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A culturally aware NLP approach for fake-news detection in Nigerian online media using BERT

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Abstract

Fake-news dissemination in multilingual Nigerian media poses serious sociopolitical risks, yet many existing detection models do not adequately account for Nigeria's linguistic and cultural diversity. This study presents a culturally aware natural language processing (NLP) model for fake-news detection based on the Bidirectional Encoder Representations from Transformers (BERT) architecture. A curated corpus of 10,000 Nigerian news articles was assembled and stratified across Standard English, Nigerian Pidgin, Yoruba, Hausa, and Igbo. The model combines language-adaptive fine-tuning with regulatory-informed annotation based on the standards of the National Broadcasting Commission (NBC), Nigerian Communications Commission (NCC), and National Information Technology Development Agency (NITDA). Experimental results show that the proposed model achieved 91.3% accuracy, 90.8% precision, and an 89.7% F1-score, outperforming vanilla multilingual BERT and traditional machine-learning baselines. The system also performed strongly on indigenous-language and code-switched content, with an average inference latency below 400 ms. The study provides a scalable and context-dependent decision-support model for real-time misinformation detection in the Nigerian online-media environment.

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Keywords: BERT, Fake-news detection, Nigerian media, Multilingual natural language processing

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1. Introduction

News is essential for transmitting information to society. It depends on relevance, accuracy, timeliness, and verified facts across broadcast, print, and digital media [1, 2]. Transparency and civic participation have been undermined by the rise of misinformation, rumours, and sensationalism [3, 4]. Progress in artificial intelligence (AI), including machine learning (ML) and deep learning (DL), has produced strong natural language processing (NLP) systems, and transformer models use self-attention to identify long-range textual dependencies [5]. As a transformer-based architecture, Bidirectional Encoder Representations from Transformers (BERT) benefits from pre-training on large datasets through masked language modelling and next-sentence prediction, followed by fine-tuning on smaller datasets. It has been effective in applications such as fake-news detection in multilingual and low-resource language settings [6].

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Table 1: Guidelines from Nigerian regulatory bodies.

Regulatory body	Rule or regulatory focus
NBC	Prohibits hate speech and mandates local-content standards.
NCC	Regulates telecommunications infrastructure and over-the-top platforms.
NITDA	Enforces data-consent and cybersecurity standards.

In Nigeria, fake news is a socially, politically, and economically harmful phenomenon amplified by more than 33 million social-media users and by the use of English, Nigerian Pidgin, Hausa, Yoruba, Igbo, and other languages [7]. During the COVID-19 pandemic and recent elections, fake news compromised public-health communication, electoral processes, and financial stability. Its spread has worsened when supported by political actors or motivated by profit [2–4]. In response, regulatory authorities, including the National Broadcasting Commission (NBC), the Nigerian Communications Commission (NCC), and the National Information Technology Development Agency (NITDA), have encouraged standards for broadcasting ethics, digital communications, cybersecurity, and data protection to support credible news, media integrity, responsible expression, and national security [8–10].

Table 1 summarizes the Nigerian regulatory bodies and the rules used in this study to contextualize online-media regulation.

2. Review of related literature

Recent research on fake-news detection highlights the need for robust NLP methods that can handle linguistic heterogeneity and transfer-learning conditions in resource-constrained environments. A recent systematic review describes the disruptive role of multilingual and cross-lingual embeddings, transfer-learning approaches, and transformer-based solutions for reducing misinformation in multilingual and low-resource language settings, while also identifying gaps in linguistic diversity and model adaptability [11]. The effectiveness of transfer learning with adaptive fine-tuning in Hausa-language misinformation detection has also been confirmed by empirical research, which showed improved classification results for non-English news items using Hausa-language fake-news datasets [12, 13].

Transformer-based architectures such as BERT and its variants have consistently performed better in detecting misinformation when fine-tuned on domain-specific corpora, supporting the usefulness of pretrained transformer models in classification tasks [14]. Multimodal fake-news detectors, which combine textual and visual cues, have also been investigated and have shown higher performance than text-only systems in some settings [15]. In addition, large-scale ML and NLP surveys describe the value of hybrid frameworks that combine NLP feature extraction with conventional classification algorithms to improve detection accuracy and resilience [16]. Collectively, these studies demonstrate progress toward more effective misinformation-detection mechanisms and show the importance of transfer learning, multilingual modelling, and context-dependent transformer fine-tuning across diverse linguistic conditions.

