Machine Learning Approaches for Detecting Fake News in the Afan Oromo

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Abstract

The proliferation of fake news in digital media poses significant challenges to information credibility, particularly in underrepresented languages such as Afan Oromo. While numerous machine learning approaches have been employed for fake news detection in widely spoken languages, research on indigenous African languages remains limited. This study explores the application of machine learning techniques to detect fake news in the Afan Oromo language. A dataset of authentic and misleading news articles is curated from various online sources, preprocessed using natural language processing (NLP) techniques, and analyzed with multiple machine learning models, including Naïve Bayes, Support Vector Machines (SVM), Random Forest, and deep learning-based approaches such as Long Short-Term Memory (LSTM) networks. The study evaluates these models' performance using precision, recall, F1-score, and accuracy metrics. Findings highlight the effectiveness of feature engineering techniques, such as word embeddings and TF-IDF, in improving model accuracy. The study also identifies key linguistic challenges in fake news detection for Afan Oromo, including limited textual resources and morphological complexity. The results demonstrate the potential of machine learning in enhancing automated fake news detection in low-resource languages and suggest directions for future research in multilingual misinformation analysis.

Keywords: Fake News Detection, Afan Oromo, Machine Learning, Natural Language Processing, Low-Resource Languages, Misinformation

1. Introduction

A. Background on Fake News and Its Impact on Society

Fake news has emerged as a critical issue in the digital age, where misinformation and disinformation rapidly spread across social media and online platforms. The proliferation of fake news can have severe consequences, including misleading the public, influencing political decisions, exacerbating social conflicts, and undermining trust in legitimate news sources. With the increasing reliance on digital media for information consumption, the need for effective fake news detection mechanisms has become more pressing than ever. Machine learning (ML) and natural language processing (NLP) techniques have been widely adopted to automate the detection of false information, ensuring that users receive credible and verified content.

B. Importance of Detecting Fake News in Underrepresented Languages like Afan Oromo

Most research on fake news detection has primarily focused on widely spoken languages such as English, Chinese, and Spanish, leaving many indigenous and underrepresented languages without adequate tools for misinformation mitigation. Afan Oromo, one of the most widely spoken languages in Ethiopia and East Africa, lacks robust digital resources for automated fake news detection. The spread of misinformation in Afan Oromo can have significant social and political consequences, influencing public perceptions and contributing to social instability. Developing effective ML-based fake news detection for Afan Oromo is crucial in preserving information integrity and fostering media literacy among its speakers.

C. Challenges in Fake News Detection for Low-Resource Languages

Detecting fake news in low-resource languages like Afan Oromo presents several challenges:

- Limited Labeled Datasets – There is a scarcity of large, annotated datasets required for training ML models effectively.
- Morphological Complexity – Afan Oromo has a rich morphology, including inflectional variations, which complicates text processing and feature extraction.

- Lack of NLP Tools – Unlike high-resource languages, Afan Oromo lacks pre-trained language models, word embeddings, and syntactic parsers, making NLP tasks more difficult.
- Code-Switching and Dialectal Variations – The presence of multiple dialects and code-switching between Afan Oromo and other languages (e.g., Amharic or English) adds another layer of complexity.
- Misinformation Patterns – Fake news in Afan Oromo may follow unique linguistic and stylistic patterns that differ from those in well-studied languages, requiring customized detection approaches.

D. Research Objectives and Contributions

This study aims to address the gap in fake news detection for underrepresented languages by developing and evaluating machine learning approaches for Afan Oromo. The specific objectives of this research include:

- Dataset Creation – Collecting and annotating a dataset of real and fake news articles in Afan Oromo from various online sources.
- Feature Engineering – Exploring different textual representation techniques, including TF-IDF, word embeddings, and deep learning-based embeddings.
- Model Development and Evaluation – Applying and comparing various machine learning models such as Naïve Bayes, Support Vector Machines (SVM), Random Forest, and deep learning approaches like Long Short-Term Memory (LSTM) networks for fake news detection.
- Performance Analysis – Assessing the models' effectiveness using precision, recall, F1-score, and accuracy to determine the best approach for detecting fake news in Afan Oromo.
- Addressing Low-Resource Challenges – Investigating techniques such as data augmentation, transfer learning, and cross-lingual embeddings to improve performance despite the language's limited NLP resources.

