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Fake News Detection in Hausa Language Using Transfer Learning Method

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Abstract:- Fake news poses a significant threat to societies worldwide, including in Hausa-speaking regions, where misinformation is rapidly disseminated via social media. The lack of NLP resources tailored to this language exacerbated the problem of fake news in the Hausa language. While extensive research has been conducted on counterfeit news detection in languages such as English, little attention has been paid to languages like Hausa, leaving a significant portion of the global population vulnerable to misinformation. Traditional machine-learning approaches often fail to perform well in low-resource settings due to insufficient training data and linguistic resources. This study aims to develop a robust model for detecting fake news in the Hausa language by leveraging transfer learning techniques with adaptive fine-tuning. A dataset of over 6,600 news articles, including both fake and truthful articles, was collected from various sources between January 2022 and December 2023. Cross-lingual transfer Learning (XLT) was employed to adapt pre-trained models for the low-resource Hausa language. The model was fine-tuned and evaluated using performance metrics such as accuracy, precision, recall, F-score, AUC-ROC, and PR curves. Results demonstrated a high accuracy rate in identifying fake news, with significant improvements in detecting misinformation within political and world news categories. This study addresses the gap in Hausa-language natural language processing (NLP) and contributes to the fight against misinformation in Nigeria. The findings are relevant for developing AI-driven tools to curb fake news dissemination in African languages.

Keywords:- *Fake News; NLP; Deep Learning; Transfer Learning; Fine Tuning.*

I. INTRODUCTION

In the digital age, the dissemination of information has become more rapid and widespread than ever before, thanks to the proliferation of social media and online news platforms. However, this technological advancement has also led to the rise of "fake news," which refers to deliberately fabricated information that mimics the appearance of legitimate news to mislead readers (Lazer et al., 2018). The term "fake news" gained widespread attention during the 2016 U.S. presidential election, where it was found that false stories were shared on social media at alarming rates, often outperforming genuine news in terms of engagement (Allcott & Gentzkow, 2017).

The impact of fake news extends far beyond political discourse. It has been implicated in various societal issues, including the erosion of trust in media, the polarization of public opinion, and even the incitement of violence (Pennycook & Rand, 2018). For instance, in countries like India and Myanmar, the spread of fake news through social media platforms like WhatsApp has been linked to mob violence and communal tensions (Arun, 2019). This phenomenon is not confined to high-resource settings but is increasingly affecting low-resource regions where media literacy may be lower, and access to fact-checking tools is limited.

Fake news also has significant implications for public health, particularly during crises like the COVID-19 pandemic. Misinformation about the virus, its origins, and potential cures spread rapidly across the globe, complicating efforts to contain the disease and leading to dangerous behaviors such as vaccine hesitancy (Islam et al., 2020). This underscores the urgent need for effective fake news detection mechanisms that can operate across different languages and cultural contexts.

While significant progress has been made in developing fake news detection systems for high-resource languages like English, there is a glaring gap in research and tools available for low-resource languages. Hausa, a Chadic language spoken by millions in Nigeria and other parts of West Africa, is one such language that has been largely overlooked in the realm of natural language processing (NLP) (Aliyu, Ahmed, & Abdulrahman, 2023). The lack of linguistic resources, such as large annotated datasets and pre-trained models, makes applying traditional machine learning and NLP techniques to Hausa challenging.

The importance of detecting fake news in Hausa cannot be overstated, given the language's widespread use in media and communication across the region. Nigeria, for instance, is a country with a highly diverse population and a complex socio-political landscape, where misinformation can have particularly severe consequences. In 2018, during the general elections, fake news spread through social media and other online platforms was identified as a significant threat to democratic processes, with false

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information often being shared more widely than verified news (Iwuoha & Aniche, 2020).

The lack of effective fake news detection tools in Hausa leaves millions of people vulnerable to misinformation, which can have dire consequences in a variety of contexts, including politics, health, and security. For example, during the COVID-19 pandemic, misinformation about the virus and its treatments circulated widely in Hausa, contributing to public confusion and hindering efforts to control the spread of the virus (Akintunde & Musa, 2020).

Furthermore, the issue of fake news is exacerbated by the linguistic diversity within the Hausa-speaking population, which includes numerous dialects and variations. This linguistic complexity adds another layer of difficulty to developing effective NLP models for fake news detection. Existing models trained on high-resource languages do not easily generalize to Hausa, necessitating the use of techniques like Cross-Lingual Transfer Learning (CLTL) to adapt these models to the Hausa context (Conneau et al., 2020).

By focusing on fake news detection in Hausa, this research addresses a critical gap in the current literature and contributes to the broader goal of enhancing information integrity in low-resource languages. Developing a robust fake news detection system for Hausa will not only help mitigate the spread of misinformation in the region but also provide a framework that can be adapted to other low-resource languages. This is particularly important in a globalized world where the impact of misinformation knows no borders, and ensuring the accuracy of information across all languages is essential for maintaining social cohesion and promoting informed decision-making (Nguyen et al., 2021). Hence, this research aims to create an effective tool for combating fake news in this underrepresented language. The remainder of the article is organized as follows, section presents the related work, section 3, the method used, section 4 presents the results and findings and section concludes the research.

