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An Evolutionary Amharic Fake News Detection Based on ML and Deep Learning Approach

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Abstract: - In recent years, the increasing dissemination of fake news threatens journalistic integrity and potentially manipulates public opinion on pivotal issues. While extensive research addresses fake news detection in dominant languages, resources for Amharic, Ethiopia's official language, are limited. This study bridges the gap by harnessing deep learning to detect Amharic fake news. We amalgamated recent genuine and fake Amharic news articles from varied sources and combined them with the available Amharic data set to enhance the robustness of our dataset. Many machine Learning mechanisms have been employed to classify Fake and Real news. This study experimented the effectiveness of Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks in classifying real and fake news specifically in the Amharic language. These recurrent neural network (RNN) architectures are well-suited for tasks like news classification due to their ability to analyze sequential data and capture long-term dependencies within text. This is particularly important for Amharic language, where word order and morphology play a crucial role in conveying meaning and identifying potential deception in fake news. LSTMs and GRUs models in Amharic fake news classification has the potential to enhance the accuracy and effectiveness of Amharic fake news detection systems. Our analysis reveals that the Gated Recurrent Unit (GRU) model achieved the highest accuracy of 98% compared to other algorithms evaluated in this study. This finding suggests that GRUs are particularly effective in the task of Amharic fake news classification. GRUs employ a gate mechanism that efficiently handles the vanishing gradient problem, a common challenge in RNNs that hinders their ability to learn long-term dependencies. This allows GRUs to effectively capture the contextual relationships between words, even when they are separated by longer distances in the text, making them particularly well-suited for Amharic language fake news classification where understanding the flow of information is crucial.

Keywords: Fake News Detection, Deep Learning Approach, Machine Learning Amharic Language, Classification, Amharic Data Set.

I. INTRODUCTION

The digital age has democratized access to information, empowering individuals and communities worldwide. However, this democratization has also presented a significant challenge: the proliferation of fake news. This phenomenon, characterized by the deliberate or unintentional dissemination of false or misleading information, has demonstrably negative consequences, eroding trust in institutions, hindering informed decision-making, and even inciting violence.

Ethiopia, a nation with a rich cultural heritage and vibrant online landscape, is not immune to the detrimental effects of fake news. With over 75 million internet users, largely concentrated in urban areas, Ethiopia has witnessed a surge in social media platforms like Facebook and Telegram becoming primary sources of news and information [1]. However, this reliance on online platforms also creates fertile ground for the spread of misinformation, often targeting sensitive topics like politics, ethnicity, and religion. The ramifications of fake news in Ethiopia are far-reaching. Studies have documented its influence on public opinion regarding crucial matters like public health initiatives and national security [2]. Therefore, the development of effective strategies to combat fake news in Ethiopia is of paramount importance. This research focuses on the potential of deep learning to address this critical challenge. Deep learning techniques, particularly recurrent neural networks (RNNs) like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models, have demonstrated remarkable success in various natural language processing (NLP) tasks, including sentiment analysis and text classification [3].

This study investigates the efficacy of LSTMs and GRUs in automatically detecting Amharic fake news, in which Amharic is the official working language of Ethiopia spoken by over 100 million people. By leveraging the strengths of deep learning architectures in analyzing sequential data and capturing long-term dependencies within

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text, this research aims to contribute to the development of robust and accurate automated systems for identifying fake news in Amharic, ultimately promoting a more informed and truthful online environment.

II. Background Of The Study

The ease of access and availability of different social media platforms have made many people use these platforms as a source of information [4]. Due to this fact, a large amount of information is easily shared in digital platforms like Blogs, online news platforms, and social media feeds [5]. On the one hand, we have witnessed unparalleled democratization of information, enabling individuals worldwide to access and share knowledge instantaneously via various social media platforms. On the other hand, the same platforms have been exploited to spread disinformation, commonly referred to as" fake news" [6]. Fake news, often crafted with the intent to deceive, mislead, or manipulate, has emerged as a global menace, with repercussions spanning from individual decisions to global politics [7]. The spreading of misinformation may lead to actual harms, including financial loss, public health crisis, violence, Erosion of trust, Polarization and social divide, fear and panic, Stigmatization and Discrimination, and Impediments to Progress [8]. Nowadays the spreading of misinformation in different social media platforms has become a bottleneck for ethnic-based disputes, religious-based disputes, political unrest, and social and economic crisis in Ethiopia. To address the growing issue of misinformation, various researchers have conducted studies on combating fake news in the Amharic language [9].

In light of the increasing fake news and misinformation, many researchers and industries have undertaken various studies and initiatives. For instance, the Ethiopian Government issued Proclamation No.1185/2020 aimed at preventing disinformation [10]. Numerous studies have explored detection methods, from content-based approaches [11][12][13] and social feature-based strategies [14][15]to deep learning algorithms. This study emphasizes a deep learning technique specifically tailored for detecting fake news in Amharic.

