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

Project Review

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Presentation Agenda

1. Aim & Objectives
2. Introduction & Background
3. System Workflow
4. Methodology Overview
5. Dataset Summary
6. Model Configurations
7. Confusion Matrix Analysis
8. Comparative Results
9. Performance Metrics Visualization
10. Conclusion & Deployment Recommendation

Aim & Objectives

Aim

Develop and evaluate deep learning models for automated fake news detection in Amharic language.

- Tackle misinformation in Amharic social media.
- Build computational solutions for a low-resource language.
- Compare BiLSTM and AfriBERTa architectures.
- Identify optimal model configuration for deployment.

Introduction

Background

- Fake news detection is vital in the digital era.
- Amharic language lacks NLP tools and labeled datasets.

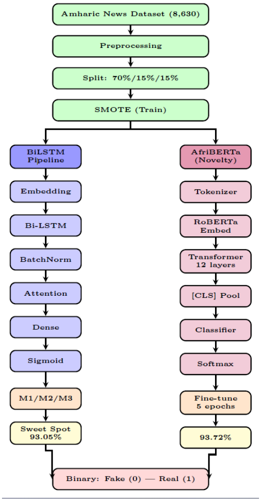
Challenges

- Limited data and high class imbalance.
- Complex Amharic script and morphology.

Approach

- Attention-based BiLSTM tuned (M1–M3 $\rightarrow$ Sweet Spot).
- AfriBERTa transformer for transfer learning comparison.

System Workflow



Pipeline: Data Preprocessing → SMOTE Balancing → Model Training (BiLSTM / AfriBERTa) → Evaluation.

Methodology Overview

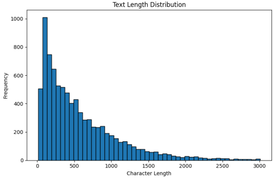
Steps:

1. **Data Preprocessing:** Cleaning, normalization, tokenization, padding (308 tokens).
2. **Balancing:** SMOTE applied on training set.
3. **Model Design:**
   - BiLSTM: Embedding $\rightarrow$ BiLSTM $\rightarrow$ Attention $\rightarrow$ Dense $\rightarrow$ Sigmoid
   - AfriBERTa: Fine-tuned XLM-RoBERTa
4. **Training:** Adam optimizer, early stopping, learning rate scheduling.
5. **Evaluation:** Accuracy, Precision, Recall, F1-score.

Dataset Summary

Dataset Details:

- Total: 8,630 Amharic news samples
- Labels: Fake (4,185), Real (4,445)
- Split: 70% Train, 15% Validation, 15% Test
- Padding: Fixed at 308 tokens (95th percentile)



Dataset Source: GitHub - Amharic Fake News Detection

Model Configurations

BiLSTM Hyperparameter Tuning

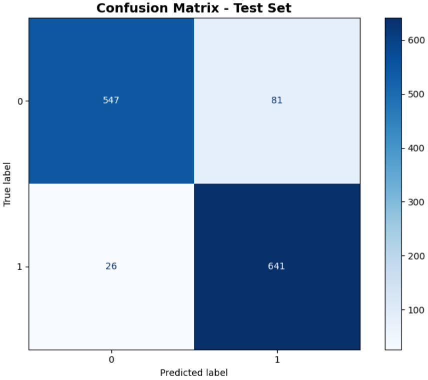
Model	Embed	LSTM	Dense	Dropout	L2
M1	128	32	16	0.40	0.015
M2	64	16	16	0.60	0.030
M3	64	16	16	0.45	0.020
Sweet Spot	**64**	**16**	**16**	**0.45**	**0.020**

AfriBERTa (Novelty)

- Backbone: XLM-RoBERTa
- Optimizer: Adam (lr=1e-5)
- Epochs: 5, Early Stopping (patience=3)
- Dropout: 0.1, Gradient Clipping: 1.0

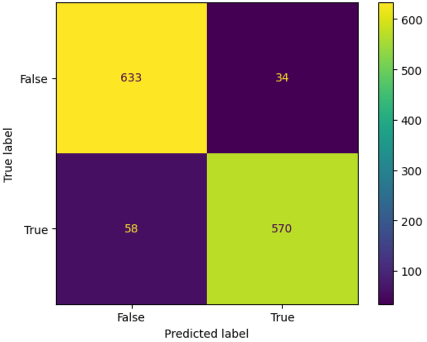
Confusion Matrix Analysis

BiLSTM (Sweet Spot)



- TN: 549, FP: 79
- FN: 25, TP: 642

AfriBERTa



- TN: 633, FP: 34
- FN: 58, TP: 570

Accuracy Calculation:

BiLSTM:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} = \frac{549+642}{1295} = \mathbf{91.97\%}$$

AfriBERTa:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} = \frac{633+570}{1295} = \mathbf{93.74\%}$$

Comparative Results - All Models

Metric	M1	M2	M3	Sweet Spot	AfriBERTa
Test Accuracy	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:

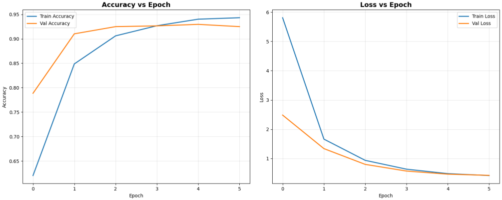
- M1: Excellent generalization (0.5% gap) but lower recall - high precision baseline.
- M2: Training instability (2.5% gap) limited performance.
- M3: High accuracy (92.5%) but overfitting (6.5% gap) disqualifies for deployment.
- Sweet Spot: Optimal balance with 91.97% accuracy and 0.5% gap.
- AfriBERTa: Best overall performance leveraging transfer learning.

**For detailed training curves of M1, M2, and M3, please refer to the project report.*

Performance Metrics Visualization

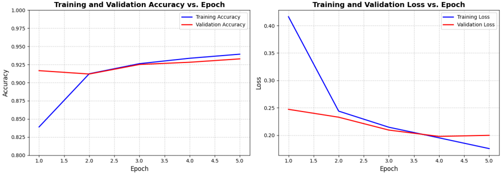
Sweet Spot BiLSTM

- Test Accuracy: 91.97% | Train-Val Gap: 0.5%
- Smooth convergence with excellent generalization



AfriBERTa

- Test Accuracy: 93.74% | Train-Val Gap: 0.7%
- Transfer learning power from multilingual pre-training



Both models demonstrate near-perfect generalization with train-validation gaps below 1%.

Conclusion & Deployment Recommendation

Key Findings:

- Progressive tuning (M1 $\rightarrow$ M2 $\rightarrow$ M3 $\rightarrow$ Sweet Spot) successfully identified optimal configuration.
- Sweet Spot BiLSTM achieved **91.97%** accuracy with near-perfect generalization (0.5% gap).
- AfriBERTa achieved **93.74%** using transfer learning on African languages.
- M3 showed highest BiLSTM accuracy (92.5%) but overfitting (6.5% gap) makes it unsuitable.

Deployment Recommendation

Sweet Spot BiLSTM – Lightweight, interpretable, ideal for resource-constrained environments.
AfriBERTa – High-performance model leveraging pre-trained embeddings for maximum accuracy.

Both models can be deployed based on computational resource availability and application requirements.

Project Repository & Access Information

Access Our Work

The complete implementation, report, and presentation for this project are available on GitHub:

`github.com/erKrishna26/Amharic-Fake-News-Detection`