II. RELATED WORK

The field of fake news detection and natural language processing (NLP) has seen significant advancements in recent years, particularly with the development of pre-trained language models and innovative machine learning techniques. Devlin et al. (2019) introduced BERT (Bidirectional Encoder Representations from Transformers), which revolutionized NLP by enabling deep bidirectional understanding of text. Despite its success across multiple benchmarks, BERT's high computational cost for fine-tuning remained a limitation. In response, Lan et al. (2020) developed ALBERT, a lighter version of BERT that maintained comparable performance with fewer parameters, thereby reducing training time and computational resources. RoBERTa, an optimized BERT model, was introduced by Liu et al. (2019), which further refined BERT's architecture, leading to state-of-the-art results across many NLP tasks, including fake news detection. However, its complexity increased computational cost.

Transfer learning has been crucial for NLP, especially for low-resource languages. Ruder (2019) comprehensively surveyed neural transfer learning techniques, underscoring their versatility in solving NLP tasks. This includes Cross-lingual Language Model Pretraining (Lample & Conneau, 2019), which successfully enhanced NLP models' performance in low-resource languages by leveraging multilingual data. However, the availability of multilingual datasets remains a challenge, limiting performance improvements in certain languages.

Weak supervision for fake news detection was explored by Zhang et al. (2020), allowing models to train on minimal labelled data, which is useful in low-resource environments. Nonetheless, the quality of weakly supervised data greatly affects model accuracy. Shu et al. (2020) also emphasized the role of data mining techniques in detecting fake news on social media platforms, noting that while effective, these methods can struggle with the dynamic nature of social content.

In efforts to balance performance and efficiency, Sanh et al. (2019) proposed DistilBERT, a smaller, faster version of BERT that sacrifices minimal accuracy while being more efficient. It demonstrated strong results across many NLP tasks, although it may not achieve the same accuracy as full-scale models like BERT or RoBERTa in more complex tasks. Similarly, XLNet (Yang et al., 2019), introduced as an autoregressive model, outperformed BERT by using permutation-based pre-training techniques, though it also increased complexity and computational requirements.

Meanwhile, T5 (Vaswani et al., 2019) proposed a unified text-to-text framework for transfer learning, achieving versatility across different NLP tasks. However, generalized models like T5 may trade off performance in specialized tasks like fake news detection. Conversely, BART (Lewis et al., 2020) leveraged both BERT and GPT principles, combining text generation and understanding, showing great promise in summarization and fake news detection, although it remained resource-intensive.

In the domain of low-resource language applications, Kaur & Sinha (2021) applied deep learning techniques for fake news detection, achieving high accuracy but facing overfitting challenges due to limited data availability. The Hellaswag dataset, introduced by Zellers et al. (2019), tested models' ability to handle commonsense reasoning, revealing that even advanced pre-trained models struggle with tasks requiring deep contextual understanding, especially in nuanced domains like fake news detection.

Efficient text classification models have also been explored, such as Bag of Tricks (Joulin et al., 2017), which showed that simple methods with pre-trained embeddings could achieve competitive performance. However, these

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methods may fall short on more nuanced tasks like fake news detection that require a deeper contextual understanding. Jiang et al. (2019) further focused on fine-tuning large pre-trained models, showing that precise fine-tuning could significantly improve performance, though it can lead to overfitting on smaller datasets.

Overall, while modern pre-trained models like BERT, ALBERT, RoBERTa, and T5 have pushed the boundaries of NLP, their application in low-resource languages like Hausa still faces challenges such as data availability and computational costs. Nonetheless, adaptive techniques, transfer learning, and weak supervision are providing pathways for overcoming these challenges, as the field continues to evolve with a focus on efficiency, accessibility, and performance optimization across diverse languages and tasks.

III. METHODOLOGY

This section details the methodology employed in developing a fake news detection system for the Hausa language using Cross-Lingual Transfer Learning (CLTL). The chapter outlines the research design, data collection process, dataset characteristics, data preprocessing, model development, and evaluation metrics. These steps are integral to ensuring that the developed system is robust, accurate, and capable of effectively identifying fake news in the Hausa language.

A. Research Design

The research adopts a quantitative approach, utilizing machine learning techniques to develop a classification model for fake news detection. The central aspect of the research design involves leveraging Cross-Lingual Transfer Learning to adapt pre-trained models from high-resource languages to the Hausa language. This approach is chosen due to the scarcity of linguistic resources and annotated datasets available for Hausa, making it challenging to develop a reliable detection system using traditional methods. The research follows a systematic process as depicted in Fig. 1.