III. LITERATURE REVIEW

A. Related Data Set

For benchmarking fake news detection in English, Wang et al. (2017) [16] introduced the LIAR dataset. This public dataset consists of 12.8K manually labeled short statements gathered from PolitiFact.com's API. Each statement is assessed for truthfulness by PolitiFact.com editors, providing a reliable source for training and evaluating fake news detection models. The LIAR dataset offers a fine-grained labeling scheme, categorizing statements as 'pants-fire,' 'false,' 'barely-true,' 'half-true,' 'mostly true,' or 'true.' This granular approach allows researchers to analyze the nuances of misinformation beyond a simple binary classification of truth and falsehood.

B. Related Works

The rapid and uncontrolled dissemination of false information, specifically in the Amharic language, has become increasingly alarming. While various methods exist to combat this global problem, adapting them to Amharic poses unique challenges. This stems from two main factors: Amharic's status as a low-resource language and its inherent complexity in terms of morphology, and the way words are formed and structured. Efforts have been made to address fake news using various methods. For instance, researchers like Tacchin et al. explored classifying social media posts based on user engagement ("likes" and "dislikes"). While this achieved promising results with small datasets, it wouldn't be effective when social interaction data is scarce (few "likes" or "dislikes"). In such instances, relying solely on this method could potentially lead to inaccurate findings[17]. To overcome this problem, content-based features were introduced, but only when the social-based methods performed poorly [18]. The model based entirely on only one type of feature at a time tested on real-world data and obtained an accuracy of 81.7%.

Shubham et al. developed a machine learning framework specifically tailored for identifying fake news by harnessing the power of Natural Language Processing (NLP). This approach incorporates various aspects of news content and social characteristics, including both the headline and main content [19]. To verify the authenticity of news articles, they analyzed indicators such as the Facebook Page ID, the news source, and the Facebook App ID. In terms of data processing, they utilized a bag-of-words technique to extract features from both the headline and main content. The classification process involved employing a probabilistic classifier, and the model's performance was assessed using the Fake Newsnet dataset, achieving an impressive accuracy rate of 90.62%. Despite the promising outcomes, it's worth noting that the feature extraction method was constrained to merely counting word occurrences, without considering the semantics or the sequential structure of the words within the news articles.

Ksieniewic et al. conducted research employing a machine learning classifier with a comprehensive analysis of various text features. They evaluated textual features proposed by recent researchers and categorized them into five distinct feature categories: language features (e.g., a bag of words, n-grams, parts of speech), lexical features (both character and word level), psycholinguistic features (e.g., linguistic inquiry and word count), semantic features, and subjectivity (utilizing Text Blob). Their study scrutinized the discriminative power of these features when combined with a range of classic and state-of-the-art classifiers, including Random Forests (RF), XGBoost (XGB),k-Nearest Neighbors (KNN), Support Vector Machine with RBF kernel (SVM), and Naive Bayes (NB). Experimental results revealed that the proposed features, when integrated with existing classifiers, exhibited a significant level of discriminative power in detecting fake news [20],[21],[22].

Ma et al. highlighted a prevailing trend in existing studies, which predominantly focus on network-oriented features, primarily limited to statistical analyses of diffusion patterns such as retweet counts and propagation times [23][24][25]. However, alternative research avenues delve into modeling the temporal aspects of transmission [26]. For instance, Kwon et al. constructed various alternative networks based on user friendship status and news transmission patterns, extracting characteristics based on the clustering coefficient and network degree [27]. Furthermore, Ma et al. developed pioneering methods for determining.

The validity of source posts by directly assessing the similarity of propagation trees[28][23]. A study by[29] explored the performance of various classification models, such as logistic regression (LR), LSVM, Na ̈ive Bayes, LSTM, BiLSTM, RNN, CNN, AmFLAIR, and AmRoBERTa. The LR and LSVM models outperformed Na ̈ive Bayes in all measures except for precision, achieving 67-68% accuracy. The deep learning models achieved lower results due to the dataset's size, while the contextual embedding models, AmFLAIR and AmRoBERTa, achieved the best scores of 72% for all measures, including precision, recall, accuracy, and F1 scores. research work [30] explores the challenges of identifying and detecting fake news in Amharic, focusing on the noisy nature of social media content. The study proposes a hybrid approach that combines stance-based features with text representation techniques to enhance fake news detection accuracy. By incorporating features like Page score, headline to article similarity, and headline-to-headline similarities, along with machine learning algorithms like Logistic regression, Passive Aggressive, and Decision tree, the research achieved improved detection results. The hybrid features showed an enhancement in accuracy, precision, recall, F1-score, and area under the curve compared to solely lexicon-based detection methods.