By tackling these objectives, this research contributes to the advancement of fake news detection in low-resource languages, providing a foundation for future studies in misinformation analysis for Afan Oromo and similar languages.

2. Literature Review

A. Overview of Fake News Detection Methods

Fake news detection methods can be broadly categorized into manual, rule-based, and automated approaches.

- Manual Verification – Traditional fact-checking organizations such as Snopes and FactCheck.org employ human experts to verify claims. However, this approach is time-consuming and not scalable.
- Rule-Based Approaches – Early automated fake news detection relied on predefined linguistic and statistical rules, such as keyword patterns, readability scores, and lexical analysis. While effective for structured misinformation, these methods struggle with evolving disinformation tactics.
- Machine Learning-Based Approaches – More recent studies leverage supervised and unsupervised learning techniques to classify news as real or fake based on textual, contextual, and social media metadata features.
- Deep Learning and NLP Models – Neural networks, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based models like BERT, have demonstrated superior performance in understanding contextual nuances and detecting misinformation.

B. Machine Learning Techniques in Fake News Detection

Machine learning techniques for fake news detection primarily focus on feature engineering and classification models. Common approaches include:

Feature Extraction

- TF-IDF (Term Frequency-Inverse Document Frequency) – Measures word importance within a document relative to a corpus.
- Word Embeddings – Word2Vec, GloVe, and fastText generate dense vector representations of words, capturing semantic relationships.
- Metadata Features – Includes article length, source credibility, and publication time.

Classification Algorithms

- Naïve Bayes – A probabilistic classifier useful for text-based classification tasks.
- Support Vector Machines (SVM) – Effective for high-dimensional text data but requires careful feature selection.
- Random Forest – A robust ensemble learning method that mitigates overfitting.

Deep Learning Models

- LSTM (Long Short-Term Memory) – Captures sequential dependencies in text, improving contextual understanding.
- Transformers (BERT, RoBERTa, T5) – Pre-trained language models that achieve state-of-the-art performance in NLP tasks.

C. Challenges in Linguistic Processing for Low-Resource Languages

Detecting fake news in low-resource languages presents several linguistic and technical challenges:

- Data Scarcity – Unlike English, which has vast labeled datasets, low-resource languages lack annotated corpora for model training.
- Morphological Complexity – Many underrepresented languages, including Afan Oromo, have rich inflectional systems, making tokenization and word embeddings challenging.
- Code-Switching and Borrowed Words – Mixing languages within a text complicates NLP processing. Afan Oromo speakers often integrate Amharic and English terms.
- Lack of Pretrained Models – Most NLP advancements are tailored for high-resource languages, requiring transfer learning or cross-lingual embeddings for adaptation.
- Ethical Considerations – Bias in training data and model predictions can disproportionately affect marginalized communities, requiring fair and explainable AI methodologies.

D. Existing Research on Afan Oromo Language Processing

Despite its large speaker base, Afan Oromo remains underrepresented in NLP research. Some existing studies include:

- Text Classification – Early works have applied rule-based and machine learning methods for sentiment analysis and topic classification in Afan Oromo.
- Named Entity Recognition (NER) – A few studies have explored entity extraction for Afan Oromo but are hindered by limited annotated datasets.

- Speech and Text Processing – Some projects have attempted speech-to-text conversion and morphological analysis, yet progress is slow due to insufficient resources.
- Machine Translation – Efforts to develop Afan Oromo-English translation models are ongoing but face accuracy limitations due to scarce parallel corpora.
- Fake News Detection – No significant research has been conducted on automated misinformation detection in Afan Oromo, highlighting the novelty and necessity of this study.

This review underscores the need for tailored machine learning solutions to enhance fake news detection in Afan Oromo and other low-resource languages, ensuring digital information integrity across diverse linguistic communities.

3. Dataset Collection and Preprocessing

A. Sources of Fake and Real News in Afan Oromo

To build an effective machine learning model for fake news detection in Afan Oromo, a reliable dataset comprising both real and fake news articles is essential. The dataset is sourced from:

- Government and Reputable News Agencies – Credible sources such as Oromia Broadcasting Network (OBN), BBC Afaan Oromo, and Ethiopian News Agency provide verified news articles.
- Independent News Portals and Blogs – News websites that focus on Oromo-related events and politics are examined to collect both real and questionable news.
- Social Media and User-Generated Content – Facebook, Twitter, and Telegram groups that circulate Afan Oromo news are scraped for potential misinformation.
- Fact-Checking Organizations – Any available fact-checked articles related to Afan Oromo are used to verify news authenticity.

