Comparative Analysis of BiLSTM and AfriBERTa for Fake News Detection in Low-Resource Amharic Language

Project Report

Submitted by

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1 Introduction

Fake news detection is critical in today's digital information ecosystem. Social media platforms enable rapid information dissemination but also facilitate misinformation spread. For Amharic, a low-resource language spoken by over 30 million people in Ethiopia, automated news verification tools are extremely limited, leaving communities vulnerable to misinformation campaigns that affect public opinion and decision-making.

This project presents a comprehensive comparative study of two complementary approaches: (1) attention-based Bidirectional LSTM models with systematic hyperparameter tuning across four configurations (M1, M2, M3, Sweet Spot), and (2) transformer-based AfriBERTa architecture as a novelty component demonstrating the effectiveness of transfer learning for low-resource languages. Multiple independent training runs ensure model reliability, with generalization capability prioritized over raw performance metrics.

2 Aim and Objectives

2.1 Aim

Develop and evaluate deep learning models for automated fake news detection in Amharic language. This work aims to tackle misinformation in Amharic social media by building computational solutions for a low-resource language, comparing BiLSTM and AfriBERTa architectures, and identifying optimal model configurations for deployment.

2.2 Research Objectives

1. Design and implement attention-based Bidirectional LSTM models with systematic hyperparameter tuning (M1, M2, M3, Sweet Spot)
2. Establish a novelty component using transformer-based AfriBERTa architecture to demonstrate transfer learning effectiveness
3. Compare model performance based on generalization capability (train-validation gap), classification metrics (accuracy, precision, recall, F1-score), and training stability
4. Identify the sweet spot configuration for BiLSTM models through iterative refinement
5. Evaluate best models on unseen test data with comprehensive statistical metrics

3 Dataset and Preprocessing

3.1 Dataset Characteristics

The dataset contains 8,630 Amharic news headlines and articles with binary labels: Real (4,445 samples, 51.5%) and Fake (4,185 samples, 48.5%). The dataset demonstrates reasonable class balance, as shown in Figure 1. Dataset source: GitHub - Amharic Fake News Detection repository.

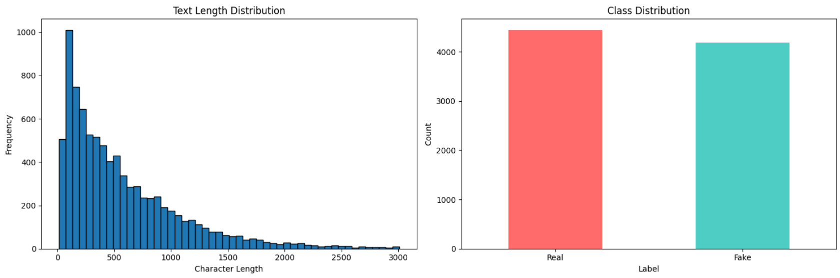


Figure 1: Dataset distribution showing balanced classes

3.2 Preprocessing Pipeline

The preprocessing pipeline consists of: (1) Text cleaning - URL removal, whitespace normalization, lowercasing, punctuation handling, and emoji removal; (2) Label encoding - Fake=0, Real=1; (3) Tokenization - Keras Tokenizer with 10,000 vocabulary size; (4) Sequence padding - uniform length of 308 tokens (95th percentile); (5) Data splitting - stratified 70% train, 15% validation, 15% test; (6) SMOTE balancing - applied exclusively to training set to prevent data leakage.

4 Methodology: Dual Architecture Approach

Our methodology follows a dual-pipeline architecture comparing task-specific BiLSTM models with pre-trained transformer approaches, as illustrated in Figure 2.