Alvaro Ibrain et al. proposes the use of deep learning techniques, including BERT-based models, to detect and categorize fake news using textual features. The proposed architectures, including LSTM-based, convolutional-based, and BERT-based models, demonstrate promising results in detecting fake news, with accuracies reaching up to 98%. The document also discusses the potential for future improvements and real-world applications of the developed systems [31]. Another work by [32] provides a comprehensive overview of NLP research in Ethiopian languages, focusing on tasks like Machine Translation (MT), Question Answering (QA), Named Entity Recognition (NER), and Text Classification. It highlights the progress and challenges faced in developing NLP technologies for languages like Amharic, Afaan Oromo, Tigrinya, and Wolaytta. The study discusses the limited research on QA and QC tasks for these languages, the advancements in MT with varying dataset sizes and performance scores, and the exploration of hate speech detection and sentiment analysis.The paper sheds light on the current landscape of NLP research for Ethiopian languages across different tasks and the need for further development in this field

IV. PROPOSED APPROACH

A. Machine Learning

1) AdaBoost (Adaptive Boosting)

AdaBoost is an ensemble machine learning algorithm that combines multiple weak learners (typically decision trees) into a single strong learner [33]. It iteratively trains weak learners by focusing on previously misclassified instances, giving them higher weights in subsequent training rounds. This approach progressively improves the overall model's performance by emphasizing challenging examples.

2)Random Forest

A Random Forest is an ensemble learning method that leverages a multitude of decision trees trained on random subsets of features and data points [34]. Each tree independently classifies an instance, and the final prediction is determined by a majority vote (for classification) or by averaging (for regression) the individual tree outputs. This approach reduces variance and enhances model robustness to overfitting.

3)Naive Bayes

A Naive Bayes classifier is a probabilistic machine learning model based on Bayes' theorem [35]. It assumes independence between features, which simplifies the calculation of posterior probabilities for each class given a data instance. Despite this simplifying assumption, Naive Bayes can be surprisingly effective in various classification tasks due to its efficiency and interpretability

4)Support Vector Machine (SVM)

An SVM is a supervised learning algorithm that seeks to identify a hyperplane in the feature space that maximizes the margin between the separate classes [36]. This margin represents the decision boundary separating the data points. SVMs are powerful tools for classification tasks, particularly when dealing with high-dimensional data and small datasets.

B. Deep Learning

1) Long Short-Term Memory (LSTM)

LSTMs are a specific type of recurrent neural network (RNN) architecture designed to effectively handle sequential data with long-term dependencies [37]. LSTMs incorporate memory cells that control the flow of information through the network, allowing them to learn temporal relationships between distant elements within a sequence. This makes LSTMs particularly suitable for tasks involving natural language processing, like fake news detection.

2) Gated Recurrent Unit (GRU)

LGRUs are another type of RNN architecture similar to LSTMs but with a simpler gating mechanism [38]. While GRUs lack a dedicated memory cell, they achieve similar functionalities using update and re-set gates. This simpler structure reduces computational complexity compared to LSTMs, making GRUs a compelling alternative for tasks where computational efficiency is a concern.

C. Word Embedding

Word embedding assigns a unique vector of real numbers to each word in a vocabulary. Words with similar meanings or usage patterns will have vectors that reside closer together in this high-dimensional space. It can be conceptualized as a semantic map, wherein each word in a given vocabulary is represented as a vector in a high-dimensional space. In this space, words with similar meanings or usage patterns tend to have vectors that reside closer together or exhibit similar directions. This property enables algorithms to capture semantic relationships between words, such as synonymy or semantic relatedness. Word embeddings are learned from large textual corpora using techniques like Word2Vec, GloVe, or fast Text. We can think of it as a semantic map, where neighboring locations represent words with analogous concepts [39].

1) Word2Vec

Word2Vec is a technique for generating word embeddings introduced by Mikolov et al. It transforms words into vectors of real numbers in a continuous vector space. Word2Vec employs neural networks to learn the distributional properties of words based on their co-occurrence patterns in a given text corpus. The underlying idea is that words with similar meanings tend to appear in similar contexts. Word2Vec comes in two main architectures: Continuous Bag of Words (CBOW) and Skip-gram. CBOW predicts a target word based on its context, whereas Skip-gram predicts the context words given a target word. CBOW architecture takes a sequence of context words as input and predicts the target word. It is faster to train compared to Skip-Gram and tends to perform well when the frequency of words is high.

V. IMPLEMENTATION

A. *Data Collection and Preprocessing*

We collect a diverse dataset of 8630 Amharic news articles from various online sources, encompassing both authentic and fake content as the distribution of fake and real content is shown in figure 1.