Collected articles are labeled as real or fake based on fact-checking, source credibility, and linguistic patterns commonly associated with misinformation.

B. Challenges in Dataset Creation (Limited Data, Labeling Difficulties)

- Scarcity of Labeled Data – Unlike English or Amharic, there are few annotated fake news datasets for Afan Oromo. Data augmentation and semi-supervised learning methods may help overcome this limitation.
- Fact-Checking Difficulties – The lack of dedicated Afan Oromo fact-checking organizations makes news validation challenging, requiring reliance on human experts and cross-referencing with reputable sources.
- Dialectal Variations – Afan Oromo has multiple dialects that may affect word meanings and context, complicating model generalization.
- Misinformation Patterns – Fake news articles often use exaggerated language, manipulated facts, and emotionally charged words, making manual labeling essential for training accurate models.

To mitigate these challenges, a hybrid labeling approach is used, combining expert validation, crowd-sourcing, and semi-supervised learning techniques.

C. Text Preprocessing Techniques

To prepare the dataset for machine learning models, various natural language processing (NLP) techniques are applied:

- Tokenization – Breaking news articles into individual words or subwords using Afan Oromo-specific tokenizers.
- Stop-Word Removal – Eliminating common words (e.g., "kan", "fi", "gara") that do not contribute to distinguishing fake from real news.
- Stemming and Lemmatization – Reducing words to their root forms to handle morphological variations (e.g., "barattoota" → "barattoo" for "students").
- Lowercasing and Punctuation Removal – Standardizing text formats to reduce variability in word representation.
- Handling Code-Switching – Detecting and processing mixed-language texts containing Amharic and English terms.

These preprocessing steps help improve the model’s ability to extract meaningful patterns from Afan Oromo text.

D. Feature Extraction

Feature engineering is a crucial step in improving model performance. The following techniques are used to convert textual data into numerical representations:

- TF-IDF (Term Frequency-Inverse Document Frequency) – Captures the importance of words in a document relative to the entire dataset.
- Word Embeddings (Word2Vec, fastText, BERT-based embeddings) – Converts words into dense vector representations, capturing semantic relationships and contextual meanings.
- Sentiment Analysis – Analyzes the sentiment polarity (positive, negative, neutral) of articles, as fake news often employs emotional language.
- N-grams and Part-of-Speech (POS) Tagging – Extracts multi-word phrases and syntactic structures that may distinguish real from fake news.

By integrating these techniques, the dataset is transformed into a structured format suitable for machine learning models, enhancing the detection of fake news in Afan Oromo.

4. Machine Learning Approaches

A. Supervised Learning Models

Supervised learning techniques involve training models on labeled datasets to classify news articles as real or fake. Common models used for fake news detection include:

- Naïve Bayes (NB) – A probabilistic classifier that works well for text classification by assuming word independence. It is simple and computationally efficient but may struggle with complex linguistic patterns in Afan Oromo.
- Support Vector Machines (SVM) – A powerful classifier that finds the optimal decision boundary between fake and real news. It performs well on text-based data, especially with TF-IDF or word embedding features.
- Logistic Regression (LR) – A baseline binary classification model that is interpretable and effective for detecting fake news based on extracted features.
- Random Forest (RF) – An ensemble learning method that combines multiple decision trees to improve classification accuracy and robustness against overfitting.
- Gradient Boosting Machines (GBM) – Algorithms like XGBoost, LightGBM, and CatBoost refine decision trees iteratively to achieve high predictive performance.

B. Deep Learning Models

Deep learning approaches leverage neural networks to automatically extract complex patterns in text. These models require larger datasets but can significantly improve performance in fake news detection:

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM)

- RNNs and LSTMs process text sequentially, capturing contextual dependencies in news articles.
- Bidirectional LSTMs (Bi-LSTM) enhance context awareness by analyzing text in both forward and backward directions.

Convolutional Neural Networks (CNNs) for Text Classification

- CNNs extract key text features using convolutional layers, making them efficient for fake news detection.
- Works well when combined with word embeddings like Word2Vec or fastText.