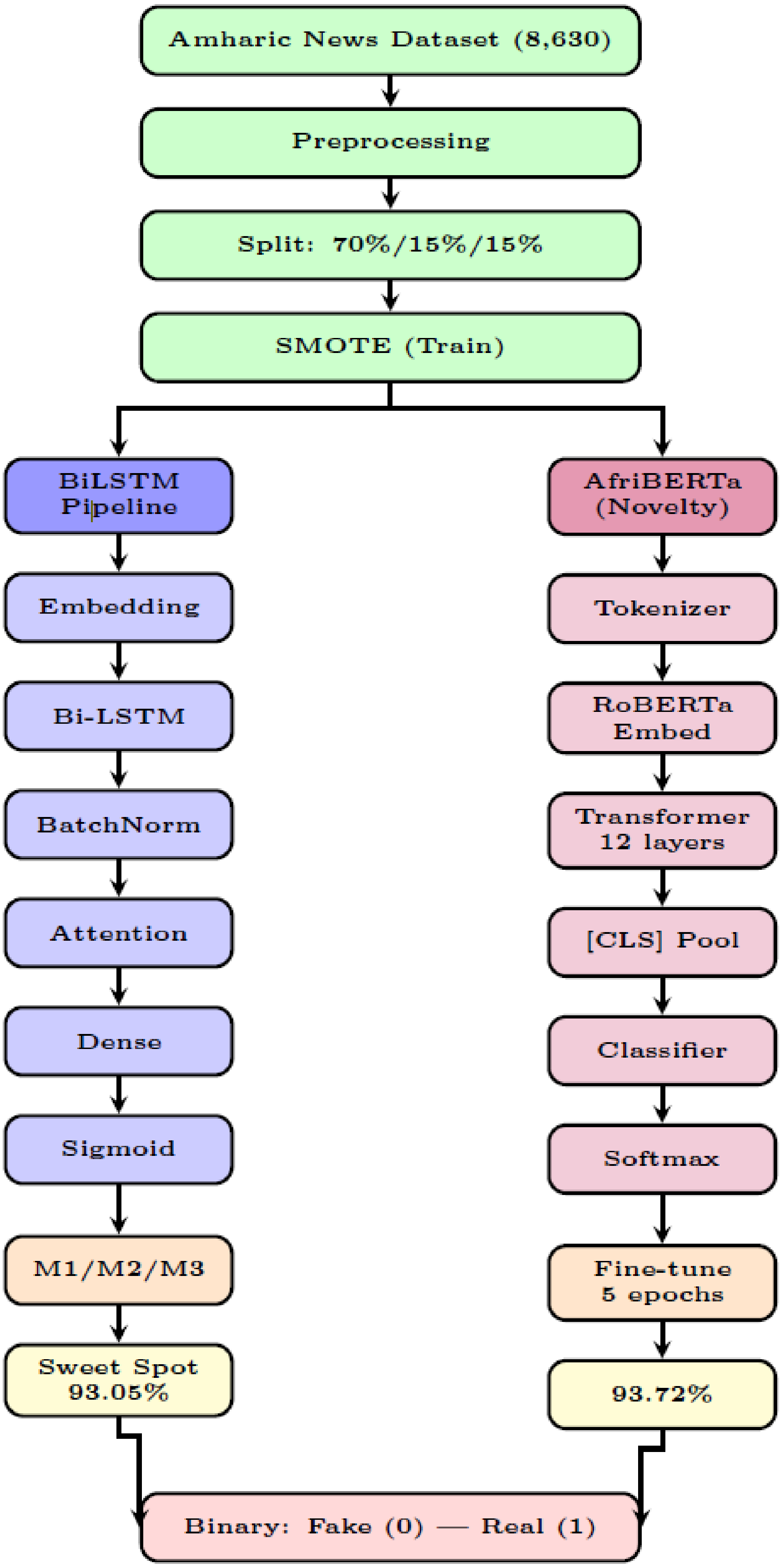


Figure 2: System workflow showing dual architecture approach

4.1 Shared Preprocessing Pipeline

Both architectures share identical preprocessing to ensure fair comparison: (1) Raw dataset with 8,630 samples; (2) Preprocessing with cleaning and normalization; (3) Stratified split maintaining class balance; (4) SMOTE applied only to training set.