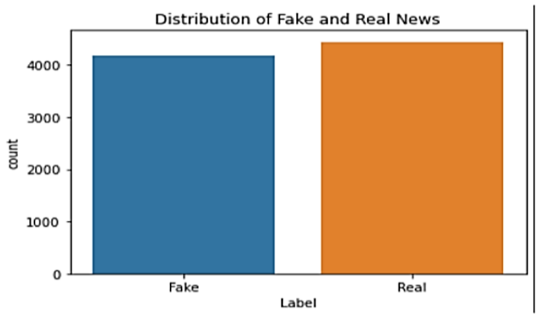

Figure 1. Distribution of Dataset

To ensure the dataset's reliability, each article is manually labeled by native Amharic speakers with expertise in journalism. The collected dataset is then pre-processed to remove noise, normalize text, and tokenize sentences. We employed a word cloud visualization to identify the most frequently occurring terms as shown in figure 2.

Figure 2. Word Cloud Representation of the Data Set

B. *Dataset splitting and pre-processing*

The Amharic datasets are loaded as Pandas Data Frames. Class labels are encoded using scikit-learn's Label Encoder. Similar to the previous approach, each dataset is divided into training and testing subsets using an 80-20% split. For effective model training and validation, all datasets undergo preprocessing to convert raw text into a format suitable for the chosen machine learning and deep learning models. The first step involves cleaning the text data. This includes removing non-Aharic letters, numbers, whitespace characters, and emojis. Regular expressions facilitated by the re-library are employed for this task. Next, the text is segmented into sentences. Following sentence segmentation, Amharic stop words, compiled into a dedicated corpus we have created, are eliminated from the remaining terms. Finally, the remaining terms are stemmed to reduce them to their base forms.

C. *Model Architecture*

We focus on two Recurrent Neural Network (RNN) architectures: Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU).

- Long Short-Term Memory (LSTM) Network LSTMs are well suited for analyzing sequential data like text, where the order of words plays a crucial role. These networks address the vanishing gradient problem that can hinder traditional RNNs in processing longer sequences. The LSTM network processes the Amharic text data sequentially. Each LSTM unit has internal gates that control the flow of information, allowing the model to capture both short-term and long-term dependencies within the text. The output from the LSTM layers is fed into fully connected layers for classification. The final layer employs a sigmoid function to predict the probability of a news article being fake or real.
- Gated Recurrent Unit (GRU) Network Similar to LSTMs, GRUs are also used for handling sequential data. These networks also have gating mechanisms that control information flow but with a simpler

structure compared to LSTMs. The GRU network processes the Amharic text data sequentially, capturing dependencies between words and contextual information relevant to fake news detection. The output from the GRU layers is then fed into fully connected layers for classification, similar to the LSTM architecture.

- Model Training and Hyperparameter Tuning Both the LSTM and GRU models are trained on our Amharic fake news dataset. The embedding Layer transforms Amharic words into numerical representations (vectors) of dimensionality 128. It captures.

