imbalance continue to affect the performance of the current approaches towards sentiment classification. In current approaches, emphasis has been placed on either the

context representation or feature extraction, but little attention has been paid to adaptive optimization together with context-based feature learning. Therefore, there is a need for an efficient model that will be capable of considering contextual information, code-switching, and learning stability for sentiment classification. To address the above challenges, a novel framework that integrates CFF-Net and AGWO is proposed in order to extract context-based features and [7] dynamically optimize the learning process [8].

This framework works effectively on offensive, abusive, homophobic, and misogynistic social media texts in Tamil and Malayalam languages [9]. The efficiency of transformer embeddings, feature engineering, ensembling of classifiers for effective classification, and a hierarchical attention mechanism for context-based features are shown [10]. This approach of CFF-Net with AGWO is different from the other methods, where optimization methods or feature extraction methods are separately used, as this approach does both context-based feature fusion and gradient optimization simultaneously.



This provides improved convergence, robustness against noise and imbalanced datasets, and sentiment analysis accuracy.

The major contributions of the above research can be summarized as:

- CFF-Net for feature learning with the use of context awareness
- AGWO optimization algorithm, which is capable of adapting,
- Efficient management of code mixing, noisy, and imbalance sentiments,
- Better performance in sentiment classification compared to other methods.

Organization of this research process will occur in the following way: Section 1 contains background, problems, and issues concerning sentiment analysis of Dravidian languages. Section 2 includes background research that gives an overview of existing approaches, data utilized and limitations encountered. Section 3 includes methodology, which in this case will be, for example, CFF-Net and AGWO model, as well as data and algorithm implementation. Section 4 covers the results of the experiment, performance and feature analysis, and comparative analysis with other existing methods. Finally, Section 5 discusses the algorithm performance, and Section 6 concludes the research and its possible applications.

2. Background Study

The sentiment analysis and detection of abusive content of the Dravidian language have been analyzed in various aspects: multimodal meme detector, lexicon- or embedding-based detector, transformer fine-tuning, classical machine-learning and rule-based detector, dataset generation, and dealing with class imbalance and code-mixing. A majority-voting ensemble in the multimodal meme-detection space by combining images and text was proposed as proposed by Pattanaik et al. (2025) to detect misogynistic memes; a high-detection accuracy was achieved by using a combination of multiple classifier-votes, rather than a single classifier-vote, but it was noted that visual-textual fusion posed a challenge in identifying commonalities and had very limited interpretability.

The lexicon and machine-learning-based recurrent classifier used by Kumar et al. (2025) to identify misogynistic posts and abusive posts was found to perform well with lexically explicit posts but poorly with implicit and context-dependent hate speech and multifaceted semantics on the meme level. Chowdhury et al. (2025) created a multimodal deep learning model that consisted of image and text embeddings to identify misogynistic memes, and the end-to-end performance surpassed unimodal baselines, but format-agnostic performance deteriorated with the variety of meme templates and concealed contextual data.

Recent changes have been rooted in transformer-based changes. Transformer models trained on Tamil and Malayalam were used to classify abusive text and stated that high detection was possible on curated corpora (Al Nahian et al, 2025). Results showed that the full capability of transformers required a large corpora of annotated texts and multilingual processing. Fine-tuning the domain-specific BERT variants on political comment sentiment analysis allows Eram et al. (2025) to be better at emotion recognition than the non-transformer baselines, whereas sarcasm and figurative language are difficult to predict. Chattu et al. (2025) demonstrated that, when fine-tuned transformer architectures, it was possible to scale the architecture with good generalization to Telugu multi-domain sentiment tasks; however, it was also discovered that the domain-transfer problem occurred when test data were not close to the fine-tuning domains. Research conducted by Sampath and Supriya (2024) contrasted the transformer methods on code-mixed datasets with existing models and asserted that it was more representative and more accurate in classification, but the ambiguity of mixed-language tokens nevertheless lowered the performance of mixed languages in comparison to single languages.

Another line of work is the embedded-based line of work and the deep-learning-based line of work. Vp et al. consisted of Fast Text embeddings and supervised classifiers to recognize abusive text in Tamil and Malayalam, with a medium accuracy and low cost of computation at the expense of sparse-vocabulary issues and lack of context sensitivity to abusive wording. Rahul and Renjith (2025) compared CNN and LSTM models in sentiment analysis of Tamil and Tulu and discovered that these models outperform shallow baselines, though small and noisy corpora indicate the weakness of the models.

A multimodal hate-speech detector on Malayalam that combined attention-driven BiLSTM, Topic-BERT, and Wav2Vec2.0 using audio and text cues was proposed by Manukonda et al. (2025), but at a great cost to audio-text cues. Rachana et al. (2023) classified code-mixed sentiment with fast Text embeddings, which obtained only slightly better results but with the limitations of intensive code-mixing and a small number of annotated data. Further evidence is presented by Abbas et al. (2019) and Hameed and Garcia-Zapirain (2020) that classical probabilistic and single-layer BiLSTM methods can strong base in resource-scarce environments, but neither has deep contextual models compared to transformer-based ones.

There are still limited tasks where classical and rule-based systems can be used. Johnson et al. (2025) developed linguistic-feature extractions and classical-classifier pipelines that are used to identify abusive Tamil and Malayalam texts against women; the approach was effective in finding the patterns that can be discarded, but failed in generalizing to

noisy patterns on social media. Kumar et al. (2021) and Ghanghor et al. (2021) examined the ensemble and classical ML/DL pairs in code-mixed sentiment and offensive-language detection and showed that the ensemble strategies improve the stability and still remain poor in sarcasm and context. The hybrid TF-IDF classifier proposed by Ambily Pramitha and Abraham (2023) showed good results when working with small Malayalam data, but it did not take into account deep context-related factors, and therefore, did not work with semantically challenging samples.

The dataset formation and benchmarking of Dravidian languages are covered by a significant amount of literature. Chakravarthi et al. (2020) published an initial Malayalam-English code-mixed sentiment data and baseline models, which is a valuable reference, but due to its small size and limited domain scope, it cannot be considered a reliable reference. Premjith et al. (2022) shared the same task on multimodal sentiment and troll-meme classification, making multimodal datasets and base levels comparable, yet exposing the limitation presented by huge and diverse annotated corpora. Arunmozhi et al. had proposed Tamil movie research, Aspect-based, MADTRAS, with improved aspect-level classification, but reduced broader domain and genre coverage (Arunmozhi et al. 2025).