2.1. Research gap

Nigeria's linguistic diversity, including English, Nigerian Pidgin, Yoruba, Hausa, and Igbo, remains a challenge for existing fake-news detection techniques [17]. This creates gaps in accuracy and cultural adaptability. Most models lack localization or regulatory alignment with NBC, NITDA, and NCC guidelines. To address dataset limitations, computational inefficiency, and poor handling of code-switching and idioms, this study proposes a BERT-based system fine-tuned on Nigerian news corpora and incorporates regulatory standards to improve dialectal and cultural sensitivity while maintaining computational efficiency for context-aware fake-news detection.

3. Methodology

This study employs a BERT-based NLP model for fake-news detection, addressing Nigeria's linguistic diversity, regulatory constraints, and previous limitations such as poor cultural adaptation and decision-making gaps. The framework uses a dashboard-driven pipeline for data ingestion, annotation, training, and evaluation, with a fine-tuned BERT model at its core. The structured approach consists of four phases: data acquisition and corpus construction; regulatory-aligned annotation; language-adaptive preprocessing and fine-tuning; and evaluation and deployment. The design maximizes computational efficiency while supporting interpretability, repeatability, and transparency.

3.1. Data acquisition and corpus construction

Newspaper3k was used to collect a corpus of 10,000 Nigerian online news articles through automated web scraping, enabling parallel extraction of text, metadata, and publication details. This procedure was designed to provide statistical strength and model robustness. The source code was supplied through the authors' Google Colab link: https://colab.research.google.com/drive/11P-ab8NcRk9tVcV2hozj2zIfl-HUawAu?usp=drive_link.

News sources were selected from *Punch NG*, *Vanguard News*, *Sahara Reporters*, *BBC News Nigeria*, and *Daily Trust*. These outlets were chosen to reflect a range of editorial positions, reporting styles, language use, and audience coverage in Nigerian online media. The articles represent contemporary content from 2022 to 2025 and include health, socioeconomic, and political topics.

The corpus is evenly distributed across Standard English, Nigerian Pidgin, Yoruba, Hausa, and Igbo, with 2,000 news articles per language category. It also includes code-switched news articles. This design enables the model to learn culturally grounded linguistic characteristics, reduce multilingual bias, and improve attention to Nigeria's heterogeneous linguistic environment.

3.2. Regulatory-guided annotation

Manual annotation can lack consistency and is prone to annotator fatigue. This study therefore employed an AI-assisted labelling method using the Gemini-3-Flash with a human-in-the-loop (HITL) review process. The national regulatory guidelines of the NBC, NCC, and NITDA were accessed from their official websites and used during annotation to create clear criteria for misinformation, hate speech, unverified claims, and harmful digital content.

A hierarchical annotation procedure was developed to provide Gemini-3-Flash with prompts based on these regulatory requirements. The system evaluated each news article for possible violations. Non-compliant articles were labelled as fake (1), and compliant articles were labelled as real (0). These binary labels were used for supervised BERT fine-tuning and were not inference-time rules; the approach enabled the model to learn regulatory and linguistic patterns implicitly.

To evaluate labelling reliability, domain experts reviewed a random sample of 500 news articles. The resulting Cohen's kappa was 0.84, indicating high agreement and supporting the reliability of the labelling process.

3.3. Data preprocessing and tokenization

News articles underwent language-sensitive preprocessing to preserve Nigerian linguistic characteristics before model training. Text cleaning involved systematic removal of HTML tags, special characters, unnecessary spaces, and irrelevant metadata. Dialect-sensitive stop-word management was used to retain contextual and sentiment information by preserving relevant Nigerian Pidgin expressions such as "na", "wey", and "dem" where appropriate.