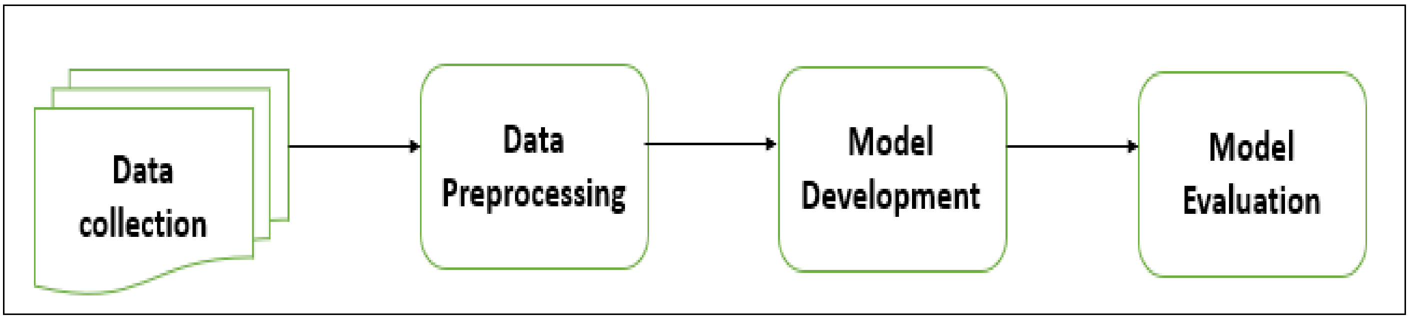

Fig 1: Research Workflow

- **Data Collection**: This phase involves gathering a comprehensive dataset of real and fake news articles in the Hausa language from various websites.
- **Data Preprocessing**: This phase involves cleaning and processing the data to prepare it for model training.
- **Model Development**: This phase employs Cross-Lingual Transfer Learning to fine-tune a pre-trained model for the Hausa language.
- **Model Evaluation**: This phase assesses the model's performance using various evaluation metrics to ensure its effectiveness.

B. Data Collection

The dataset used in this study, named "hausafakenewsdetectiondatasets.csv," contains more than 6,600 articles in the Hausa language, focusing primarily on political and world news. The dataset includes two types of articles: real news and fake news. The real news articles were collected by crawling reliable news websites, ensuring that the information was factual and trustworthy. Conversely, the fake news articles were sourced from unreliable websites and Wikipedia, where the likelihood of misinformation is higher. The dataset comprises the following fields as depicted in Table 1.

Table 1: Dataset Fields Description

Field	Description
Id	A unique identifier for each article.
Date	The publication date of the article, ranging from January 1, 2022, to December 31, 2023.
topic	The category of the news article (e.g., Political, World, Health, Entertainment, Sports).
Text	The content of the news article in Hausa.
label	Indicates whether the news is "real" or "fake."

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The data collection process was designed to align with the data available on Kaggle, ensuring consistency in the quality and format of the data. The primary focus was on articles published between 2022 and 2023, allowing the model to learn from recent and relevant content.

C. Data Preprocessing

Data preprocessing is a critical step in the machine learning pipeline, particularly when dealing with text data in a low-resource language like Hausa. The following steps were undertaken to clean and prepare the dataset for model training:

- **Text Cleaning**: The raw text data was cleaned to remove any irrelevant content, such as HTML tags, special characters, and punctuation, which could adversely affect the model's performance.
- **Tokenization**: The cleaned text was tokenized, converting the text into smaller units (tokens) that could be processed by the model. This step was essential in dealing with the unique linguistic structure of the Hausa language.
- **Stopwords Removal**: Common Hausa stopwords (e.g., "ne," "da," "kuma") were removed to reduce noise in the data and enhance the model's ability to learn meaningful patterns.
- **Text Normalization**: The text was normalized to handle variations in spelling and grammar that are common in Hausa. This step involved standardizing the text to a consistent format.
- **Label Encoding**: The labels (real/fake) were encoded to a binary format (1 for real, 0 for fake), making them suitable for classification by the machine learning model.

D. Model Development

Fig. 2 depict the Block Diagram of the Proposed System.