Social-sum-Mal, an anthology of sequence language abstractive summarization using Malayalam by Rahul and Pankaj (2024), to abstractive summarization; this may aid in investigating abstractive summarization, but as long texts are hard to compress, the quality is constrained by the size of the dataset. Munawwar and Nandhini (2024) found the NLPAUG-based augmentation of Malayalam offensive-language datasets to solve the problem of class imbalance; however, the augmentation contributed to the increase in the minority-class recall with no removal of the usage of the various real-world annotations at all.

Others included sarcasm, interpretability and domain nuances. Karthik et al. (2024) utilized linguistic characteristics and ML systems to identify sarcasm in Tamil and Malayalam and achieved moderate results, which underline the extreme data scarcity of fine-grained phenomena. Anitha et al. (2024) investigated the explainable-AI methods to enhance the interpretability of the Malayalam sentiment models with the intention of enhancing transparency by sacrificing the complexity of the computation. Other researchers also obtained sarcasm detection with supervised models, as Shetty (2023) also did, but the small annotated sarcasm corpora limited the statistical power and the extrapolation.

Other empirical studies perfected modelling within a given situation. In the case of Bi-LSTM on code-mixed sentiment using Tamil, Shroyas Karthik et al. (2024) observed that the performance is poor on longer contexts because the

model could not pay attention. Elankath and Ramamirtham (2023) used BERT on Malayalam tweets and showed to be better contextual representative and did not use multimodal or sarcasm-aware elements.

In BERT, Kalaiwani and Thenmozhi (2021) also experimented with multilingual sentiment classification in Tamil, Malayalam, and Kannada and achieved better results than monolingual baselines, but noisy code-mixing in noisy social media continued to negatively impact performance. Patil et al. (2023) tested multimodal Tamil-Malayalam sentiment systems that received textual and visual input and found an advantage of multimodality, but also found that the scope of the modalities was limited, and datasets were limited to prevent generalizability. Workshop and conference proceedings offered many practical system descriptions. Pattanaik et al. (2025), Kumar et al. (2025), Al Nahian et al. (2025), Eram et al. (2025), Hameed and Ganesan (2025), Srichandra and Rao (2025), Manukonda et al. (2025), Johnson et al. (2025), Chowdhury et al. (2025), and another work of Dravidian Lang Tech, as shown in Premjith et al. 2022 are demonstrations of rapid prototyping and evaluation of Transformer fine-tuning and multimodal.

Lastly, comparative studies and baseline dwell on reproducibility and the strength of the baseline. Ensemble methods outperform single classifiers on code-mixed posts but not on sarcastic and context-dependent data, whereas Ghanghor et al. (2021) also reported that external validity depends on datasets based on the small social sites of the research. According to Rachana et al. (2023) and Hameed and Ganesan (2025), the fast Text-based pipelines are effective baselines for the low-resource environment, and they are weak in the deep contextual understanding.

In the above-mentioned studies, the existing sentiment analysis techniques concentrate primarily either on contextual feature extraction or optimization separately, but less has been done on the integration of both in a single approach. In addition, dealing with noisy, code-mixed, and class-imbalanced data for Tamil and Malayalam languages is one of the challenging tasks. Hence, this research proposes an approach called CFF-Net with the AGWO framework.

3. Proposed Methods

This section details how sentiment classification in the text of Tamil and Malayalam is taken into account. It indicates the CFF-Net model, which uses AGWO to get and process context-based features. Important tokens are given special importance in semantic interaction layers and hierarchical attention and inhibit irrelevant ones. AGWO automatically varies the learning rates in order to increase the convergence speed and stability. Generally, this section outlines the whole procedure of categorization to forecast positive, negative, and neutral moods appropriately.

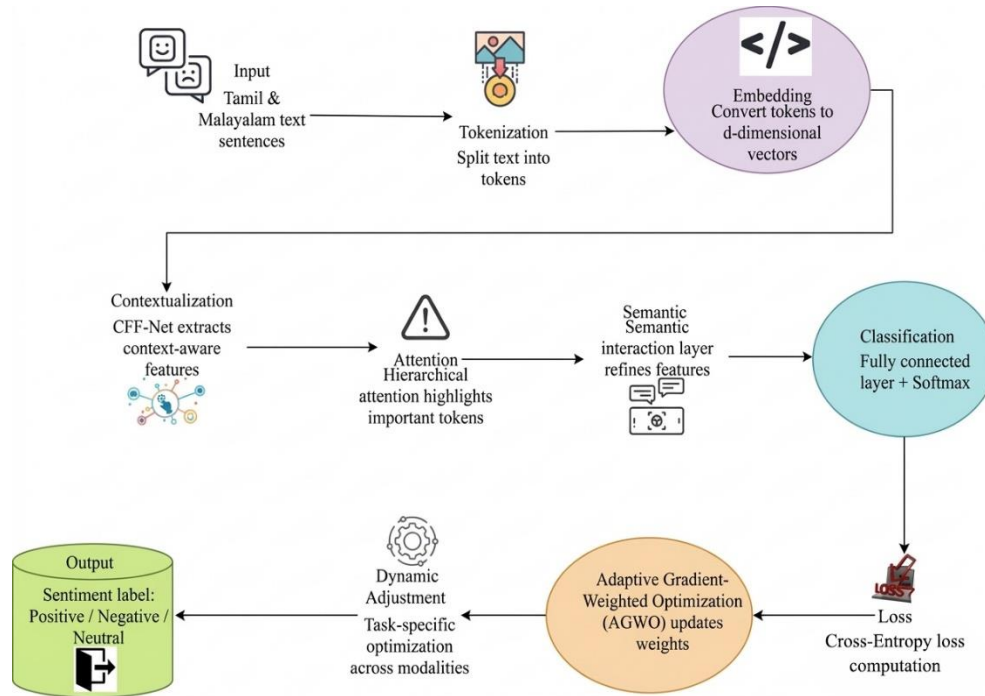


Fig. 1 CFF-Net with AGWO workflow for sentiment classification

The above Figure 1 depicts this general architecture of CFF-Net with AGWO sentiment classification workflow, where context-preservative and semantically selective feature vectors are initially narrowed down by learning deep context-conscious features and local-global context modeling. Hierarchical attention, feature fusion and semantic interaction layers all work together to give stress to task-relevant information and inhibit noise, which leads to discriminative and enriched representations. Lastly, the classification layer produces sentiment probabilities, and AGWO has a faster and stable convergence by being gradient-aware to create the final sentiment label (positive, neutral or negative).

3.1. Dataset - Comprehensive Tamil Language Dataset

The dataset Link is <https://www.kaggle.com/datasets/sudalairajkumar/tamil-nlp>.