The predominant language of each news article was automatically identified to support multilingual and code-switched material. Tokenization was performed using the WordPiece tokenizer associated with the BERT-base multilingual cased model. This tokenizer manages out-of-vocabulary terms, indigenous words, spelling variations, and mixed-language expressions in Nigerian news content. Each input sequence was structured with the required special tokens: `[CLS]`, which represents the whole article, and `[SEP]`, which marks sentence or segment boundaries. This structure maintains compatibility with BERT's transformer architecture and enables contextual representation during training and inference.

3.4. Model architecture and fine-tuning strategy

The model used in this study is BERT-base multilingual cased, which was trained on more than 70 languages and was selected because of its cross-lingual transfer capability and preservation of casing and language complexity. The final latent representation of the `[CLS]` token, which summarizes the semantics of each article, was connected to a task-specific classification head for fake-news prediction.

Fine-tuning used AdamW with a learning rate of 2.0×10^{-5}, a weight decay of 0.01, a batch size of 32, and four epochs to avoid overfitting while maintaining stable convergence. Binary cross-entropy was used to optimize the fake-versus-real classification task. The model was trained in a GPU-accelerated environment using TensorFlow and Hugging Face Transformers, while NumPy, Pandas, and scikit-learn were used for data processing and evaluation. This arrangement enabled the model to learn dialectal variation, code-switching, and culturally specific expressions in Nigerian news data.

During inference, inputs were processed through the same preprocessing and tokenization pipeline and passed through the BERT transformer layers. The representation associated with the `[CLS]` token was then classified using a softmax layer, and the output with the highest probability was used as the predicted label. No rule-based logic, keyword matching, or heuristic thresholding was applied; all decisions were made by the fine-tuned BERT model.

The proposed model was compared with vanilla multilingual BERT, which did not use language-adaptive preprocessing, and with a term frequency–inverse document frequency plus support vector machine (TF–IDF + SVM) classifier. These baselines provided transformer-based and traditional ML controls to show the advantages of dialect-sensitive tokenization and regulatory-informed labelling.

Table 2: Model performance metrics.

Metric	Calculation	Result (%)	Interpretation
Accuracy	(757 + 1069)/2000	91.3	High accuracy in multilingual Nigerian news
Precision	757/(757 + 77)	90.8	Strong ability to avoid falsely labelling real news as fake
Recall	757/(757 + 97)	88.6	Effective detection of fake-news instances
F1-score	$2 \times (0.908 \times 0.886)/(0.908 + 0.886)$	89.7	Balanced performance under class imbalance

Table 3: Confusion matrix results.

	Predicted real	Predicted fake
Actual real	1069	77
Actual fake	97	757

3.5. Evaluation strategy and validation

An 80:20 train–test split and fivefold cross-validation were used to evaluate the model. News articles from the same source were kept in the same split to reduce data leakage. Accuracy, precision, recall, F1-score, and confusion matrices were used as performance measures to provide a balanced assessment despite possible class imbalance between real and fake news.

3.6. System implementation and interface

A cloud-based microservices architecture was used to deploy the model. The front end was created using Next.js, TypeScript, and Material-UI. The interface allows users to input news text and receive real-time predictions and confidence scores, making the system accessible to journalists, researchers, regulators, and members of the public.

3.7. Ethical considerations

The research was conducted with attention to ethical standards because it used publicly available news material and anonymized personal details where necessary. Individual news articles were labelled rather than media organizations to avoid reputational damage. Annotations followed NBC, NCC, and NITDA guidelines to reduce bias across Nigerian languages and dialects. The system is intended as a transparent decision-support mechanism and acknowledges deployment risks such as false positives and misuse.

4. Results

The culturally aware BERT-based fake-news detector was empirically evaluated using 8,000 news articles (80% of the corpus) for training and 2,000 held-out articles (20%) for testing. The test set included English, Yoruba, Hausa, Igbo, Nigerian Pidgin, and code-switched English–Yoruba posts and articles. To reduce the effect of class imbalance and provide detailed analysis, performance was measured using accuracy, precision, recall, F1-score, and confusion matrices.