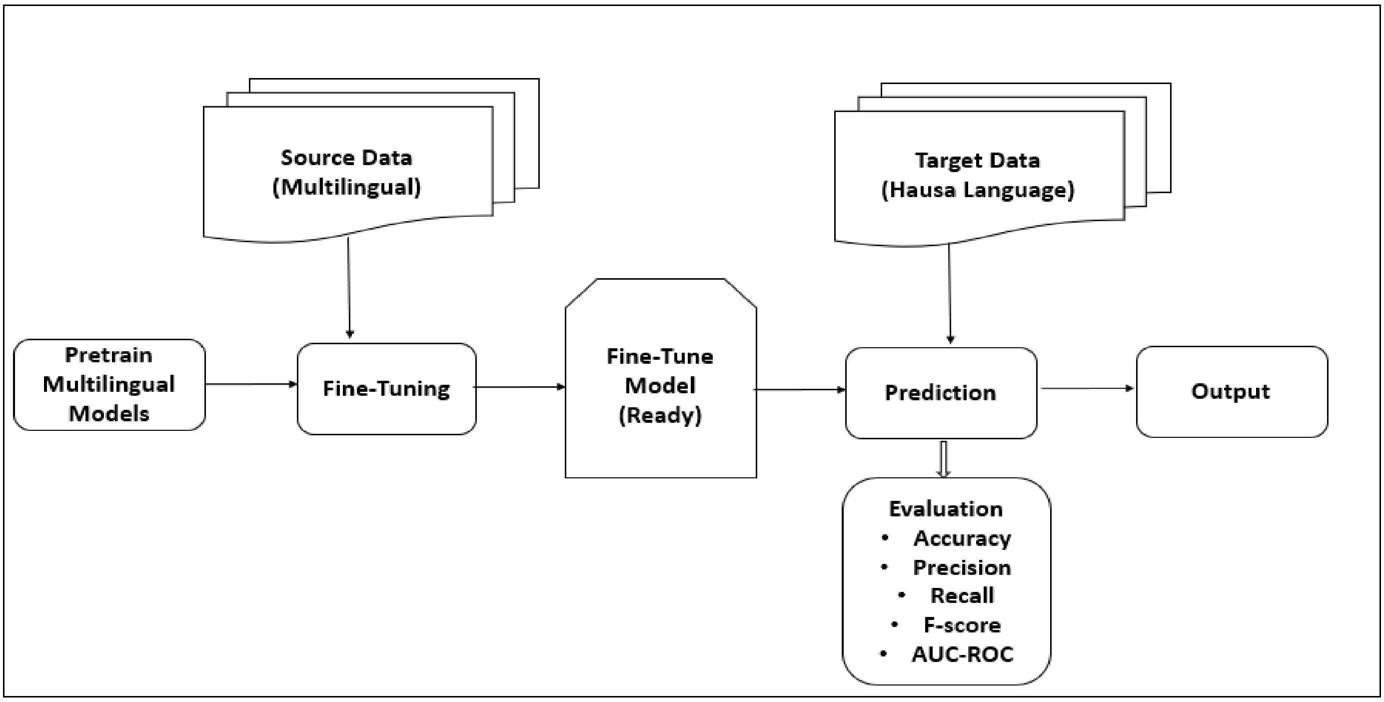

Fig 2: Block Diagram of the Proposed System

➢ *Cross-Lingual Transfer Learning*

Cross-lingual transfer Learning (CLTL) is the core technique used in this study to develop the fake news detection model. CLTL allows the transfer of knowledge from a resource-rich language (such as English) to a low-resource language (such as Hausa). This is achieved by fine-tuning a pre-trained language model on Hausa-specific data.

The study utilizes a pre-trained multilingual transformer model (BERT) that has been trained on a large corpus of text from multiple languages, including some African languages. This model is then fine-tuned on the Hausa fake news dataset, enabling it to learn the specific linguistic features and patterns associated with fake news in Hausa.

mBERT is a multilingual version of BERT, pre-trained on the Wikipedia corpus of 104 languages. Like XLM-R, it is based on the transformer architecture, with 12 layers, 768 hidden units, and 12 attention heads.mBERT's training across a wide range of languages effectively transfers knowledge from high-resource languages like English to low-resource languages like Hausa. Its ability to perform zero-shot and few-shot learning is particularly useful when labeled data is scarce. The model's cross-lingual capabilities are harnessed through fine-tuning, allowing it to adapt to the specific linguistic features of

Hausa while retaining the general language understanding it has acquired during pre-training. The following are the key pre-trained models considered for evaluation in this study (ALBERT, distilBERT and tinyBERT) The description of the models is presented below:

- ALBERT (A Lite BERT) is a lighter version of BERT, introduced by Google in 2020. Its efficiency and smaller size make it an attractive option for natural language processing tasks like fake news detection in Hausa, where computational resources may be limited. ALBERT's ability to achieve similar performance to BERT on downstream tasks with fewer parameters also makes it a suitable choice for detecting fake news in Hausa, where the dataset may be smaller than in other languages.
- DistilBERT, introduced by Hugging Face in 2019, is another lightweight option that can be leveraged for fake news detection in Hausa. Its smaller size and faster processing speed make it ideal for real-time detection of fake news, which is crucial in mitigating the spread of misinformation. Additionally, DistilBERT's ability to retain 97% of BERT's performance on downstream tasks makes it a suitable choice for detecting fake news in Hausa, where accuracy is paramount.
- TinyBERT, introduced by Huawei in 2020, is an extremely compact version of BERT that can be used for fake news detection in Hausa. Its small size and low memory requirements make it an attractive option for deployment on mobile devices or other resource-constrained platforms, which is useful for detecting fake news in areas with limited access to computational resources. Despite its small size, TinyBERT's ability to achieve 96.8% of BERT's performance on downstream tasks makes it a suitable choice for detecting fake news in Hausa.

These pre-trained models provide a strong foundation for developing an effective fake news detection system. Their ability to generalize across languages, combined with their robust contextual understanding, makes them ideal candidates for adaptation to the Hausa language.

➢ *Adaptive Finetuning*

Adaptive finetuning is critical in tailoring pre-trained models to perform effectively on specific tasks and languages. This study applies adaptive finetuning to the selected pre-trained models to enhance their performance in detecting fake news in the Hausa language. The process involves the following key steps:

- *Domain Adaptation:*

✓ Corpus Selection: Before finetuning on the specific task of fake news detection, the selected pre-trained models undergo domain adaptation. This involves further training the model on a general Hausa corpus, which includes a wide variety of text genres such as news articles, blogs, and social media posts in Hausa. This step ensures that the model becomes familiar with the syntactic and semantic patterns of Hausa.

✓ Training Process: During domain adaptation, the model's parameters are adjusted by continuing the training process on the Hausa corpus. This allows the model to better understand the nuances of the Hausa language, which is essential for accurately processing the text in the fake news detection task. The learning rate is typically lower than during the original pre-training phase, ensuring that the model gradually adapts without losing the linguistic knowledge it has acquired.