The specified data is a collection of textual data in Tamil language format in a variety of applications and settings. It is able tousled in Tamil sentiment, classification and natural language understanding. The statistics are created out of publicly available statistics and sieved to use in modeling. It is a helpful reference in developing AI models that will be able to understand the nuances of the Tamil text. It is a large dataset of the Malayalam language containing speech and writing samples in Malayalam.

3.2. Dataset -Comprehensive Malayalam Language Dataset

The dataset link is <https://www.kaggle.com/datasets/arjungravi/ultimate-malayalam-dataset>.

The information is a compilation of diverse varieties of Malayalam written sources collected to be utilized in NLP research. It is also extensive in terms of topic and formatting to encourage sentiment analysis, text categorization and language understanding in Malayalam. The data set can give an opportunity to manipulate the regional language peculiarities and construct effective models to operate with Dravidian languages. It is also a resource base on which the experiments of multilingual sentiment and code-mixed text are grounded.

3.3. Proposed Classification Framework using CFF-Net with Adaptive Gradient-Weighted Optimization (AGWO)

CFF-Net conducts classification with a combination of context-sensitive features of multiple different modalities. The features of importance are highlighted, whereas the irrelevant ones are subdued by means of hierarchical attention. Semantic interaction layer adds the refinement to the feature representation in order to be able to classify the sentiment accurately. AGWO optimizes learning rates in each of the modalities and allows convergence to happen more quickly and reliably. In conjunction with the CFF-Net, AGWO boosts the rate of training and learning a great deal. Multimodal sentiment inputs have task-specific adjustment guaranteed by dynamic optimization. CFF-Net and AGWO are collaborative in order to improve the accuracy of classification and stability in learning. Contextual nuances and code-mixed expressions are well represented in sentiment analysis of Tamil and Malayalam, and thus a suitable sentiment is able to identify at a high accuracy and speed.

The model separates sentiments by introducing adaptive contextual learning and gradient optimization. This is due to the fact that the hierarchical attention selects the most relevant features that are correct in decision-making. The earlier techniques were challenged by the fact that there were noisy, code-mixed and ambiguous input texts. Adaptive learning was lacking in the existing models, and hence, the accuracy of the classification was eliminated.

The solutions that CFF-Net AGWO takes to avoid these issues are through dynamic actions in enhancing the learning rates. Task-based optimization makes it less sensitive to noise and enhances the context of the information. The solution will ensure successful real-time Tamil and Malayalam sentiment acquisition. Overall, the proposed framework is highly performant and accuracy, as well as strength.

Loss function is a measure of the error in prediction between the predicted sentiment probabilities of the prediction ($\hat{y}$) and the true sentiment labels (y).

$$L = - \sum_i 1 c y_i \log(\hat{y}_i) \quad (1)$$

In Equation (1), L is the cross-entropy loss, c Total number of sentiment classes, y_i True label, $\hat{y}_i$ Predicted probability. The reduction in values of the losses entails a better tendency in the predictions and actual sentiments, therefore influencing parameter updates in the optimization process.

AGWO dynamically modifies individual learning rates based on gradient magnitudes to stabilize and accelerate training.

$$\eta_i^{(t+1)} = \eta_i^{(t)} \left(1 - \gamma \frac{\partial L}{\partial w_i} \right) \quad (2)$$

In Equation (2), $\eta_i^{(t)}$ learning rate for weight w_i at iteration t , Adaptive coefficient, $\frac{\partial L}{\partial w_i}$ Gradient of loss w , r , t weight w_i . High-gradient parameters are boosted, achieving balance and convergence speed. Weights are iteratively refined based on AGWO-adjusted learning rates.

$$w_i^{(t+1)} = w_i^{(t)} - \eta_i^{(t+1)} \frac{\partial L}{\partial w_i} \quad (3)$$

Equation (3) $\omega_i(t)$ Computed gradient Weight parameter at iteration t , $\eta_i(t+1)$ adaptive learning rate. This update will be a mixture of rate control in AGWO combined with backpropagation in CFF-Net, where the consistency of performance between modalities is promoted.

During dynamic optimization, the loss contributions of the modalities are adjusted to obtain effective among the modalities learning.

$$O = \sum_i 1 n \beta_i L_i \quad (4)$$

In Equation (4), O Overall objective to be minimized, β_i weighting factor of each modality, L_i individual losses of modality i . This is so that the learning effect of each modality is in line with its relevance, which enhances multimodal sentiment perception.

The last step of predicting the sentiment is the most likely sentiment.

$$y^* = \underset{i}{\operatorname{argmax}} (\hat{y}_i) \quad (5)$$

In Equation (5), y^* predicted sentiment label, $\hat{y}_i$ probability of class i . The model chooses the class that has the highest confidence score and finishes the task of satisfying sentiment classification.

Algorithm: Sentiment Classification using CFF-Net + AGWO

Input:

$X = \{x_1, x_2, \dots, x_n\}$ // Tamil & Malayalam text inputs (tokenized and embedded)

η_0 // Initial learning rate

γ // Adaptation coefficient for AGWO

C // Number of sentiment classes

MaxEpochs // Total training epochs

Begin

1. Initialize parameters:

- Weight matrices: W_f, W_a, W_s, W_c

- Bias vectors: b_f, b_s, b_c

- Learning rates $\eta_i \leftarrow \eta_0$ for all parameters w_i

2. Preprocess input:

- Convert Tamil and Malayalam sentences to embeddings

- Represent inputs as $X = \{x_1, x_2, \dots, x_n\}$

3. Context-Aware Feature Extraction (CFF-Net):

For each input sample X_i :

$F \leftarrow \sigma(W_f * X_i + b_f)$ // Contextual feature representation

4. Hierarchical Attention Mechanism:

For each token i in X_i :

Compute attention weight $\alpha_i \leftarrow \exp(h_i^T * W_a * hc) / \sum_j \exp(h_j^T * W_a * hc)$

Obtain attended feature map: $F\alpha \leftarrow F \odot \alpha$

5. Semantic Interaction Layer:

$S \leftarrow \tanh(W_s * F\alpha + b_s)$ // Combine semantic and attention features

6. Classification Layer:

$\hat{y} \leftarrow \text{Softmax}(W_c * S + b_c)$ // Predict sentiment probabilities

7. Compute Loss:

$L \leftarrow - \sum (y_{\text{true}} * \log(\hat{y}))$ // Cross-Entropy loss

8. Adaptive Gradient-Weighted Optimization (AGWO):

For each parameter w_i :