Table 2 shows that the culturally aware fine-tuned BERT model was tested on 2,000 held-out Nigerian news articles. Ground-truth labels were produced through regulatory-guided annotation based on NBC, NCC, and NITDA criteria. The confusion matrix reported 757 true positives, 1,069 true negatives, 77 false positives, and 97 false negatives. These values indicate that the model differentiated between fake and real news in multilingual and code-switched Nigerian media. All predictions were based on supervised BERT fine-tuning without heuristic thresholds or rule-based inference.

Figure 1 shows the bar chart for accuracy, precision, recall, and F1-score. Accuracy is the highest metric, followed by precision, F1-score, and recall.

The false-positive rate (FPR) was calculated as

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TN}} = \frac{77}{77 + 1069} = 0.067. \tag{1}$$

The test set in Table 3 had 757 true positives, 1,069 true negatives, 77 false positives, and 97 false negatives, yielding an FPR of approximately 6.7%. This low FPR indicates high accuracy in identifying real news. Most false negatives involved subtle misinformation, opinion-driven political commentary, or news stories with ambiguous regulatory breaches.

Table 4 shows that the model maintained high F1-scores across language categories: 91.5% for English, 88.9% for Nigerian Pidgin, 87.6% for Yoruba, 88.1% for Hausa, 87.9% for Igbo, and 86.8% for code-switched text. The slight reduction for code-switched text reflects the difficulty of this category but also supports the model's cultural and linguistic flexibility. The result suggests that WordPiece tokenization and language-specific fine-tuning were effective for Nigerian languages and colloquial expressions.

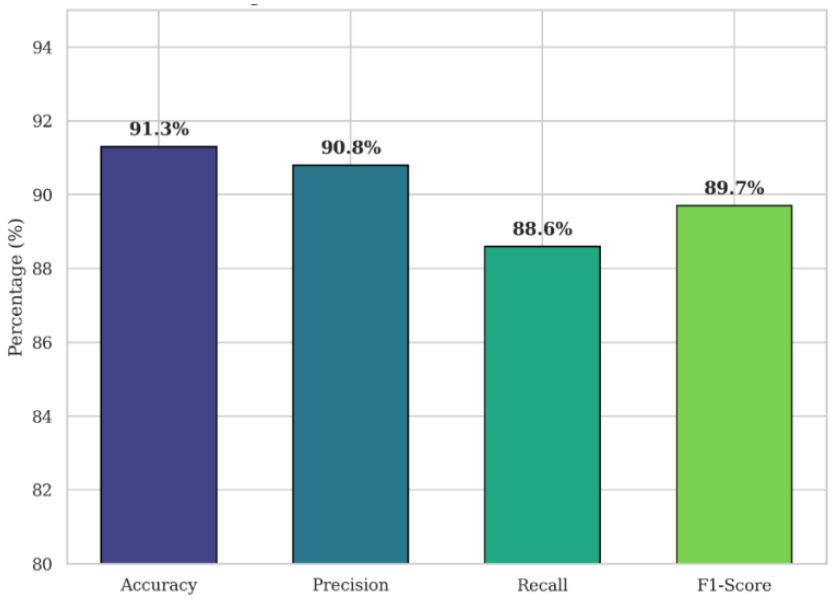


Figure 1: Model performance metrics.

Table 4: F1-score by language category.

Language	English	Nigerian Pidgin	Yoruba	Hausa	Igbo	Code-switched text
F1-score (%)	91.5	88.9	87.6	88.1	87.9	86.8

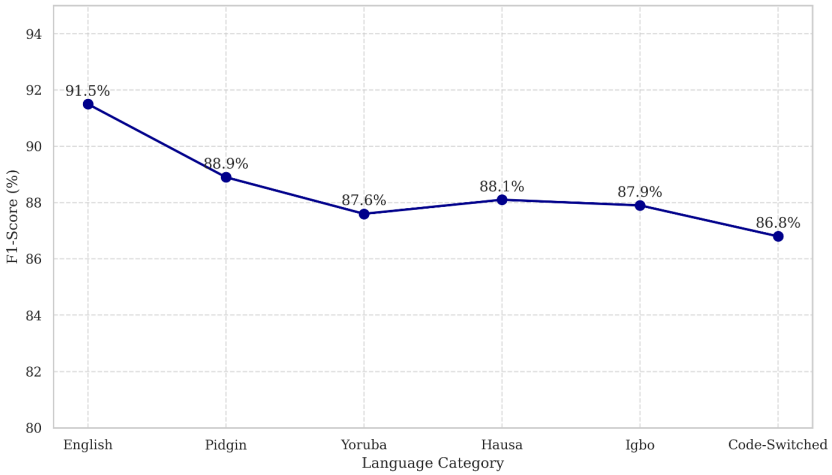


Figure 2: F1-score distribution across Nigerian languages.