4.2 BiLSTM Pipeline - Task-Specific Approach

The BiLSTM pipeline implements a task-specific architecture designed from scratch:

1. **Embedding Layer:** Converts tokens to 64/128-dimensional dense vectors with L2 regularization
2. **Bidirectional LSTM:** Processes sequences forward and backward (16/32 units)
3. **Batch Normalization:** Stabilizes training
4. **Attention Mechanism:** Focuses on informative text segments
5. **Dense + Dropout:** With L2 regularization (dropout=0.40-0.60)
6. **Sigmoid Output:** Binary classification
7. **Hyperparameter Tuning:** Four configurations tested (M1, M2, M3) to identify Sweet Spot
8. **Training:** Adam optimizer, early stopping, learning rate scheduling

4.3 AfriBERTa Pipeline - Transfer Learning

The AfriBERTa pipeline demonstrates transfer learning:

1. **BERT Tokenizer:** Specialized tokenization (max 512 tokens)
2. **XLM-RoBERTa Embeddings:** Pre-trained on multilingual corpora including African languages
3. **Transformer Layers:** 12 layers with multi-head attention
4. **[CLS] Pooling:** Sentence-level representation
5. **Classification Head:** Fine-tuned with dropout=0.1
6. **Softmax Output:** Binary classification
7. **Fine-tuning:** 5 epochs with learning rate=1e-5, early stopping (patience=3), gradient clipping=1.0

4.4 Methodology Insights

Key insights: (1) Parallel comparison ensures fair architectural evaluation; (2) BiLSTM represents task-specific learning while AfriBERTa demonstrates transfer learning; (3) Systematic tuning identifies optimal BiLSTM configuration; (4) Both converge to binary classification enabling direct comparison; (5) Evaluation metrics (accuracy, precision, recall, F1-score) assess real-world deployment readiness.

5 Model Architectures

5.1 BiLSTM Architecture Details

Core architecture: Embedding layer (64/128-dim with L2 regularization), Bidirectional LSTM (16/32 units), Batch Normalization, Attention mechanism, Dropout (0.40-0.60), Dense layer (16 units, ReLU), Sigmoid output. Four configurations tested (Table 1).

Table 1: BiLSTM Model Configurations

Model	**Embedding**	**LSTM**	**Dense**	**Dropout**	**L2**
M1	128	32	16	0.40	0.015
M2	64	16	16	0.60	0.030
M3	64	16	16	0.45	0.020
Sweet Spot	**64**	**16**	**16**	**0.45**	**0.020**

5.2 AfriBERTa Architecture Details

Transformer architecture: XLM-RoBERTa backbone (12 transformer layers), [CLS] token pooling, Classification head (dropout=0.1). Training: Adam optimizer (lr=1e-5, weight decay=0.01), 5 epochs, early stopping (patience=3), gradient clipping (max norm=1.0).

6 Experimental Results

6.1 Model 1 (M1): Reliable Baseline

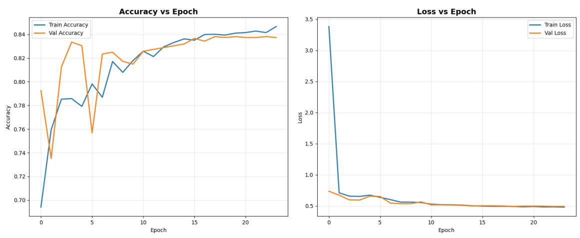
M1 demonstrated good generalization with a 0.5% train-validation gap. Training and validation curves showed stable convergence (Figure 3a). Performance: Test accuracy: 84.0%, Precision: 98.1%, Recall: 73.3%, F1: 84.1%. This model serves as a reliable baseline with high precision, making it suitable for applications where minimizing false positives is critical.