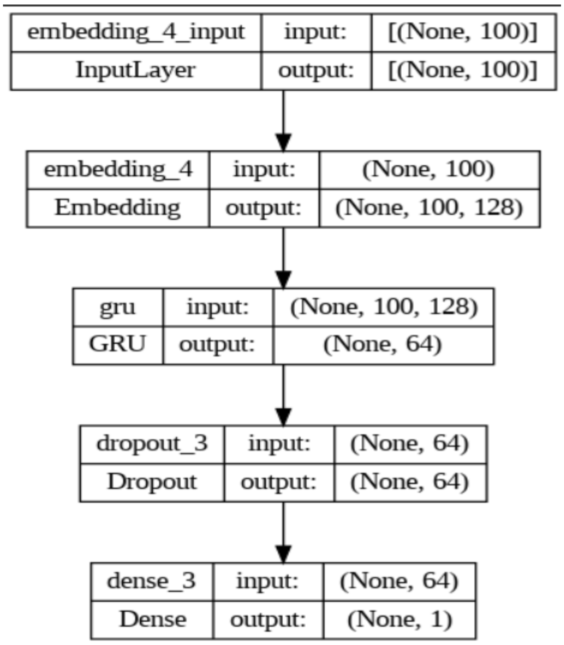

Figure 3. GRU Architecture

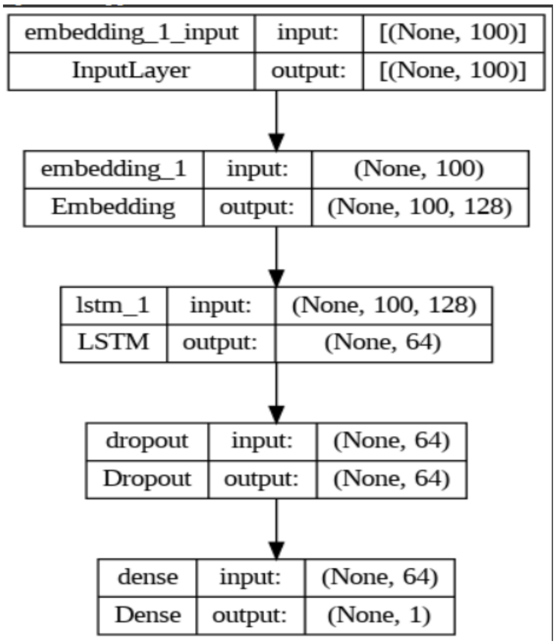

Figure 4. LSTM Architecture

semantic relationships between words, allowing the model to understand the context within news articles. A single LSTM layer and GRU layer with 64 hidden units is implemented for enabling the model to learn long-term dependencies within sentences. A dropout layer with a rate of 0.2 is incorporated to prevent overfitting. During training, this layer randomly drops 20% of the neurons from the LSTM layer, forcing the model to learn from various features within the data and avoid overreliance on specific characteristics. The Output Layer is a dense layer with a single neuron and a sigmoid activation function, that outputs a probability value between 0 and 1, signifying the likelihood of a news article being classified as fake or real as depicted in Figures 3 and 4, respectively.

D. *Model Comparison*

To assess the effectiveness of the proposed deep learning model against established methods, four supervised classification algorithms (as detailed in Table 4) were evaluated on both the LIAR dataset (English) and our Amharic dataset. The training-testing split ratio (80-20%) remained consistent across all datasets and models for a fair comparison. The performance of the proposed deep learning architecture was further analyzed by considering scenarios where only the LSTM or GRU layers were utilized, excluding the other components of the full model. This allows for a more granular understanding of the contribution of each element within the proposed deep-learning approach.

VI. RESULT AND DISCUSSION

A. *Result of models on Amharic data set*

We explored two model architectures. The first model utilized a Long Short-Term Memory (LSTM) layer, while the second employed a Gated Recurrent Unit (GRU) layer. Both models shared a common structure, including an embedding layer, a dropout layer to mitigate overfitting, and a dense output layer with sigmoid activation for binary classification. The performance of our models was evaluated using standard metrics like accuracy, precision, recall, and F1-score as shown in Table 1.

Table 1: Comparison of Performance Metrics between LSTM and GRU Models

Metric	LSTM Model	GRU Model	Improvement (%)
Accuracy	0.9359	0.9659	+3.00
Precision	0.9257	0.9666	+4.09
Recall	0.9606	0.9554	+.1.48
F1-Score	0.9376	0.966	+2.84

The GRU model outperformed the LSTM model across all evaluation metrics, achieving an accuracy of 96.59%, precision of 96.66%, recall of 95.54%, and an F1-score of 96.60%. This suggests that the GRU layer's structure might be better suited to capture the temporal dependencies within our dataset.

The model's encouraging performance, suggests its promising potential for Amharic fake news detection. Its ability to effectively distinguish between genuine and fake news articles in Amharic can be a valuable tool in combating the spread of misinformation, while our model demonstrates impressive performance on the test set, addressing potential overfitting remains crucial and We've taken a two-pronged approach to reduce this risk:

Dropout Layer Integration: A dropout layer is incorporated into the model architecture. This technique randomly drops out a certain percentage of neurons during training, preventing the model from becoming overly reliant on specific features and encouraging it to learn more robust patterns [40].

Early Stopping with Validation: Early stopping, a callback function, is implemented to monitor the validation loss during training. If the validation loss stops improving for a predefined number of epochs (patience in this case is set to 3), training is halted. This prevents the model from memorizing irrelevant details from the training data and helps to improve its generalizability to unseen data [41].