Table 5: Cross-validation accuracy.

Fold	1	2	3	4	5	Mean
Accuracy (%)	90.6	91.2	91.9	90.8	91.0	91.1 ± 0.7

Figure 2 shows the F1-score by language category. The highest F1-score was obtained for English, and performance remained relatively consistent across the other languages and code-switched text.

The fivefold cross-validation results in Table 5 show a mean accuracy of 91.1% with a standard deviation of 0.7%. These results indicate stable performance with only minor variation among folds. The mean inference latency was less than 400 ms per news article, indicating that the system is suitable for real-time operation.

Figure 3 illustrates the accuracy distribution across the five cross-validation folds, with a mean of 91.1%. The result indicates

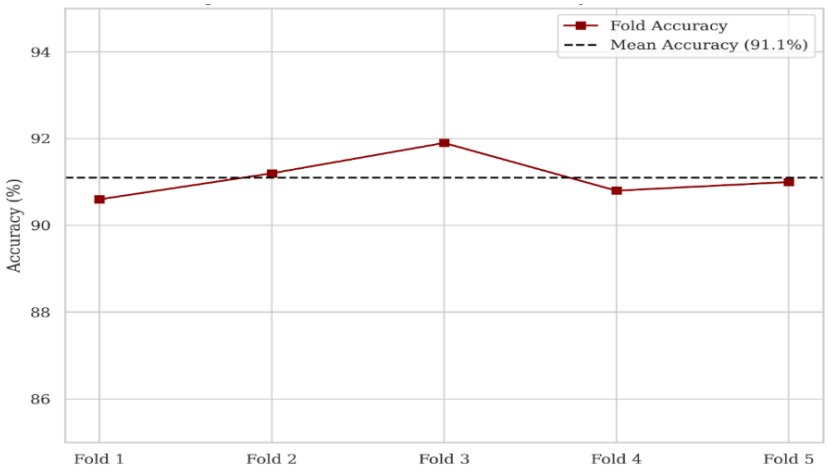


Figure 3: Fivefold cross-validation accuracy distribution.

Table 6: Performance comparison of the proposed model and baselines.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
TF–IDF + SVM	79.4	77.2	75.8	76.5
Vanilla mBERT	86.1	85.5	83.2	84.3
Proposed BERT (culturally aware)	91.3	90.8	88.6	89.7