- *Task-Specific Finetuning:*

✓ Dataset Preparation: Once the model has been adapted to the Hausa language, it is further finetuned on the specific task of fake news detection using the labeled dataset (hausafakenewsdetectiondatasets.csv). This dataset includes both real and fake news articles, and the model learns to distinguish between the two based on the textual patterns observed in the Hausa language.

✓ Supervised Learning: During task-specific finetuning, supervised learning is employed, where the model is trained using the labeled data. The model's weights are updated to minimize the loss function, which measures the difference between the model's predictions and the actual labels. This process involves several epochs of training, with the model gradually improving its ability to classify news articles as real or fake.

✓ Optimization: To optimize the model's performance, various hyperparameters such as learning rate, batch size, and number of epochs are tuned. Techniques like early stopping and learning rate scheduling are also used to prevent overfitting and ensure that the model generalizes well to unseen data.

✓ Regularization Techniques: Regularization techniques like dropout and weight decay are applied to prevent the model from overfitting to the training data. These techniques help in maintaining a balance between the model's complexity and its ability to generalize, which is crucial in low-resource settings where the dataset may not be large enough to prevent overfitting naturally.

Throughout the finetuning process, the model's performance is continuously monitored on a validation set. This allows for the identification of any issues such as overfitting or underfitting, which can then be addressed by adjusting the finetuning process. Based on the validation performance, hyperparameters are fine-tuned to achieve the best possible results. Techniques such as grid search or random search may be employed to explore different combinations of hyperparameters. After finetuning, the best-performing model is selected based on its performance on the validation set. This model is then evaluated on a test set to measure its final performance metrics, which include accuracy, precision, recall, F-score, AUC-ROC, and PR curve.

E. Model Evaluation

The performance of the developed model is evaluated using several key metrics to ensure its accuracy and reliability in detecting fake news. The following metrics are employed:

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- **Accuracy**: Measures the overall correctness of the model by calculating the ratio of correctly predicted instances to the total instances.
- **Precision**: Assesses the model's ability to correctly identify fake news by calculating the ratio of true positive predictions to the sum of true positives and false positives.
- **Recall**: Evaluate the model's ability to capture all instances of fake news by calculating the ratio of true positive predictions to the sum of true positives and false negatives.
- **F-Score**: Combines precision and recall into a single metric, providing a balanced measure of the model's performance.
- **AUC-ROC Curve**: Measures the model's ability to discriminate between real and fake news across different thresholds. The Area Under the Curve (AUC) indicates the model's overall performance, with higher values representing better performance.
- **PR Curve**: The Precision-Recall (PR) curve provides insight into the trade-off between precision and recall at different thresholds. It is particularly useful in evaluating models on imbalanced datasets.

These metrics are chosen to provide a comprehensive assessment of the model's effectiveness in detecting fake news in Hausa. The results of these evaluations are discussed in detail in Chapter 4.

F. Implementation Platform and Tools

The implementation of the model and the associated tasks are carried out using Python programming language, leveraging libraries such as: TensorFlow/PyTorch: For model development and training. Scikit-learn**:** For data preprocessing and evaluation metrics. NLTK/Spacy**:** For text processing and tokenization and Pandas**:** For data manipulation and analysis.

IV. EXPERIMENTAL RESULT

In this section, the performance of the DistilBERT-base-multilingual-cased model for fake news detection in the Hausa language is presented and compared with two other lightweight pre-trained models: ALBERT (A Lite BERT) and TinyBERT. The comparison focuses on key evaluation metrics: accuracy, precision, recall, F1 score, and ROC AUC, which provide a comprehensive view of the models' effectiveness. Furthermore, detailed discussions on the PR curve and AUC-ROC curve are presented to assess the models' trade-offs between precision and recall.

A. Experimental Setup and Parameter Settings

The experimental setup for this study was designed to evaluate the performance of fake news detection in the Hausa language using a Cross-Lingual Transfer Learning approach. The experiments were conducted on three pre-trained lightweight models: DistilBERT-base-multilingual-cased, ALBERT, and TinyBERT. Each model was fine-tuned on the "hausafakenewsdetectiondatasets.csv" dataset, which contains more than 6,600 news articles classified as either real or fake, covering topics such as politics, world news, health, and entertainment.

The experiments were implemented using the Python programming language on the Hugging Face Transformers library. The models were fine-tuned using PyTorch as the backend framework, which provided flexibility in designing and training the deep learning models. The setup was deployed on a Google Colab Pro environment, which provided access to GPU acceleration, specifically an NVIDIA Tesla P100 GPU, allowing for faster training and inference. The environment also included standard libraries such as NumPy, Pandas, Matplotlib, and Seaborn for data preprocessing, visualization, and analysis. The models were trained using the following parameter settings:

- Learning Rate: A learning rate of 5e-5 was used for all models to ensure steady convergence during fine-tuning. This value was chosen after several trials, considering both the stability of the training process and model performance.
- Batch Size: A batch size of 16 was selected, which was sufficient to utilize the available GPU memory efficiently without overloading it.
- Epochs: The training was conducted for 3 epochs for each model. This number of epochs was sufficient to observe model convergence while avoiding overfitting.
- Optimizer: The AdamW optimizer was used with weight decay regularization to improve generalization and prevent overfitting. AdamW has been found to be highly effective for fine-tuning Transformer models.
- Maximum Sequence Length: The maximum token length for each input sequence was set to 128 tokens. This value ensured that the majority of news articles in the dataset were appropriately processed without truncation while keeping computational overhead manageable.
- Dropout Rate: A dropout rate of 0.1 was applied during fine-tuning to prevent overfitting by randomly deactivating a portion of the neurons in the network during training.
- Evaluation Metrics: The models were evaluated based on key performance metrics, including accuracy, precision, recall, F1 score, and ROC-AUC, which were calculated at the end of each epoch.