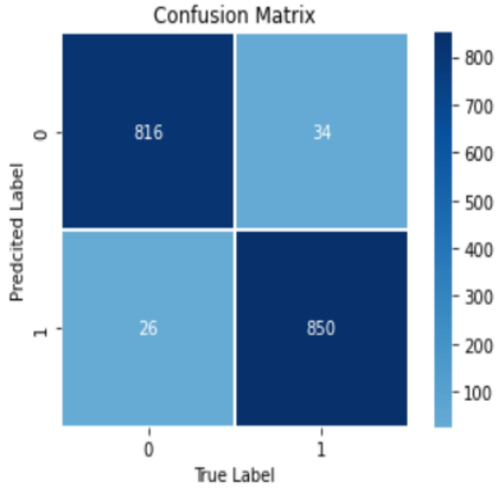

Figure 5(a). LSTM Architecture

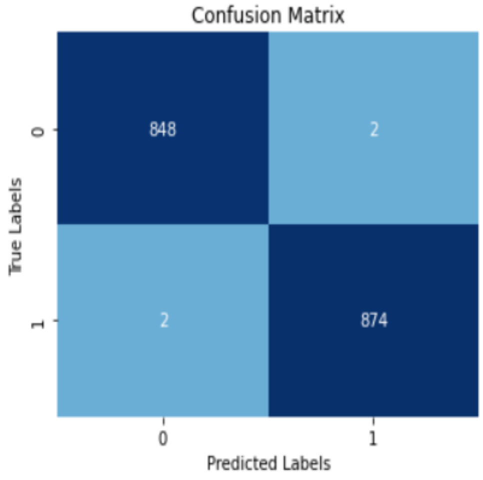

Figure 5(b) GRU confusion matrix

Table 2: Performance of Machine Learning Models on Amharic data set

Model	Accuracy	Precision	Recall	F1-Score
AdaBoost	0.81	0.78	0.85	0.82
Random Forest	0.89	0.87	0.91	0.89
Naïve Bayes	0.91	0.85	0.93	0.89
SVM	0.9	0.86	0.92	0.89

Our evaluation of the Amharic dataset revealed that the deep learning models, specifically LSTMs and GRUs, achieved superior performance compared to the traditional machine learning models (AdaBoost, Random Forest, Naive Bayes, SVM) employed in this study as it is shown in Figure 6. This suggests that the deep learning models were better equipped to capture the complexities inherent in the Amharic language data for fake news detection.

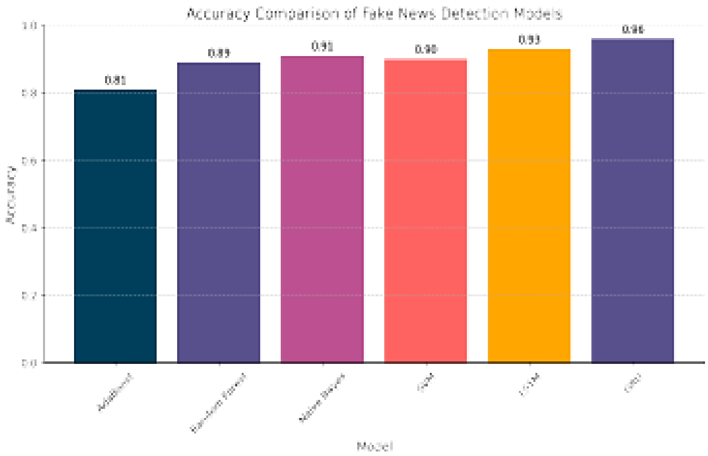

Figure 6: Comparison of fake news detection models using Amharic data set.

As shown in Table 3, deep learning models, particularly LSTMs and GRUs, demonstrated robust performance on the Amharic dataset, exhibiting high accuracy, recall, precision, and F1-score. Although their performance may not have precisely mirrored the results obtained on the LIAR dataset, both LSTMs and GRUs consistently outperformed all other classification algorithms utilized in this study for the Amharic data. This observation underscores the effectiveness of deep learning models for fake news detection in Amharic.

Table 3: Model performance on LIAR dataset

Model	**Performance**			
	Accuracy	**Precision**	**Recall**	**F1-Score**
AdaBoost	0.83	0.94	0.82	0.83
Random Forest	0.91	0.90	0.91	0.93
Naïve Bayes	0.92	0.91	0.93	0.90
SVM	0.90	0.89	0.92	0.91
LSTM	0.94	0.93	0.96	0.95
GRU	0.97	0.96	0.97	0.96

However, it is important to acknowledge that further fine-tuning may be required to achieve optimal performance, particularly when compared to a language such as English, as represented by the LIAR dataset.

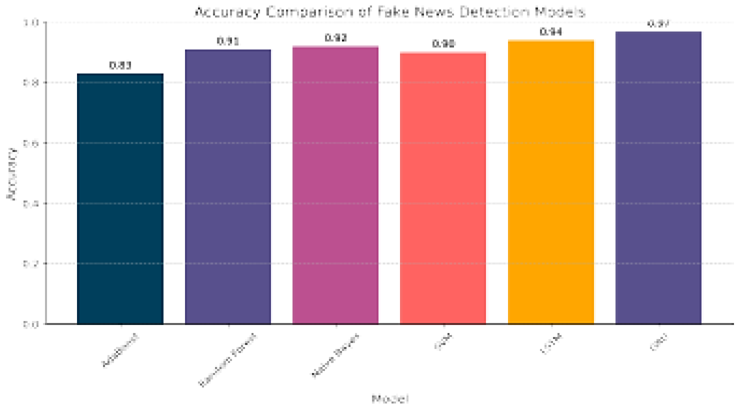

Figure 7: Comparison of fake news detection models using LIAR data set.