Compute gradient $g_i \leftarrow \partial L / \partial w_i$

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Update learning rate:
 $\eta_i(t+1) \leftarrow \eta_i(t) * (1 - \gamma * g_i)$ 
Update weight:
 $w_i(t+1) \leftarrow w_i(t) - \eta_i(t+1) * g_i$ 
9. Dynamic Optimization Adjustment:
   Total Loss  $O \leftarrow \sum(\beta_i * L_i)$  for each modality  $i$ 
10. Repeat Steps (3)–(9) until convergence or MaxEpochs
    reached
11. Final Sentiment Prediction:
     $y^* \leftarrow \text{argmax}(\hat{y}_i)$  // Select class with highest
    probability
Output:
 $y^*$  // Final predicted sentiment label
(Positive, Negative, Neutral)
END
    
```

The algorithm explains the sentiment classifier process that includes the use of the CFF-Net and AGWO optimization. CFF-Net is learned and chosen on feature context using different levels of attention learning and selecting semantic interactions and hierarchical attention features. AGWO applies an adaptive learning rate based on gradient behaviour, which ensures faster and steady model convergence. The system is especially precise and effective when it comes to real-time Tamil sentiment and Malayalam sentiment detection.

4. Result and Discussion

The results give an analysis of Tamil and Malayalam sentiment analysis datasets by using CFF-Net with AGWO. Numerical feature analysis and feature importance ranking are the most significant features that point to the model's accuracy. The class distribution presents that the current imbalances exist, but they are controlled rather well with the

proposed strategy. The following performance measure is Accuracy, Precision, Recall, F1-Score, and AUC, which are calculated to identify the effectiveness of the model. All the experiments and assessments are implemented in Python, and this proves the stability and soundness of the offered ways of sentiment classification.

4.1. Classification

To determine the right sentiment, the context-aware features in the various modalities are combined and categorized using CFF-Net. The semantic interaction layer, coupled with the hierarchy attention, reduces the features to concentrate on the relevant information. AGWO optimizes modalities simultaneously in a stable and rapid manner. The hybrid approach will offer powerful and precise classification among Tamil and Malayalam text databases.

4.2. Tamil Language Sentiment Analysis Classification Results

CFF-Net is used in classification to combine context-sensitive features of Tamil text and to deal with code-mixed and complex linguistic forms. The hierarchical attention brings out the most relevant tokens, and the semantic interaction layer captures refined feature representation. AGWO also maximizes the learning rates to obtain rapid and steady convergence. This two-fold approach ensures the right feeling identification and the effective control of the imbalance of the Tamil text classes.