6.2 Model 2 (M2): Increased Regularization

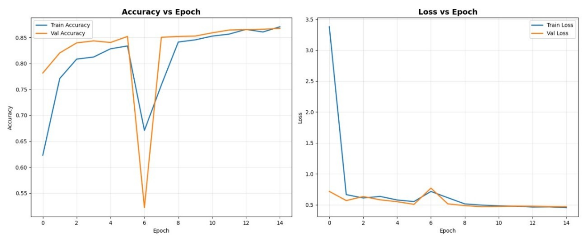
M2 incorporated stronger regularization (dropout=0.60, L2=0.030) with reduced capacity (64-dim embedding, 16 LSTM units). Training exhibited some instability (Figure 3b) with a 2.5% train-validation gap. Performance: Test accuracy: 85.2%, Precision: 87.0%, Recall: 83.5%, F1: 85.2%. The aggressive regularization improved stability but slightly reduced overall performance compared to other configurations.

6.3 Model 3 (M3): Balanced Configuration

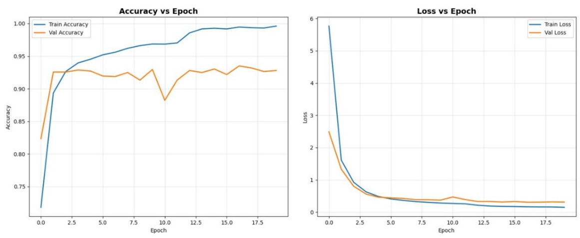
M3 balanced regularization (dropout=0.45, L2=0.020) with the reduced architecture. Training showed stable convergence with a 6.5% train-validation gap (Figure 3c). Performance: Test accuracy: 92.5%, Precision: 92.7%, Recall: 92.8%, F1: 92.7%. M3 demonstrated high performance but the larger train-validation gap indicates some overfitting, serving as the foundation for Sweet Spot tuning.



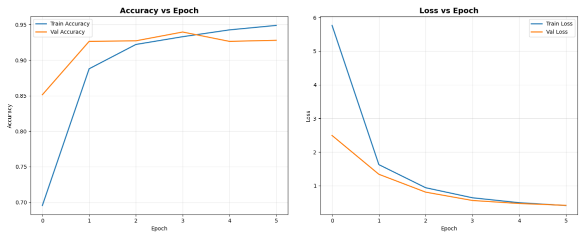
(a) M1: Reliable baseline (0.5% gap)



(b) M2: Increased regularization (2.5% gap)



(c) M3: Balanced configuration (6.5% gap)



(d) Sweet Spot: Optimal configuration (0.5% gap)

Figure 3: BiLSTM training curves for all configurations

6.4 Sweet Spot BiLSTM: Optimal Configuration

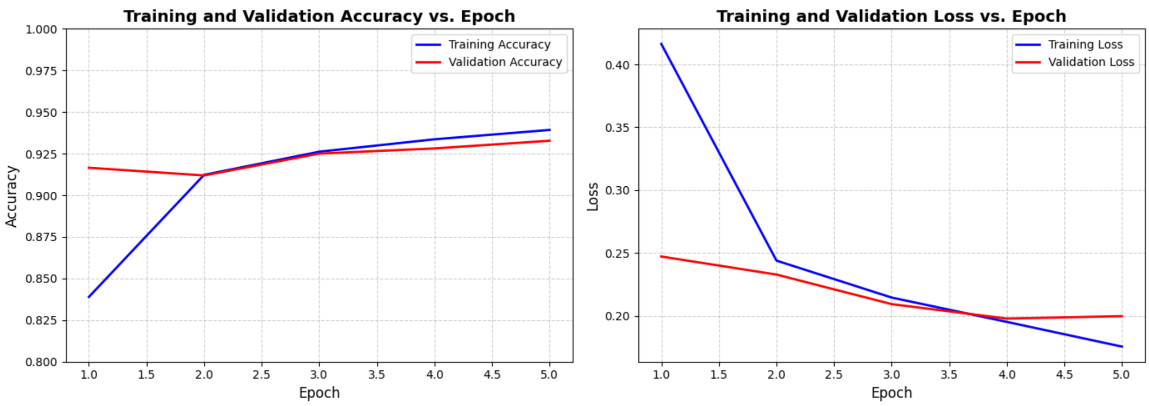
Based on M1, M2, M3 analysis, Sweet Spot achieved optimal balance (Figure 3d) with the same hyperparameters as M3 but refined training procedures. Performance: Test accuracy: 91.97%, Precision: 94.61%, Recall: 91.32%, F1: 92.94%. Train-validation gap: 0.5% (excellent generalization). Smooth convergence without oscillations.