VII. CONCLUSION

The proliferation of fake news and disinformation poses a significant threat to public discourse and informed decision-making in our digital age. The identification of fake news remains a complex challenge with numerous unresolved aspects. Understanding the key factors that influence its spread is a critical first step toward curbing its proliferation. Deep learning approaches were proposed in this study to classify Amharic news as fake or authentic. The research uses Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models for detecting fake news articles written in Amharic. Our finding demonstrates that both LSTM and GRU models achieved promising results in identifying Amharic fake news content as compared with other ML classification algorithms. However, it is crucial to acknowledge that the fight against fake news is an ongoing battle. Further research is necessary to explore additional techniques that can enhance the robustness and generalizability of these models. Here are some potential areas for future exploration:

- Data Augmentation: Techniques like back-translation or synonym replacement can be used to artificially increase the size and diversity of the Amharic training data, potentially improving model performance.
- Ensemble Learning: Combining predictions from multiple LSTM or GRU models may lead to more robust and accurate results compared to a single model.

VIII. CONTRIBUTION OF THE RESEARCH

A. Establishment of a Benchmark Amharic Fake News Dataset:
We address the critical lack of resources for Amharic fake news detection by creating a novel Amharic fake news identification dataset. This dataset serves as a valuable foundation for future research efforts aimed at developing and evaluating fake news detection models specifically tailored for the Amharic language.

B. Comparative Evaluation of Machine Learning and Deep Learning Models:
To identify the most suitable approach for Amharic fake news detection, we conducted a comprehensive evaluation using a combination of machine learning and deep learning algorithms. This comparative analysis provides valuable insights into the effectiveness of different To identify the most suitable approach for Amharic fake news detection, we conducted a comprehensive evaluation using a combination of machine learning and deep learning algorithms. This comparative analysis provides valuable insights into the effectiveness of different

C. Generalizability of Deep Learning Models for Cross-Lingual Fake News Detection:
By evaluating the performance of the deep learning models on both the Amharic and English (LIAR) datasets, we contribute to the understanding of their generalizability across languages. While their performance dipped slightly on the Amharic dataset compared to English, they still surpassed all other models. This suggests the potential of deep learning approaches for fake news detection in Amharic, potentially with further adaptation for optimal performance in this specific language context.

REFERENCES

[1] GSMA: The state of mobile internet connectivity, 2023.
[2] European Institute of Peace. Fake news, misinformation, and hate speech in Ethiopia: A vulnerability assessment, 2021.

[3] E. O. Arkhangelskaya and Sergei Igorevich Nikolenko. Deep learning for natural language processing: a survey. Journal of Mathematical Sciences, pages 1–50, 2023.

[4] Perrin. Social media usage: 2005-2015, 2015.

[5] L. Howell. Digital wildfres in a hyperconnected world. Technical report, 2013.

[6] D. M. J. Lazer, M. A. Baum, Y. Benkler, A. J. Berinsky, K. M.Greenhill, F. Menczer, M. J. Metzger, and B. Nyhan.The science of fake news. Science, 359(6380):1094–1096, 2018.

[7] F. Gereme, W. Zhu, T. Ayall, and D. Alemu. Combating fake news in “low-resource” languages: Amharic fake news detection accompanied by resource crafting. Information, 12:20, 2021.

[8] Wardle and H. Derakhshan. Information disorder: Toward an interdisciplinary framework for research and policymaking. Technical Report 27(2017), 2017.

[9] HaqCheck. Annual report on disinformation in Ethiopia. Addis Zeybe - Digital Newspaper, 2021.

[10] F. N. Gazette. Federal negarit gazette of the federal democratic republic of Ethiopia, content. pages 2–7, 2020.

[11] H. Ahmed, I. Traore, and S. Saad. Detection of online fake news using n-gram analysis and machine learning techniques. In International Workshop on Digital Forensics and Watermarking, pages 127–138. Springer International Publishing AG, Oct 2017.

[12] Riedel, I. Augenstein, G. P. Spithourakis, and S. Riedel. A simple but tough-to-beat baseline for the fake news challenge stance detection task. arXiv preprint, arXiv:1707.03264, 2017.

[13] F. A. Ozbay and B. Alatas. Fake news detection within online social media using supervised artificial intelligence algorithms. Physica A, 2019.

[14] Tacchini, G. Ballarin, M. L. D. Vedova, S. Moret, and L. d. Alfaro. Some like it a hoax: Automated fake news detection in social networks. In Proceedings of the Second Workshop on Data Science for Social Good (SoGood), Skopje, Macedonia, 2017. CEUR Workshop Proceedings Volume 1960.

[15] Tilahun and D. Beshah. Fake news detection model using machine learning approach: the case of Amharic news on social media, February 2020.

[16] William Wang, Helen Huang, Zhiwei Wang, Yiqing Tan, and Xin Rong. ”liar, liar pants on fire”: A new benchmark dataset for fake news detection. In Proceedings of the ACL Workshop on NLP for Fake News Detection, pages 422–426, July 2017.

[17] Tacchini, G. Ballarin, Della M. Vedova, S. More, and L. d. Alfato. Some like it a hoax: Automated fake news detection in social networks. arXiv preprint, arXiv:1704.07506, 2017.