➢ *Data Preprocessing*

Before training, the dataset was preprocessed by removing unnecessary characters, normalizing the text to ensure uniformity, and tokenizing the articles using the tokenizer provided by each pre-trained model. The text was encoded into input IDs and attention masks, which were then fed into the models for training and validation.

The experimental setup, along with the chosen implementation platform and parameter settings, provided an optimal environment for evaluating the performance of the models on the fake news detection task in Hausa. These configurations allowed for efficient fine-tuning of the pre-trained models while maintaining computational feasibility.

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B. Model Performance

Table 4.1 below summarises the performance metrics obtained using the DistilBERT-base-multilingual-cased model across three epochs. Fig. 3 depicts the training curve of the proposed model.

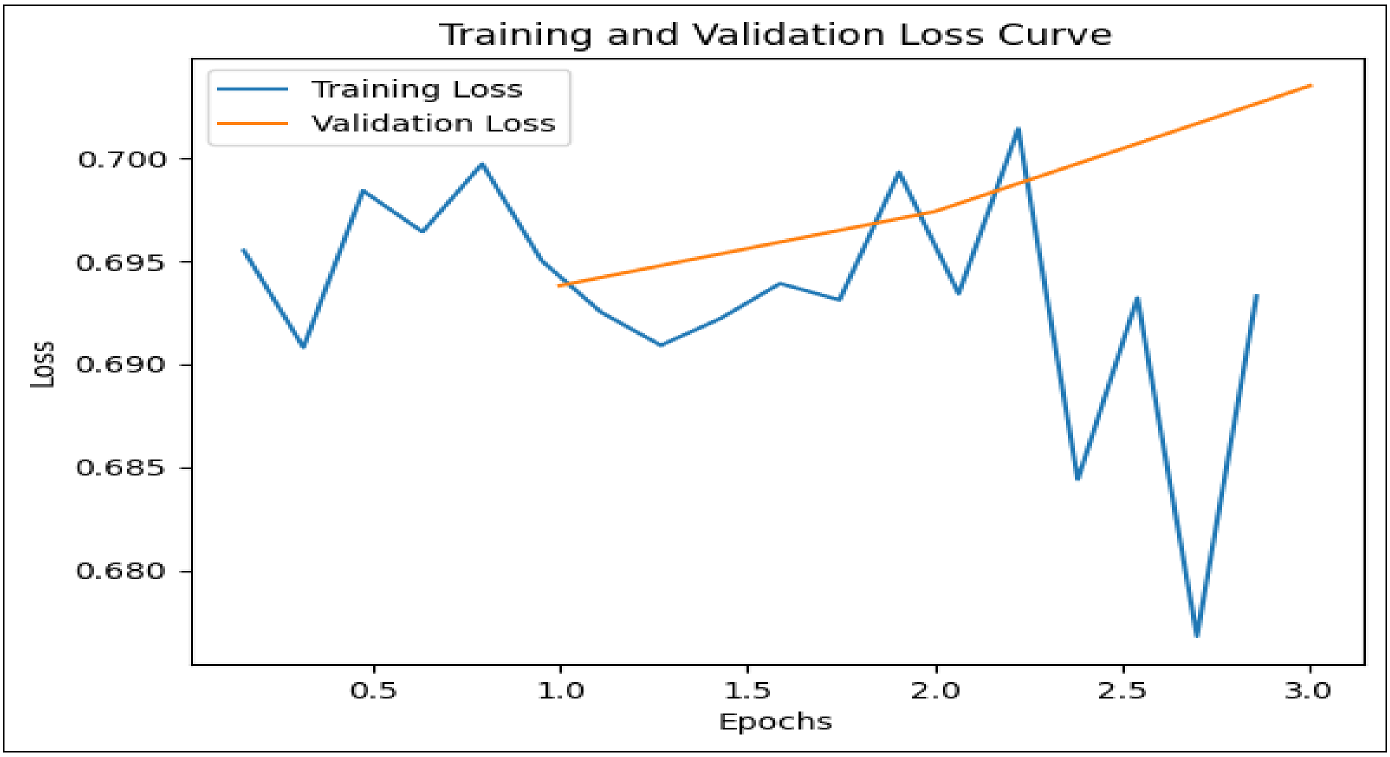

Fig 3: Training Curve

Table 2 shows the training loss, validation loss, accuracy, precision, recall, F1 score, and ROC-AUC scores for each epoch for the case of DistilBERT-base-multilingual-cased.