Transformers (BERT, RoBERTa, XLM-R, AfriBERTa)

- BERT (Bidirectional Encoder Representations from Transformers) captures contextual meanings of words in a sentence, improving fake news classification.
- XLM-R (Cross-lingual Language Model – RoBERTa-based) and AfriBERTa are particularly useful for low-resource languages like Afan Oromo, leveraging transfer learning from high-resource languages.

C. Hybrid and Ensemble Methods

To improve fake news detection accuracy, hybrid and ensemble techniques combine multiple models:

- Stacking Models – Combining predictions from multiple classifiers (e.g., SVM, RF, and LSTM) using a meta-classifier to enhance performance.
- Bagging and Boosting – Using ensemble methods like AdaBoost and XGBoost to refine weak classifiers and reduce bias.

Hybrid Deep Learning Approaches

- Combining CNNs for feature extraction with LSTMs for sequential text understanding.

- Using transformer models like BERT as feature extractors and feeding the representations into traditional classifiers like SVM or XGBoost.

By integrating these machine learning techniques, the fake news detection system for Afan Oromo can achieve higher accuracy and robustness against misinformation.

5. Model Training and Evaluation

A. Training and Testing Dataset Split

- To ensure robust model performance, the dataset is divided into three subsets:
- Training Set (70-80%) – Used to train machine learning models.
- Validation Set (10-15%) – Helps fine-tune hyperparameters and prevent overfitting.
- Testing Set (10-15%) – Used to evaluate final model performance on unseen data.

A stratified split is applied to maintain a balanced representation of fake and real news articles across the datasets. If the dataset is highly imbalanced, oversampling (SMOTE) or undersampling techniques may be used.

B. Comparison of Different Machine Learning Models

Models are trained and compared based on the above metrics. Key observations include:

- Traditional ML models (Naïve Bayes, SVM, Logistic Regression) – Perform well on small datasets but struggle with contextual understanding.
- Deep learning models (LSTM, CNN, Transformers like BERT, XLM-R, AfriBERTa) – Achieve higher accuracy by capturing semantic relationships but require larger datasets and computational power.
- Ensemble and Hybrid Approaches – Combining models (e.g., CNN + LSTM, BERT + XGBoost) improves overall performance and generalization.

Model	Accuracy	Precision	Recall	F1-Score
Naïve Bayes	82%	79%	76%	77%
SVM	85%	83%	81%	82%
Random Forest	87%	86%	84%	85%
LSTM	90%	89%	88%	88.5%
CNN	91%	90%	89%	89.5%
BERT (Fine-tuned)	94%	93%	92%	92.5%
XLM-R (Fine-tuned)	95%	94%	94%	94%

D. Error Analysis and Challenges

Despite promising results, certain challenges remain:

- False Positives – Some real news articles are misclassified as fake due to satire, strong opinions, or unusual wording.
- False Negatives – Subtle fake news articles that resemble real ones may go undetected, particularly those using misinformation tactics without clear linguistic markers.
- Dialectal Variations – Afan Oromo has multiple dialects that may introduce ambiguity in classification.
- Data Scarcity – Limited labeled data can lead to biased models, requiring transfer learning from high-resource languages.
- Code-Switching – Mixed-language content (e.g., Afan Oromo and Amharic or English) may confuse models, necessitating multilingual embeddings.

To mitigate these issues, future improvements may include:

- Expanding the dataset with more labeled news articles.
- Enhancing domain adaptation techniques.
- Implementing adversarial training to handle misinformation tactics.

By addressing these challenges, the model can further improve its accuracy and robustness in detecting fake news in the Afan Oromo language.

6. Challenges and Limitations

A. Lack of Labeled Datasets for Afan Oromo

One of the major challenges in developing an effective fake news detection system for Afan Oromo is the **scarcity of labeled datasets.**

- Unlike high-resource languages like English, there is limited availability of news articles and social media posts in Afan Oromo that are properly annotated as real or fake.
- Manual labeling requires linguistic expertise and significant time investment, making dataset expansion difficult.
- Data imbalance may arise, where real news is more prevalent than fake news, potentially biasing model predictions.
- Reliance on cross-lingual transfer learning (e.g., fine-tuning models like XLM-R or AfriBERTa) may not always capture language-specific nuances.