[18] D. Vedova, E. Tacchini, S. Moret, G. Ballarin, and M. D. a. L. d. Alfaro. Automatic online fake news detection combining content and.

[19] B. Shubham, B. Vijay, P. Jain, and M. Chawla. Natural language processing-based hybrid model for detecting fake news using content-based features and social features. Information Engineering and Electronic Business, 4:1–10, 2019.

[20] Pawel Ksieniewicz, Micha l Chora´s, Pawel Zyblewski, Rafa l Kozik, Micha l Wo´zniak, and Agata Gie lczyk. Fake news detection from data streams. 2020.

[21] Julio C. S. Reis, Andr´e Correia, Fabr´ıcio Murai, Adriano Veloso, and Fabr´ıcio Benevenuto. Supervised learning for fake news detection. IEEE, 1541-1672, 2019.

[22] Vasu Agarwal et al. Analysis of classifiers for fake news detection. In an international conference on recent trends in advanced computing, 2019. ICRTAC 2019.

[23] Duc Minh Nguyen, Tien Huu Do, Robert Calderbank, and Nikos Deligiannis. Fake news detection using deep Markov random fields. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 1391–1400, Minneapolis, Minnesota, 2019. Association for Computational Linguistics.

[24] Jing Ma, Wei Gao, Zhongyu Wei, Yueming Lu, and Kam-Fai Wong. Detect rumors using time series of social context information on microblogging websites. In Proceedings of the 24th ACM International Conference on Information and Knowledge Management, page 1751–1754. Association for Computing Machinery, 2015.

[25] Sardar Hamidian and Mona T. Diab. Rumor detection and classification for Twitter data. arXiv preprint arXiv:1912.08926, 2019.

[26] Yang, Y. Liu, X. Yu, and M. Yang. Automatic detection of rumors on Sina Weibo. In Proceedings of the ACM SIGKDD Workshop on Mining Data Semantics, pages 1–7. Association for Computing Machinery, August 2012.

[27] Sejeong Kwon, Meeyoung Cha, and Kyomin Jung. Rumor detection over varying time windows. PloS one, 12(1):e0168344, 2017.

[28] Soroush Vosoughi, Mostafa ‘Neo’ Mohsenvand, and Deb Roy. Rumor gauge: Predicting the veracity of rumors on Twitter. ACM Trans. Knowl. Discov. Data, 11(4), Jul 2017.

[29] Abinew Ali Ayele, Seid Muhie Yimam, Tadesse Destaw Belay, Tesfa Asfaw, and Chris Biemann. Exploring Amharic hate speech data collection and classification approaches. In Proceedings of the 14th International Conference on Recent Advances in Natural Language Processing, pages 49–59, 2023.

[30] Ibrahim N. Awol and Sosina M. Gashaw. Lexicon-stance-based amharic fake news detection. Journal of Artificial Intelligence Research and Applications, 7(2):53–65, 2023.

[31] Angel Ismael Rodr´ıguez and Luis L´opez Iglesias. Fake news detection using deep learning. Technical report, Department of Computer Science, University of Cantabria, Spain, 2019.

[32] Atnafu Lambebo Tonja, Tadesse Destaw Belay, Israel Abebe Azime, Abinew Ali Ayele, Moges Ahmed Mehamed, Olga Kolesnikova, and Seid Muhie Yimam. Natural language processing in Ethiopian languages: Current state, challenges, and opportunities. arXiv preprint arXiv:2303.14406, 2023.
[33] Yoav Freund and Robert E Schapire. A decision-theoretic generalization of online learning and an application to boosting. Journal of Computer and System Sciences, 55(1):119–139, 1997.
[34] Leo Breiman. Random forests. Machine Learning, 45(3):5–32, 2001.
[35] George H John and Pat Langley. Estimating continuous distributions in Bayesian classifiers. In Proceedings of the Eleventh International Conference on Artificial Intelligence, volume 1, pages 394–400, 1995.
[36] Corinna Cortes and Vladimir Vapnik. Support-vector networks. Machine Learning, 20(3):273–297, 1995.
[37] Sepp Hochreiter and J¨urgen Schmidhuber. Long short-term memory. Neural Computation, 9(8):1735–1780, 1997.
[38] Kyunghyun Cho, Bart van Merri¨enboer, Dzmitry Bahdanau, and Yoshua Bengio. On the properties of neural machine translation: Encoder-decoder approaches. arXiv preprint arXiv:1409.1145, 2014.
[39] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781, 2013.
[40] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Dropout: A simple way to prevent neural networks from overfitting. Journal of Machine Learning Research, 15(1):1929–1958, 2014.
[41] Xue Ying. An overview of overfitting and its solutions. In Journal of Physics: Conference Series, volume 1168, page 022022. IOP Publishing, 2019.