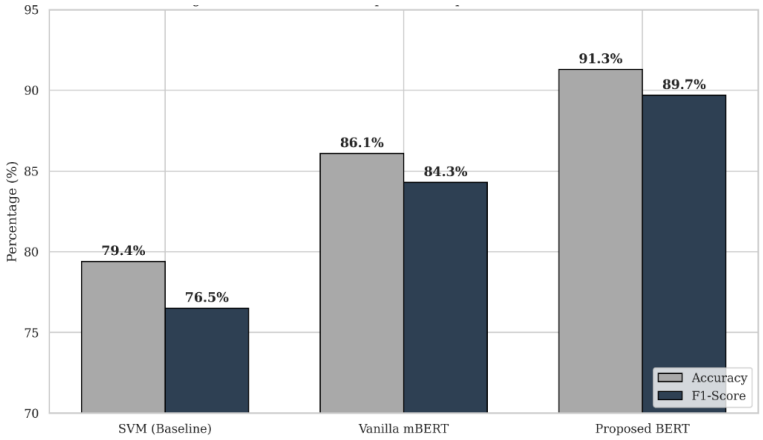


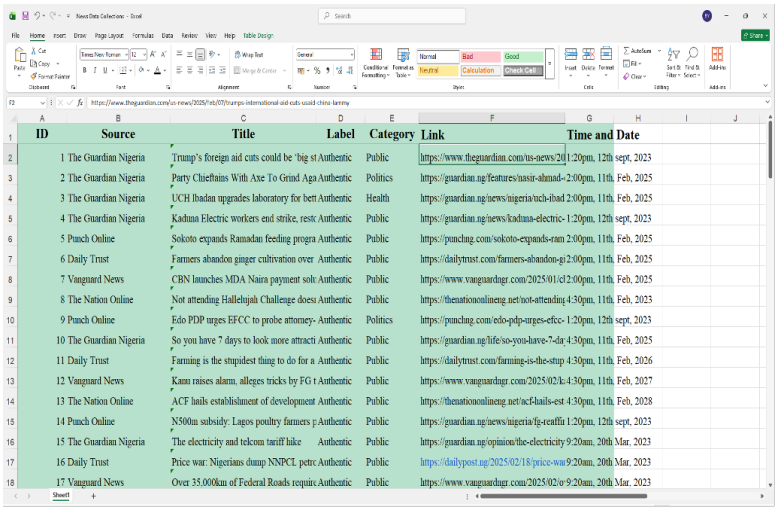
Figure 4: Baseline comparison.

high consistency across folds.

Table 6 shows that the proposed culturally aware BERT model outperformed both the conventional TF–IDF + SVM classifier and unmodified multilingual BERT across all evaluation measures. The TF–IDF + SVM baseline achieved the lowest accuracy (79.4%) and F1-score (76.5%), indicating the limitations of keyword-based models for identifying contextual and culturally embedded misinformation in Nigerian news.

Vanilla mBERT used contextual embeddings and achieved higher performance, with 86.1% accuracy and an 84.3% F1-score. However, it was still affected by representation bias and vocabulary mismatch for Nigerian Pidgin, indigenous languages, and code-switched data [7, 11]. The proposed model preserved contextual cues and culturally relevant tokens, achieving 90.8% precision and 91.3% accuracy. In regulatory practice, this improvement would reduce false flags when large volumes of news stories are screened. Such reduction is important in Nigeria's sociopolitical context because false classification can affect press freedom, media credibility, and public trust.

Figure 4 shows that although vanilla multilingual BERT had satisfactory overall performance, it performed less effectively on code-switched text and Nigerian Pidgin. The proposed culturally aware BERT model produced a 5.2 percentage-point improvement over vanilla mBERT, supporting the need for language-adaptive tuning in Nigerian media. The proposed model also outperformed the TF–IDF + SVM baseline.



ID	Source	Title	Label	Category	Link	Time and Date
1	The Guardian Nigeria	Trump's foreign aid cuts could be 'big st	Authentic	Public	https://www.theguardian.com/us-news/20	1:20pm, 12th sept, 2023
2	The Guardian Nigeria	Party Chieftains With Axe To Grind Aga	Authentic	Politics	https://guardian.ng/features/nasir-ahmad-	2:00pm, 11th Feb, 2025
3	The Guardian Nigeria	UCH Ibadan upgrades laboratory for bett	Authentic	Health	https://guardian.ng/news/nigeria/uch-ibad	2:00pm, 11th Feb, 2025
4	The Guardian Nigeria	Kaduna Electric workers end strike, reste	Authentic	Public	https://guardian.ng/news/kaduna-electric-	1:20pm, 12th sept, 2023
5	Punch Online	Sokoto expands Ramadan feeding progra	Authentic	Public	https://punchng.com/sokoto-expands-ram	2:00pm, 11th Feb, 2025
6	Daily Trust	Farmers abandon ginger cultivation over	Authentic	Public	https://dailytrust.com/farmers-abandon-gi	2:00pm, 11th Feb, 2025
7	Vanguard News	CBN launches MDA Naira payment solu	Authentic	Public	https://www.vanguardngr.com/2025/01/cl	2:00pm, 11th Feb, 2025
8	The Nation Online	Not attending Hallelujah Challenge does	Authentic	Public	https://thenationonlineng.net/not-attending	4:30pm, 11th Feb, 2023
9	Punch Online	Edo PDP urges EFCC to probe attorney-	Authentic	Politics	https://punchng.com/edo-pdp-urges-efcc-	1:20pm, 12th sept, 2023
10	The Guardian Nigeria	So you have 7 days to look more attracti	Authentic	Public	https://guardian.ng/life/so-you-have-7-day	4:30pm, 11th Feb, 2025
11	Daily Trust	Farming is the stupidest thing to do for a	Authentic	Public	https://dailytrust.com/farming-is-the-stup	4:30pm, 11th Feb, 2026
12	Vanguard News	Kanu raises alarm, alleges tricks by FG t	Authentic	Public	https://www.vanguardngr.com/2025/02/k-	4:30pm, 11th Feb, 2027
13	The Nation Online	ACF hails establishment of development	Authentic	Public	https://thenationonlineng.net/acf-hails-est	4:30pm, 11th Feb, 2028
14	Punch Online	N500m subsidy: Lagos poultry farmers p	Authentic	Public	https://guardian.ng/news/nigeria/fg-reaffir	1:20pm, 12th sept, 2023
15	The Guardian Nigeria	The electricity and telcom tariff hike	Authentic	Public	https://guardian.ng/opinion/the-electricity	9:20am, 20th Mar, 2023
16	Daily Trust	Price war: Nigerians dump NNPCL petro	Authentic	Public	https://dailypost.ng/2025/02/18/price-war	9:20am, 20th Mar, 2023
17	Vanguard News	Over 35,000km of Federal Roads require	Authentic	Public	https://www.vanguardngr.com/2025/02/o	9:20am, 20th Mar, 2023