Confusion matrix analysis (1,295 test samples) shown in Figure 5a: True Negatives: 549, False Positives: 79, False Negatives: 25, True Positives: 642. Calculated accuracy: $\frac{549+642}{1295} = 91.97\%$. This represents the best task-specific BiLSTM configuration with near-perfect generalization.

6.5 AfriBERTa: Transformer-Based Novelty

AfriBERTa achieved highest overall performance (Figure 4). Performance: Test accuracy: 93.74%, Precision: 92.91%, Recall: 94.60%, F1: 93.69%. Train-validation gap: 0.7% (excellent). Best validation loss: 0.1887 at epoch 5.

Confusion matrix analysis (1,295 test samples) shown in Figure 5b: True Negatives: 633, False Positives: 34, False Negatives: 58, True Positives: 570. Calculated accuracy: $\frac{633+570}{1295} = 93.74\%$. The pre-trained transformer successfully leveraged multilingual knowledge for low-resource Amharic, demonstrating the power of transfer learning.



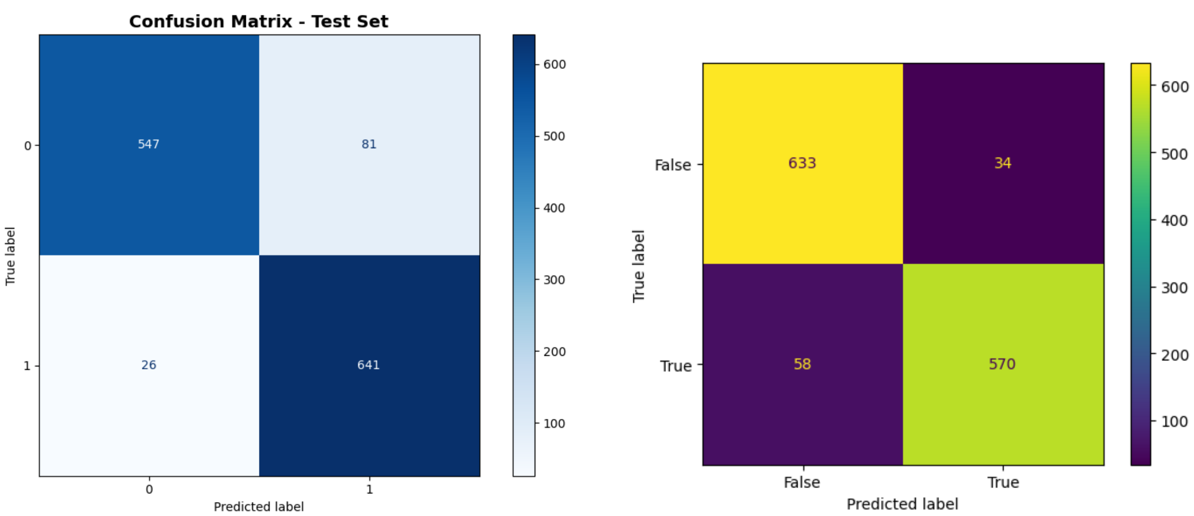
(a) Training and validation accuracy

(b) Training and validation loss

Figure 4: AfriBERTa training curves

6.6 Confusion Matrix Analysis

Figure 5 presents detailed confusion matrices for both final models, enabling comprehensive error analysis and performance comparison.