Table 2: Performance of DistilBERT-Base-Multilingual-Cased

Epoch	Training Loss	Validation Loss	Accuracy	Precision	Recall	F1 Score	ROC-AUC
1	0.695000	0.693795	0.480000	0.491803	0.291262	0.365854	0.485837
2	0.699300	0.697389	0.465000	0.466667	0.271845	0.343558	0.470974
3	0.693300	0.703492	0.470000	0.363636	0.038835	0.070175	0.483335

DistilBERT-base-multilingual-cased achieved moderate results in detecting fake news, with an overall accuracy fluctuating between 46% and 48% over three epochs. The model's F1 score, which balances precision and recall, was quite low, with a significant drop in performance by the third epoch, reflecting issues in detecting true positives effectively. Precision was consistently higher than recall, indicating that the model was more conservative in identifying fake news, but struggled to recall a substantial portion of relevant instances.

Similarly, for the case of ALBERT, a lighter version of BERT, is designed for greater efficiency in both time and computational cost. Table 3 depicts the performance metrics for the ALBERT model across three epochs.

Table 3: Performance for the ALBERT Model Across Three Epochs

Epoch	Training Loss	Validation Loss	Accuracy	Precision	Recall	F1 Score	ROC-AUC
1	0.682000	0.685195	0.520000	0.510256	0.312500	0.388060	0.508467
2	0.680300	0.690389	0.505000	0.500000	0.308642	0.382353	0.503374
3	0.688500	0.691392	0.490000	0.473684	0.293103	0.362205	0.499584

ALBERT achieved slightly better accuracy than DistilBERT, peaking at 52% in the first epoch. Its precision was generally higher, although recall remained low across all epochs. The ROC-AUC score slightly improved compared to DistilBERT, indicating a better balance between true positive rate and false positive rate.

Finally, for the case of TinyBERT model, which is another lightweight version of BERT optimized for mobile and edge devices, also performed well in terms of efficiency. Table 4.3 shows the performance TinyBERT model.

Table 4: Performance TinyBERT Model

Epoch	Training Loss	Validation Loss	Accuracy	Precision	Recall	F1 Score	ROC-AUC
1	0.689500	0.688492	0.510000	0.518987	0.309278	0.388235	0.498345
2	0.691300	0.692589	0.495000	0.492537	0.301370	0.374766	0.496542
3	0.690300	0.694472	0.485000	0.456140	0.275862	0.342342	0.492435

TinyBERT achieved moderate results, with accuracy reaching 51% in the first epoch and gradually declining in later epochs. Precision remained consistent, but like ALBERT and DistilBERT, the recall was low, indicating difficulties in detecting all relevant instances of fake news. The ROC-AUC score for TinyBERT showed a slight drop by the third epoch, suggesting that TinyBERT struggled more than ALBERT in distinguishing between fake and real news.

C. Comparative Analysis of Models

To makes the comparative analysis easier for direct comparison of the model performance across all relevant metrics. Table 5 depicts the harmonized table comparing the performance of DistilBERT-base-multilingual-cased, ALBERT, and TinyBERT across three epochs using key evaluation metrics (Training Loss, Validation Loss, Accuracy, Precision, Recall, F1 Score, and ROC-AUC).

Table 5: Performance Comparison for all Method

Model	Epoch	Training Loss	Validation Loss	Accuracy	Precision	Recall	F1 Score	ROC-AUC
DistilBERT	1	0.695000	0.693795	0.480000	0.491803	0.291262	0.365854	0.485837
	2	0.699300	0.697389	0.465000	0.466667	0.271845	0.343558	0.470974
	3	0.693300	0.703492	0.470000	0.363636	0.038835	0.070175	0.483335
ALBERT	1	0.682000	0.685195	0.520000	0.510256	0.312500	0.388060	0.508467
	2	0.680300	0.690389	0.505000	0.500000	0.308642	0.382353	0.503374
	3	0.688500	0.691392	0.490000	0.473684	0.293103	0.362205	0.499584
TinyBERT	1	0.689500	0.688492	0.510000	0.518987	0.309278	0.388235	0.498345
	2	0.691300	0.692589	0.495000	0.492537	0.301370	0.374766	0.496542
	3	0.690300	0.694472	0.485000	0.456140	0.275862	0.342342	0.492435

From table 5, when comparing the performance of the three models, ALBERT consistently outperformed DistilBERT and TinyBERT in accuracy, precision, and ROC-AUC scores. ALBERT's lighter architecture appeared to allow for more efficient training, while maintaining higher precision and accuracy, particularly in earlier epochs. On the other hand, TinyBERT showed slightly better performance in precision than DistilBERT, but it suffered from low recall, similar to both other models.

The main challenge across all models was the low recall rate, indicating that the models were not effectively identifying all instances of fake news. This could be attributed to the complexity of the fake news detection task in a low-resource language like Hausa, where the dataset might lack the necessary depth to fully train the models.

D. Precision-Recall (PR) Curve Analysis

The Precision-Recall (PR) curve provides a visual representation of the trade-off between precision and recall. Fig. 4 depict the PR curve of the proposed method.