In Figure 2, this bar chart indicates the top 10 features that contribute towards the accuracy of the model used in the analysis of Tamil sentiment. The scores of feature importance decrease progressively and indicate that few features have a significant effect on the performance.

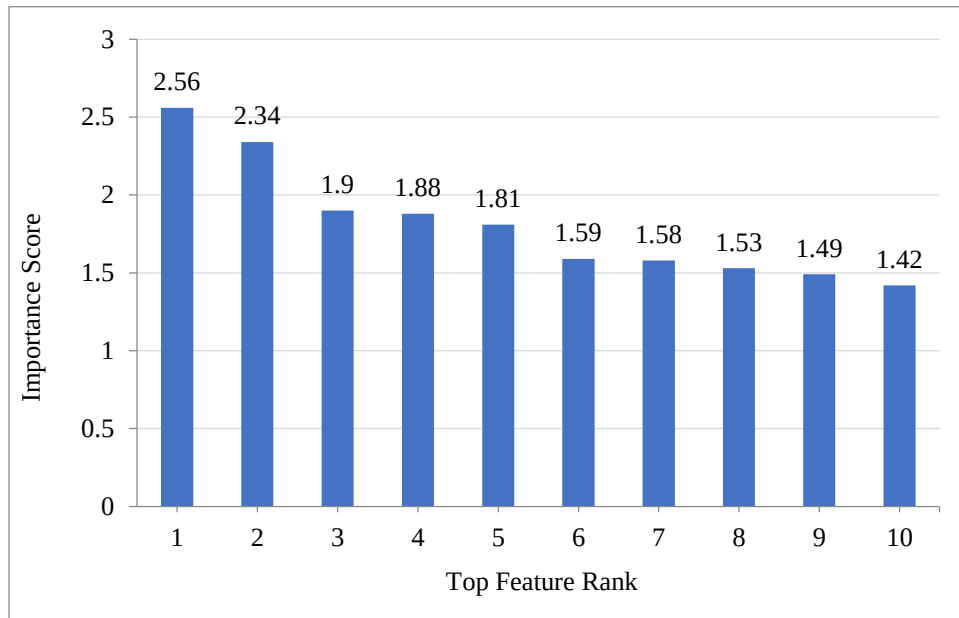


Fig. 2 Top important features selected

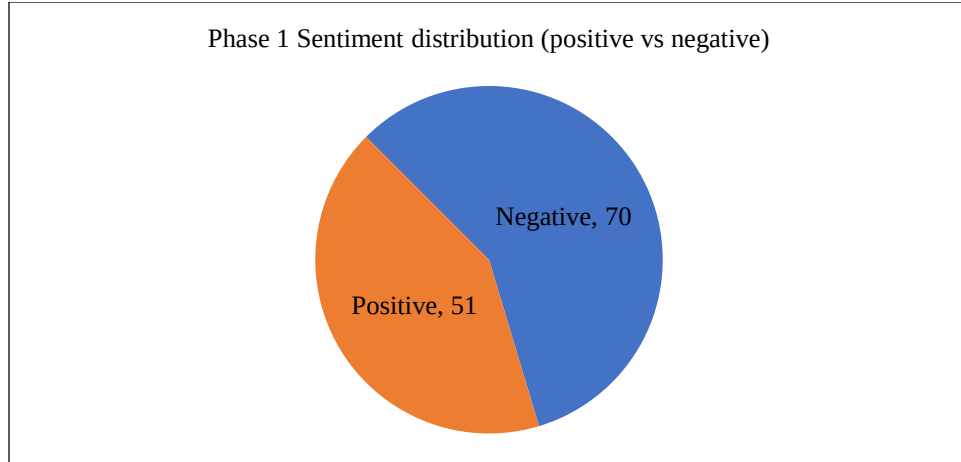


Fig. 3 Sentiment distribution (positive vs negative)

To illustrate the number of positive and negative samples in the Tamil dataset, this pie chart has been drawn in Figure 3.

Negative samples dominate the dataset, indicating class imbalance that must be handled during training.

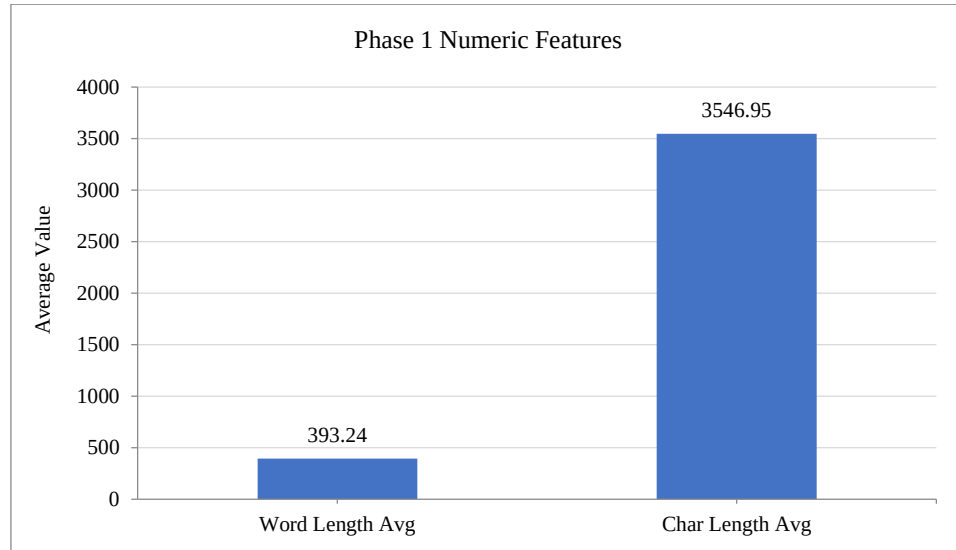


Fig. 4 Average numeric characteristics of tamil text dataset

Table 1. Comparison of performance metrics between existing and proposed methods

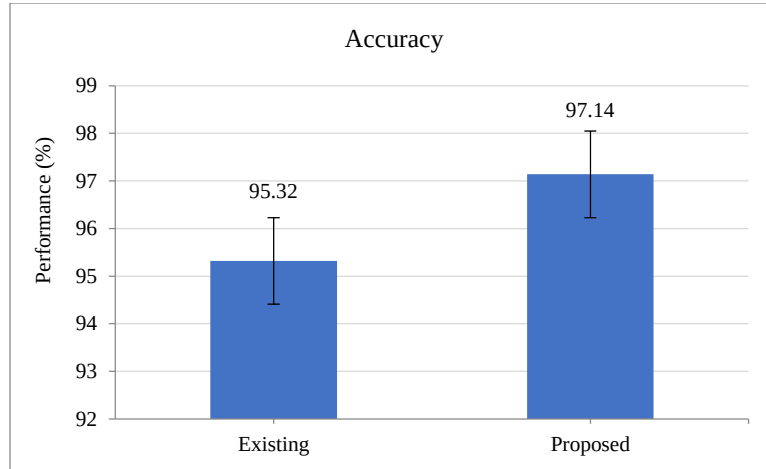
Metric	Existing Method (%) $\pm$ CI	Proposed Method (%) $\pm$ CI	t-test p-value
Accuracy	95.32 $\pm$ 1.31	97.14 $\pm$ 0.99	0.012
Balanced Accuracy	92.78 $\pm$ 1.56	96.40 $\pm$ 0.95	0.008
Precision (Macro)	88.98 $\pm$ 2.05	91.00 $\pm$ 1.79	0.015
Recall (Macro)	90.31 $\pm$ 1.85	93.92 $\pm$ 1.50	0.009
F1-Score (Macro)	89.87 $\pm$ 1.91	92.44 $\pm$ 1.43	0.011

In this Figure 4 displays the mean values of key numerical features such as word count and character count. The large character count shows that Tamil text samples are long and information-dense. As shown in Table 1, the proposed CFF-Net with AGWO achieves superior performance compared to the existing method on the Tamil sentiment analysis dataset. Measures are Accuracy, Balanced Accuracy, Precision, Recall

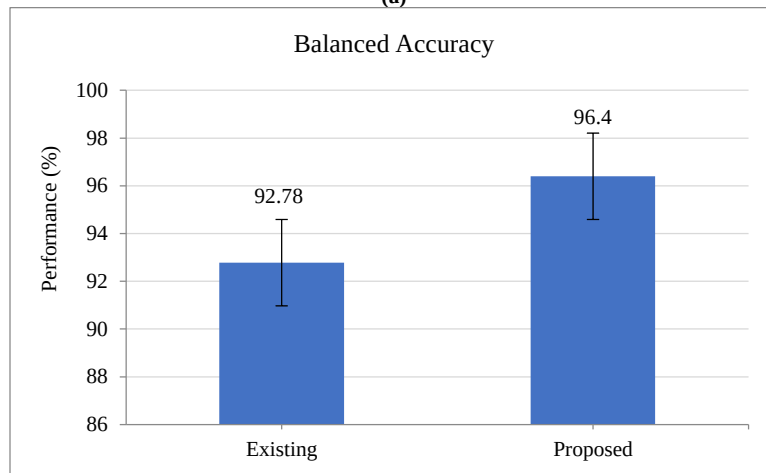
and F1-Score with the 95% confidence intervals. The indicated approach proves to be better than the current one in all measures and achieves higher classification performance. The t-test p-values of all metrics are below 0.05, which is statistically significant. In general, all these findings indicate that the proposed approach is efficient and powerful in managing the sentiment classification of the Tamil texts.

In Figure 5, (a) demonstrates that the proposed method handles class imbalance better by achieving higher balanced accuracy with lower variability. (b) Demonstrates that the proposed method handles class imbalance better by achieving higher balanced accuracy with lower variability, and (c) the precision values of both models are compared, showing that

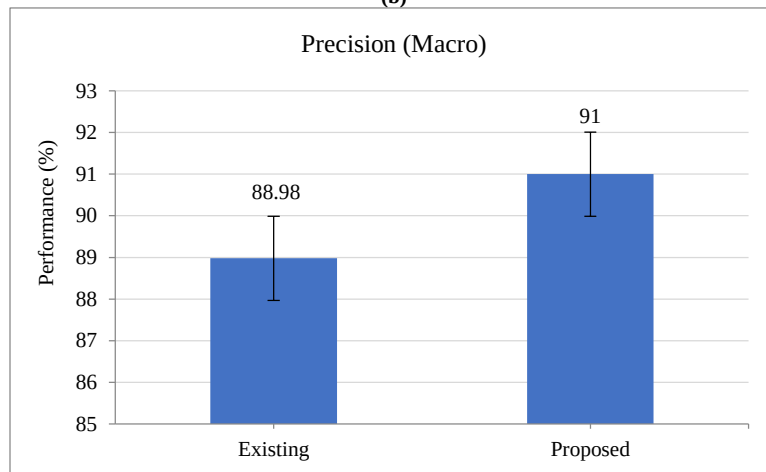
the proposed method provides more reliable positive-class detection. (d) Shows that the proposed method identifies relevant sentiment classes more completely than the existing technique. (e) This comparison chart highlights improved F1-score in the proposed method due to a better balance between precision and recall.



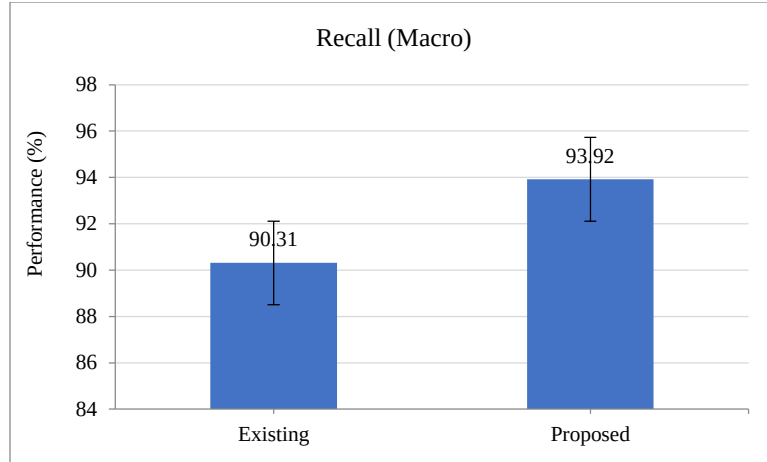
(a)