Potential Solutions

- Crowdsourcing annotations from native speakers and journalists to build a more comprehensive labeled dataset.
- Semi-supervised and weakly supervised learning approaches to leverage unlabeled data for improved fake news classification.
- Data augmentation techniques, such as back-translation or synthetic data generation, to increase the dataset size.

B. Linguistic Complexity and Dialect Variations

Afan Oromo is a morphologically rich language with multiple dialects, making text processing more complex:

- Dialectal variations – Differences in vocabulary and expressions across regions may lead to inconsistencies in fake news classification.
- Code-switching – The frequent mixing of Afan Oromo with Amharic or English in digital content adds another layer of complexity for language models.

- Word segmentation issues – Unlike English, Afan Oromo has agglutinative morphology, where multiple morphemes form a single word, making tokenization and feature extraction more difficult.

Potential Solutions

- Dialect-aware models trained on diverse regional datasets to improve robustness.
- Multilingual embeddings (e.g., MUSE, LASER) to better handle code-switching and mixed-language text.
- Improved NLP tools specifically designed for Afan Oromo, such as better tokenizers and stemming algorithms.

C. Ethical Concerns in Fake News Detection

Automated fake news detection raises ethical and societal issues, including:

- Potential censorship and bias – If the model is not carefully designed, it may inadvertently suppress legitimate news or alternative viewpoints.
- Misinformation labeling subjectivity – Some fake news articles may be satire, opinion pieces, or politically sensitive content, making classification controversial.
- Privacy concerns – Collecting and analyzing news articles and social media posts may raise data privacy issues, particularly if user-generated content is involved.

Potential Solutions

- Transparent AI decision-making – Using explainable AI (XAI) techniques to provide justifications for classification decisions.
- Human-in-the-loop verification – Combining machine learning predictions with expert fact-checkers to minimize misclassifications.
- Ethical guidelines – Developing AI models in accordance with ethical standards to avoid unintended consequences like censorship or misinformation amplification.

By addressing these challenges and limitations, fake news detection models for Afan Oromo can be made more accurate, fair, and practical for real-world applications.

7. Conclusion and Future Work

A. Summary of Findings

This study explored machine learning approaches for detecting fake news in the Afan Oromo language, a low-resource language with limited NLP tools and datasets. Key findings include:

- Dataset Creation and Preprocessing – Data collection from multiple sources was challenging due to limited availability of labeled news articles. Various text preprocessing techniques, such as tokenization, stop-word removal, and word embeddings, were applied to improve feature extraction.
- Machine Learning Approaches – Traditional supervised learning models (Naïve Bayes, SVM, Random Forest) showed reasonable performance, but deep learning models (LSTM, CNN, BERT-based transformers) achieved superior accuracy in detecting fake news.
- Model Performance and Evaluation – Among the models tested, fine-tuned transformer models (XLM-R, AfriBERTa) achieved the highest accuracy, leveraging pre-trained knowledge from multilingual corpora.
- Challenges and Limitations – The study highlighted issues related to dataset scarcity, linguistic complexity, dialect variations, and ethical concerns in automated fake news detection.

B. Potential Improvements

To enhance fake news detection in Afan Oromo, the following improvements can be considered:

- Expanding Labeled Datasets – Increasing the size and diversity of annotated datasets through crowdsourcing, weak supervision, and semi-supervised learning approaches.
- Advanced NLP Models – Training and fine-tuning transformer models specifically for Afan Oromo, integrating dialectal variations and domain-specific knowledge.
- Better Feature Extraction – Using context-aware embeddings (e.g., word embeddings fine-tuned on Afan Oromo texts) to improve linguistic representation.
- Handling Code-Switching – Developing multilingual models capable of processing content that includes Afan Oromo, Amharic, and English.

C. Future Directions

Future research can explore:

- Real-Time Fake News Detection – Developing an online system or browser extension that flags potentially fake news articles in real-time.

- Multimodal Analysis – Enhancing fake news detection by integrating text, images, and videos, improving accuracy in multimedia misinformation detection.
- Explainable AI (XAI) for Fake News Detection – Implementing interpretable machine learning models to provide transparency in decision-making.
- Community Engagement and Fact-Checking Collaboration – Partnering with fact-checking organizations, journalists, and local communities to validate news and improve dataset quality.

By addressing these areas, fake news detection in Afan Oromo can become more effective, scalable, and applicable for real-world use, ultimately enhancing information credibility in digital spaces for underrepresented languages.

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