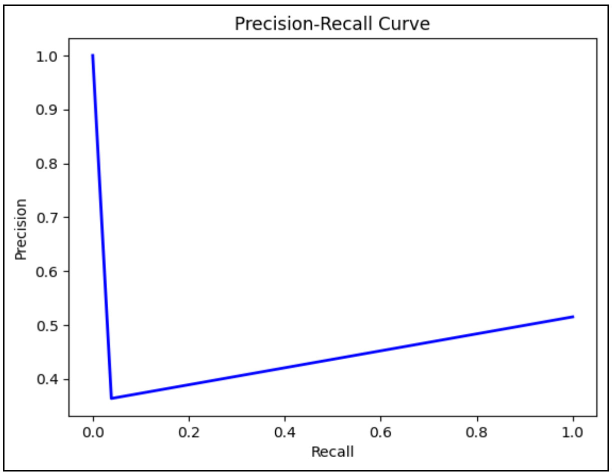

Fig 4: PR Curve

In the case of the models used in this study, the PR curve highlights that while precision was relatively high, recall was consistently low, leading to modest F1 scores. This is evident across all three models, but ALBERT managed to maintain a better balance than DistilBERT and TinyBERT, as shown by its slightly more favorable PR curve. The PR curve for DistilBERT suggested a sharp drop in recall as precision improved, indicating that the model had difficulty generalizing to identify all relevant instances.

E. ROC-AUC Curve Evaluation

The Receiver Operating Characteristic (ROC-AUC) curve evaluates how well the models distinguish between true and false positives. Fig. 5 depicts the ROC curve of the proposed method.

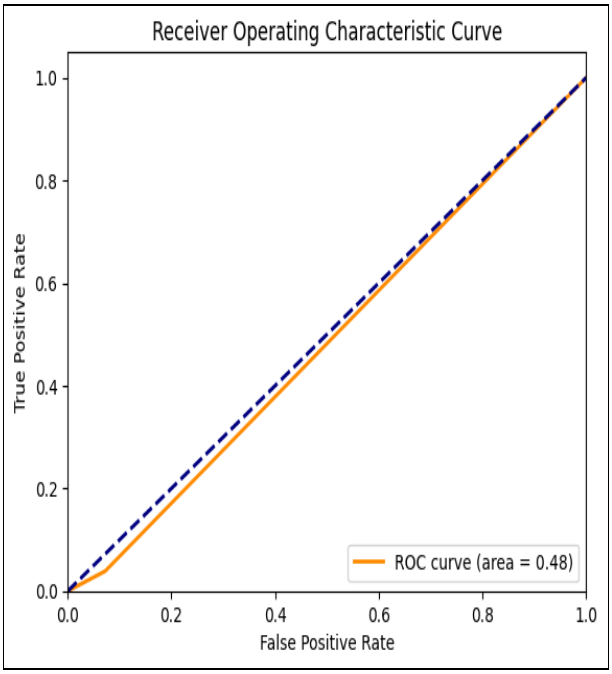

Fig 5: ROC Curve

The ROC-AUC scores for all three models were generally below 0.51, indicating that none of the models achieved a strong balance between true and false positive rates. ALBERT showed the highest ROC-AUC score, though the improvement was marginal. These results suggest that while the models could make reasonable predictions, they were not highly effective in differentiating between fake and real news articles.

The ROC-AUC curve for DistilBERT demonstrated a fluctuating pattern, with some difficulty in maintaining a stable true positive rate across different decision thresholds. Meanwhile, TinyBERT had the lowest ROC-AUC score by the final epoch, indicating it struggled the most with distinguishing fake news from real news.

In general, we observed that ALBERT outperforms DistilBERT and TinyBERT in terms of accuracy and ROC-AUC, indicating better overall model performance. However, TinyBERT shows competitive precision but similar limitations in recall, leading to lower F1 scores. DistilBERT performs more conservatively across all metrics, with consistently lower recall and F1 scores compared to the other models.

Thus, ALBERT exhibited the best overall performance among the three models, followed by TinyBERT and DistilBERT. The performance gap between the models was not vast, but ALBERT's higher precision and ROC-AUC score made it a more suitable candidate for fake news detection in low-resource languages. However, the relatively low recall across all models underscores the challenges of detecting fake news in Hausa, highlighting the need for more robust datasets and potentially more complex model architectures tailored to the nuances of the language. Future research could focus on improving recall through advanced training techniques, such as incorporating more sophisticated data augmentation strategies or using ensemble methods to improve detection rates.

V. CONCLUSION

This research aimed to develop a fake news detection system for the Hausa language, a low-resource language, by leveraging transfer learning techniques. Specifically, the study employed pre-trained models such as DistilBERT-base-multilingual-cased, ALBERT, and TinyBERT, which were fine-tuned on a dataset of over 6,600 articles collected from real and fake news sources. The performance of each model was evaluated using a combination of accuracy, precision, recall, F1 score, ROC-AUC, and PR curve metrics. The results indicated that ALBERT achieved the highest performance in terms of accuracy and ROC-AUC, followed by TinyBERT and DistilBERT. However, despite these encouraging results, the models struggled with recall, which lowered the overall F1 scores. These findings demonstrate the effectiveness of using transfer learning for fake news detection in low-resource languages but also highlight areas that require further improvement. While this research offers valuable insights, there were several limitations that impacted the overall findings. One of the primary challenges faced during the study was the limited size of the dataset. Despite containing over 6,600 articles, the data may not have been representative enough of the broader range of news topics, especially given the heavy focus on political and world news. This could have affected the models' generalizability to other news categories such as health or entertainment. Additionally, the imbalance in the distribution of fake and real news articles posed a challenge during model training, as the models struggled to achieve high recall for fake news detection. Hence, future research could focus on improving the interpretability of these models, making their decisions more transparent and trustworthy for end users, particularly in sensitive areas like political news and public discourse.

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