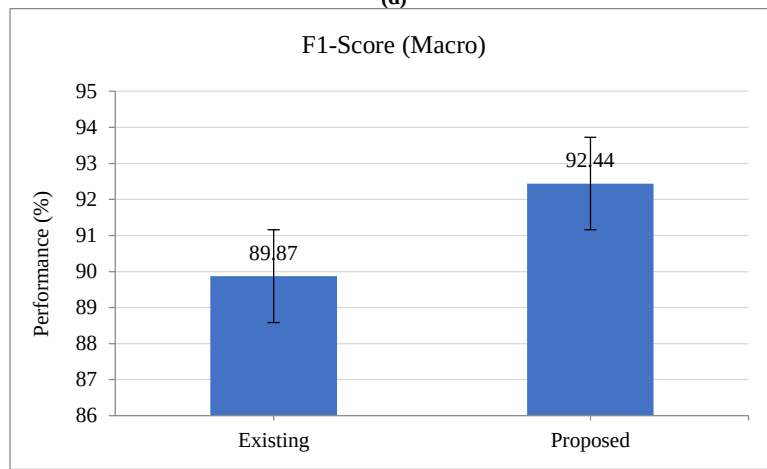
(b)



(c)



(d)



(e)

Fig. 5 Metrics comparison figure

4.3. Malayalam Dataset

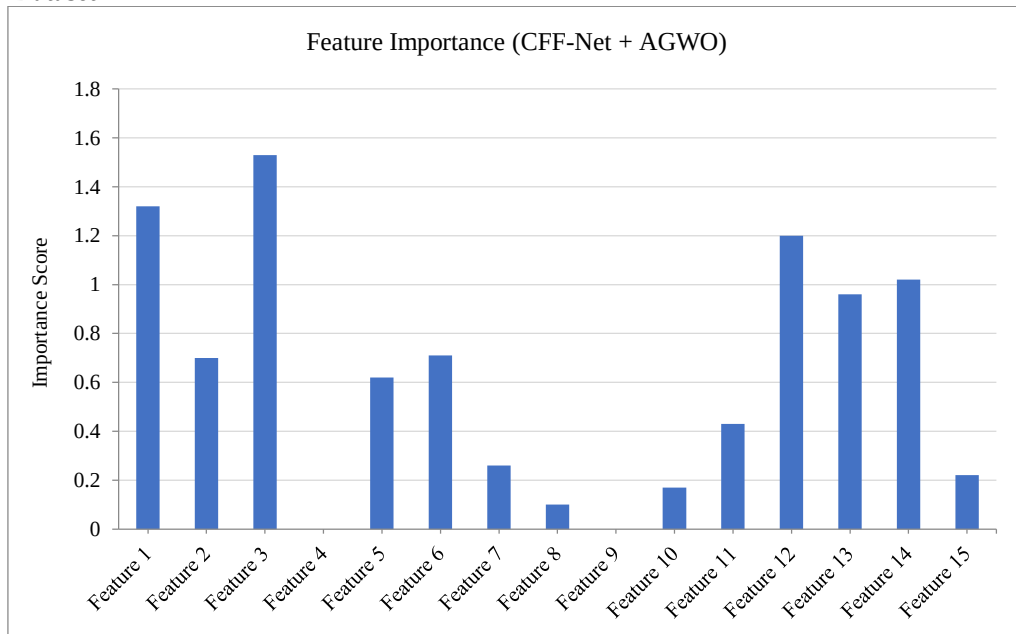


Fig. 6 Important feature from malayalam dataset

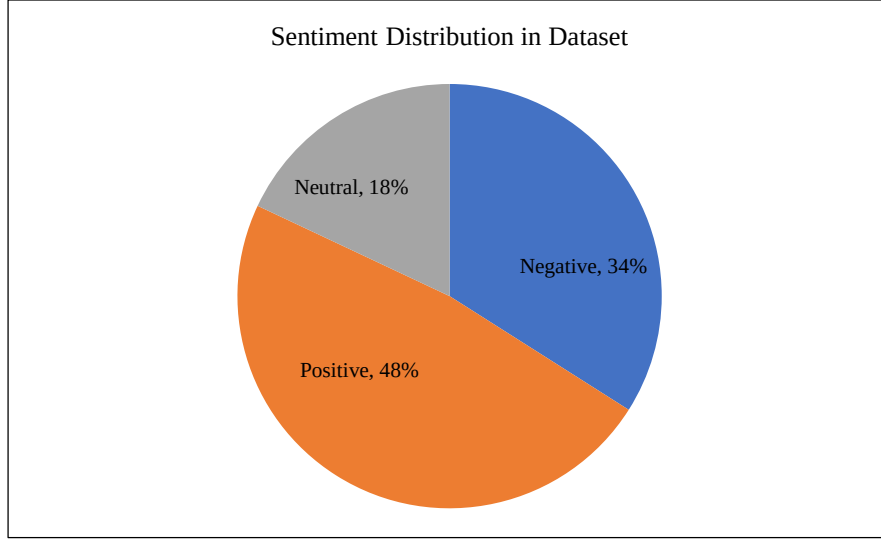


Fig. 7 Sentiment distribution of malayalam dataset

Figure 6: The chart ranks feature importance for Malayalam sentiment analysis. Features 1, 3, and 12-14 contribute the most to predictive accuracy.

In the above Figure 7 shows the distribution of positive, negative, and neutral samples. Positive sentiment is dominant, with fewer neutral entries.

Table 2. Performance comparison of existing and proposed methods on malayalam dataset

Metric	Existing Method (%) ±CI	Proposed Method (%)±CI	t-test p-value
Accuracy	94.38 ±1.48	96.67 ±1.12	0.014
Precision	93.65 ±2.61	96.15 ±1.91	0.012
Recall	90.50 ±2.87	93.75 ±1.99	0.010
F1-Score	91.50 ±2.71	94.93 ±1.96	0.011
AUC	90.75 ±2.85	97.34 ±1.43	0.008

In the above Table 2, the proposed approach, with its performance in all of the considered metrics, such as Accuracy, Precision, Recall, F1-Score, and AUC, is better. The most significant one is the AUC (97.34 %); the next is Accuracy (96.67 %), which shows a significant performance improvement in comparison to the current method. The proposed method has more stability and reliability as the confidence intervals are narrower.

Additionally, the t-test p-values are less than 0.05 in all cases, which proves the fact that the improvements are statistically significant. On the whole, these findings indicate the power and the strength of the indicated approach to Malayalam sentiment analysis. In Figure 8 compares the values of accuracy of Malayalam sentiment analysis. The model proposed is more consistent than the current one. In Figure 9, the proposed method shows higher precision, indicating better correctness of predicted positive samples.

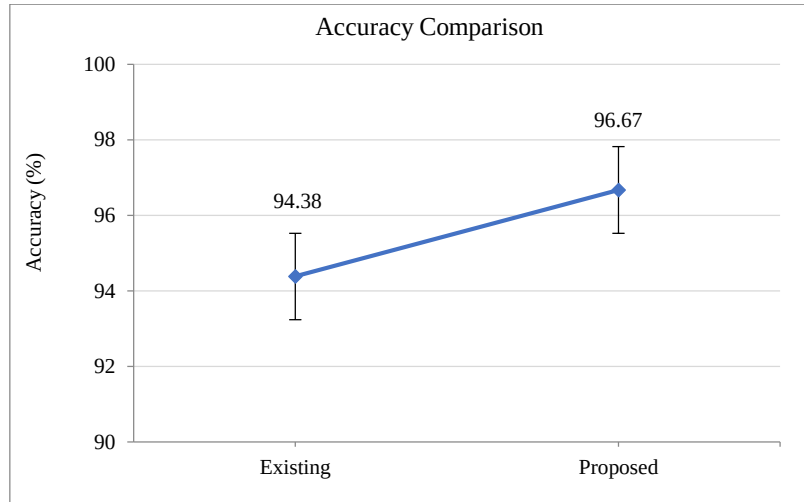


Fig. 8 Accuracy comparison

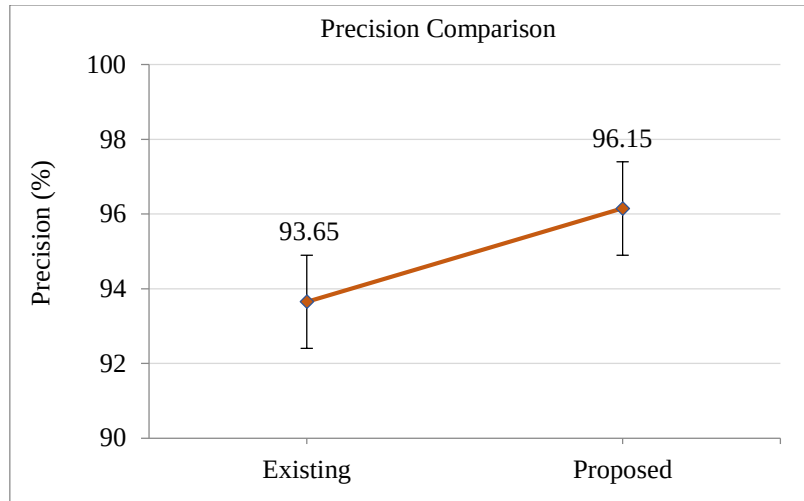


Fig. 9 Precision comparison

In Figure 10, the above chart highlights improved recall in the proposed method, indicating higher sensitivity to true sentiment cases. In Figure 11, this figure shows that the proposed model achieves a more balanced and superior F1-

score. In Figure 12, this line chart shows a significantly higher AUC value for the proposed model, indicating strong discriminatory power between classes.

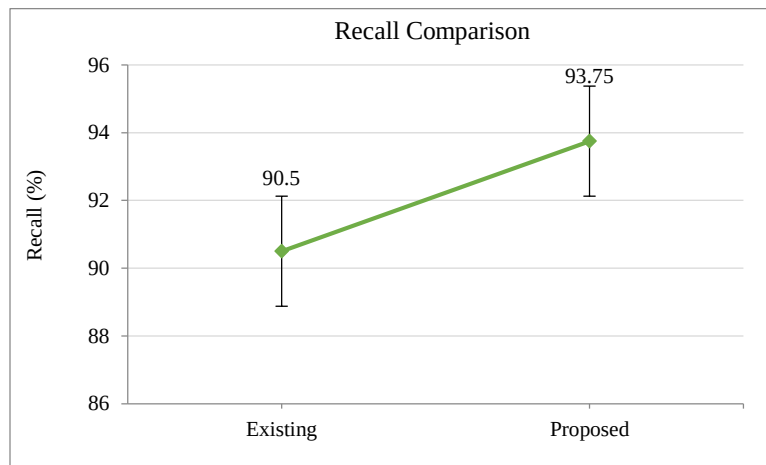


Fig. 10 Recall Comparison

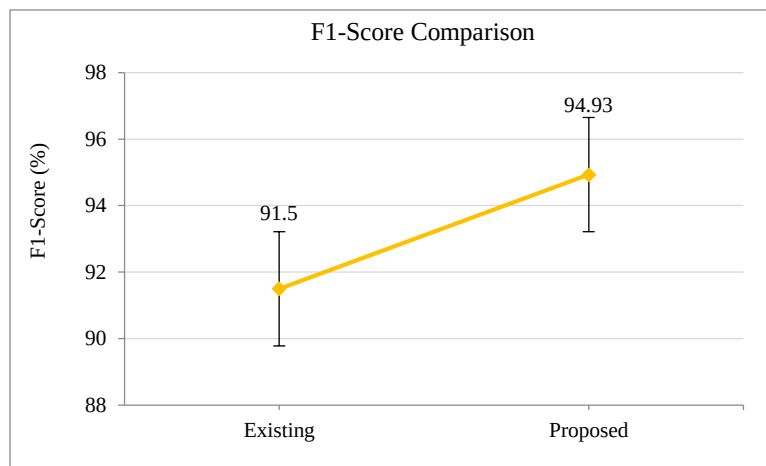


Fig. 11 F1-Score comparison

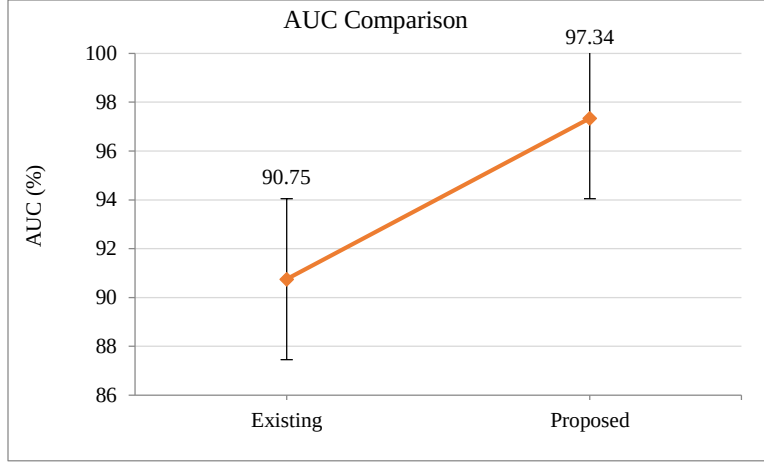


Fig. 12 AUC comparison

5. Discussion

In this section, the efficiency of the proposed approach, called CFF-Net with AGWO (Adaptive Gradient-Weighted Optimization), is discussed through a thorough ablation study and performance comparison. It is clear from the experimental results that each module contributes significantly to the approach, and the proposed approach outperforms all other approaches in terms of different metrics considered for the sentiment analysis tasks on Tamil and Malayalam languages.