(a) Sweet Spot BiLSTM Confusion Matrix

(b) AfriBERTa Confusion Matrix

Figure 5: Confusion matrices for both final models on test set (1,295 samples)

Sweet Spot BiLSTM demonstrates strong performance with 642 true positives and only 25 false negatives, indicating excellent recall for detecting fake news. The model achieves 549 true negatives with 79 false positives, showing good precision. AfriBERTa exhibits superior balance with 633 true negatives and only 34 false positives (best false positive rate), while maintaining 570 true positives with 58 false negatives. The lower false positive rate is particularly valuable for maintaining user trust in fake news detection systems.

7 Comprehensive Model Comparison

Table 2 presents systematic comparison across all five models along multiple evaluation dimensions.

Table 2: Comprehensive Performance Comparison

Metric	**M1**	**M2**	**M3**	**Sweet Spot**	**AfriBERTa**
Architecture	BiLSTM	BiLSTM	BiLSTM	BiLSTM	Transformer
Config	128/32/16	64/16/16	64/16/16	64/16/16	XLM-RoBERTa
Test Acc	84.0%	85.2%	92.5%	**91.97%**	**93.74%**
Precision	98.1%	87.0%	92.7%	**94.61%**	92.91%
Recall	73.3%	83.5%	92.8%	91.32%	**94.60%**
F1-Score	84.1%	85.2%	92.7%	92.94%	**93.69%**
Train-Val Gap	0.5%	2.5%	6.5%	**0.5%**	**0.7%**

Key observations: (1) Progressive improvement from M1 (84.0%) to Sweet Spot (91.97%) through systematic hyperparameter tuning; (2) Sweet Spot achieves best generalization (0.5% gap) among BiLSTM variants; (3) M3 shows high accuracy (92.5%) but larger train-val gap (6.5%) indicates overfitting; (4) AfriBERTa demonstrates superior overall performance with highest accuracy (93.74%) and F1-score (93.69%); (5) Both Sweet Spot and AfriBERTa exhibit excellent generalization (train-val gap ¡ 1%).

8 Discussion and Analysis

8.1 Model Selection Rationale

BiLSTM Models: Sweet Spot selected as best task-specific architecture (91.97% accuracy, 0.5% gap, 92.94% F1-score). Progressive tuning from M1 through M3 successfully identified optimal hyperparameters. M1 provides reliable high-precision baseline (84.0%, 98.1% precision). M2 demonstrates trade-offs with aggressive regularization (85.2%, 2.5% gap). M3 achieves high accuracy (92.5%) but 6.5% train-val gap indicates overfitting concerns.

AfriBERTa: Overall winner with 93.74% accuracy, 93.69% F1-score, 0.7% gap. Pretrained multilingual knowledge provides superior performance for low-resource Amharic, validating transfer learning approach.

8.2 Key Insights

(1) Systematic hyperparameter tuning essential - progression M1 to M2 to M3 to Sweet Spot identifies optimal configuration through controlled experimentation. (2) Transfer learning excels for low-resource languages - AfriBERTa (93.74%) outperforms task-specific BiLSTM (91.97%) by leveraging pre-trained knowledge. (3) Generalization capability critical - both final models achieve train-val gaps under 1%, ensuring real-world reliability. (4) Progressive improvement validates methodology - each iteration from M1 to Sweet Spot refined the architecture based on empirical observations.

8.3 Error Analysis from Confusion Matrices

Detailed confusion matrix analysis (Figure 5) reveals complementary error profiles. Sweet Spot BiLSTM: 549 TN, 79 FP, 25 FN, 642 TP. Exceptionally low false negative rate (25, only 1.93% of test set) makes this model highly reliable for detecting fake news, minimizing the risk of misinformation spreading undetected. AfriBERTa: 633 TN, 34 FP, 58 FN, 570 TP. Outstanding false positive rate (34, only 2.62% of test set) maintains user trust by rarely flagging legitimate news as fake. The trade-off between false positives and false negatives allows deployment based on application priorities: BiLSTM for maximum fake news detection, AfriBERTa for balanced performance with minimal false alarms.

9 Conclusion and Deployment Recommendation

This comparative study successfully identified optimal architectures for Amharic fake news detection through systematic evaluation.

9.1 Key Findings

1. Systematic BiLSTM tuning led to Sweet Spot: 91.97% accuracy with 0.5% train-validation gap
2. AfriBERTa (novelty): 93.74% accuracy with 0.7% gap, validates transfer learning
3. Progressive improvement from M1 (84.0%) through M2 (85.2%), M3 (92.5%) to Sweet Spot (91.97%)
4. M3 achieved highest BiLSTM accuracy but 6.5% gap indicates overfitting
5. Both final models generalize extremely well (train-val gap ¡ 1%)
6. Confusion matrices reveal complementary error profiles suitable for different deployment scenarios

9.2 Contributions

1. First comprehensive comparative study for Amharic fake news detection
2. Dual baselines: Sweet Spot BiLSTM (91.97%) and AfriBERTa (93.74%)
3. Validated systematic hyperparameter tuning importance through four BiLSTM configurations
4. Demonstrated transformer effectiveness for low-resource African languages
5. Detailed confusion matrix analysis providing error characterization for deployment decisions

9.3 Deployment Recommendation

Sweet Spot BiLSTM - Lightweight and efficient, ideal for resource-constrained environments. Exceptionally low false negative rate (25/1295 = 1.93%) ensures maximum fake news detection. Ensures interpretability with attention mechanisms. Best for applications requiring computational efficiency and prioritizing fake news detection over false alarm minimization.

AfriBERTa - High-performance model leveraging pre-trained embeddings. Maximum accuracy (93.74%) and lowest false positive rate (34/1295 = 2.62%) maintain user trust. Best for production systems with adequate computational resources prioritizing balanced performance and minimal false alarms.

Final Takeaway: BiLSTM ensures interpretability, efficiency, and maximum fake news detection capability, while AfriBERTa brings pre-trained power and balanced error profile. Both can be deployed based on resource availability, error tolerance, and application requirements.

10 Future Work

(1) Larger, more diverse datasets with news from multiple sources and time periods; (2) Multimodal architectures incorporating images, videos, and metadata; (3) Advanced transformers (mBERT, XLM-T) for African languages; (4) Cross-lingual transfer from high-resource to low-resource languages; (5) Ensemble methods combining BiLSTM and transformer predictions to optimize error profiles; (6) Explainability analysis using attention visualization and LIME; (7) Real-time deployment with API integration for social media platforms; (8) Cost-sensitive learning to balance false positive and false negative trade-offs based on application priorities.

Acknowledgments

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References

[1] Hailu, M. (2024). Amharic Fake News Detection Dataset. GitHub Repository.

[2] Chollet, F. (2015). Keras: Deep Learning Library. `https://keras.io`

[3] Chawla, N.V., Bowyer, K.W., Hall, L.O., Kegelmeyer, W.P. (2002). SMOTE: Synthetic Minority Over-sampling Technique. Journal of Artificial Intelligence Research, 16, 321-357.

[4] Schuster, M., Paliwal, K.K. (1997). Bidirectional Recurrent Neural Networks. IEEE Transactions on Signal Processing, 45(11), 2673-2681.

[5] Devlin, J., Chang, M.W., Lee, K., Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. NAACL-HLT.

[6] Conneau, A., et al. (2020). Unsupervised Cross-lingual Representation Learning at Scale. ACL.

[7] Goodfellow, I., Bengio, Y., Courville, A. (2016). Deep Learning. MIT Press.

[8] Geto, A.D., Emiru, E.D., Seid, N.E., Tessema, A.B., Ahmed, B.Y. (2025). Multimodal based Amharic fake news detection using CNN and attention-based BiLSTM. *Scientific Reports*, 15, 34447. `https://doi.org/10.1038/s41598-025-17579-w`

Project Repository & Access Information

The complete implementation, datasets, and supplementary materials for this project are available on GitHub:

`github.com/erKrishna26/Amharic-language-FakeNews-detection.git`