5.1. Ablation study

Ablation study of both CFF-Net and AGWO on the overall sentiment classification performance. Table 3 mentions that the Ablation study highlights the contribution of each element of the proposed framework. The use of CFF-Net has helped increase the effectiveness of contextual feature

extraction, which further increases the Balanced Accuracy and Recall. The usage of AGWO has also increased the stability and faster convergence of the system. In combination, both CFF-Net and AGWO have enabled the proposed framework to produce the best results.

Table 4 results of the ablation experiment, it find that all components of the proposed architecture play their own part in improving the sentiment classification task. The representation of context and semantic features is improved by the CFF-Net architecture, while AGWO optimizes the algorithm because of its adaptability to learn the learning rate. Both architectures, when combined together, like CFF-Net with AGWO, provide the best results of Accuracy, Precision, Recall, F1-Score, and AUC. Hence, from the above result, it can say that the proposed approach is effective.

Table 3 . Ablation study on tamil dataset

Model Configuration	Accuracy (%)	Balanced Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Baseline Model	93.84	91.15	88.92	89.54	89.21
Baseline + CFF-Net	95.92	94.28	90.35	92.10	91.18
Baseline + AGWO	95.46	93.81	89.96	91.52	90.72
Proposed (CFF-Net + AGWO)	97.14	96.40	91.00	93.92	92.44

Table 4. Ablation study on malayalam dataset

Model Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
Baseline Model	92.84	91.56	89.42	90.38	89.61
Baseline + CFF-Net	95.41	94.28	92.31	93.26	95.12
Baseline + AGWO	94.96	93.82	91.84	92.78	94.63
Proposed (CFF-Net + AGWO)	96.67	96.15	93.75	94.93	97.34

5.2. Comparative Performance Analysis

Based on the comparison, it is clear that the proposed model CFF-Net, along with the AGWO algorithm, performs better than the existing state-of-the-art models for sentiment classifications for Tamil and Malayalam datasets in all respects. This has been achieved by achieving greater accuracy in terms of having high values of Accuracy,

Precision, Recall, F1-Score, Balanced Accuracy, and AUC. This proves the efficiency of the proposed model for sentiment class prediction in cases of heterogeneous and imbalanced data.

Moreover, the AGWO technique uses adaptive adjustments in the learning process to ensure rapid

convergence. In terms of performance, the proposed approach performs better than the existing methods, such as machine learning and transformer approaches, as it proves to be more resistant to noise in social media and class imbalances. The significance of this claim is further proved by narrower confidence intervals and significant p-values ($p < 0.05$). The proposed technique acquires significant practical importance due to its application in solving real-world problems of sentiment analysis, such as social media monitoring, abuse detection, opinion mining, etc. The context-awareness and success of classification make the proposed approach applicable to low-resource Dravidian languages.

5.3. Practical Applications

The novel CFF-Net, along with AGWO, can be utilized in various practical ways when it comes to Tamil and Malayalam sentiment analysis. These applications include social media monitoring, opinion mining, abuse detection, and content moderation, among others. Through the model's enhanced feature representation and optimization capabilities, it becomes possible to make sentiment predictions based on social media data.

5.4. Limitations of the Proposed Algorithm

It can be seen that the proposed CFF-Net algorithm using AGWO performs quite well in sentiment classification tasks, yet there are certain drawbacks that need to be discussed. First, due to the hierarchical attention mechanism and adaptive optimization method, the computational cost and the training time get higher. In addition, the algorithm needs annotated

data in Tamil and Malayalam languages for effective learning; thus, it might perform worse in heterogeneous environments. Further research will be conducted towards the reduction of the computational costs and expansion of the scope of languages.

6. Conclusion

The finding indicates that the proposed hybrid architecture, like CFF-Net combined with AGWO, demonstrates robust and precise sentiment classification for the Tamil and Malayalam datasets. CFF-Net, which represents context-based feature extraction with the hierarchical attention and semantic interactions layers, represents an efficient approach to select the most important tokens and remove irrelevant information from the dataset. Moreover, AGWO improves convergence and stability due to the dynamic optimization of learning rates for each modality. In addition, measures of evaluation like Accuracy, Balanced Accuracy, Precision, Recall, F1-Score and AUC consistently perform better in comparison with current approaches with a statistically significant difference according to the t-test. The importance of the features analysis produces a small set of dominant features, which greatly impact the classification results, while class distributions visualizations represent an approach to tackle the problem of class imbalance. Overall, the presented hybrid approach is ensured to be efficient, precise and consistent in detecting the sentiment in complex code-mixed linguistic structures, solving the problem of sentiment classification in Dravidian language texts and real-time sentiment classifications.

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