Figure 5: Sample of collected news data.

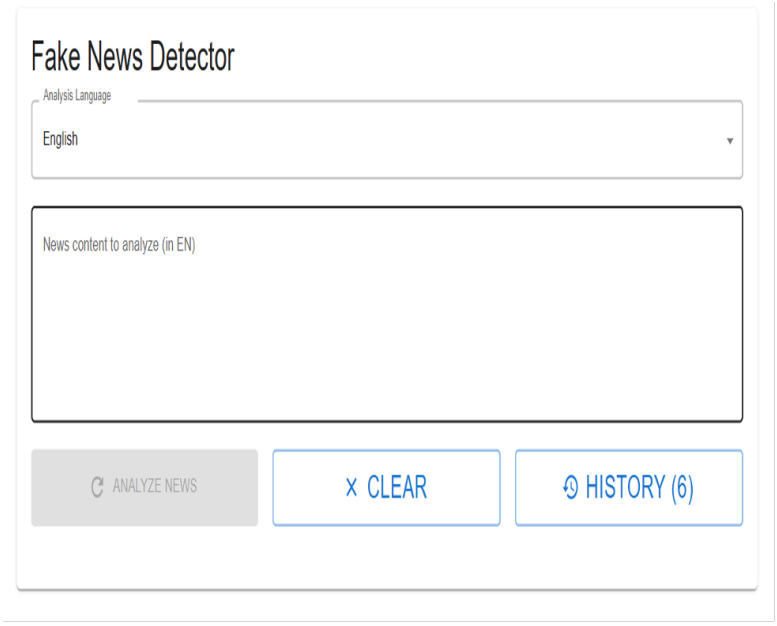


Figure 6: Landing interface.

4.1. Dataset preview and availability

Figure 5 shows a spreadsheet sample of the collected dataset. The sample was screened against linguistic and regulatory standards, and labels assigned to newspaper articles were aligned with protections and guidelines from the NBC, NCC, and NITDA. The authors reported that annotators were trained to focus on objective and verifiable violations, reducing bias and supporting a fair dataset. The dataset links provided by the authors are a dataset file and a dataset spreadsheet.

4.2. System interface

Figure 5 shows the system interface in which users input news text for verification.
Figure 7 shows the interface used to select the preferred language for verification.
Figure 8 shows an English-language news article that the system verified as authentic.
Figure 9 shows an English-language news article that the system verified as false.
Figures 6–9 illustrate the system interface for real-time news verification: the landing interface, language selection, real-news output, and fake-news output. The interface was developed using Next.js, TypeScript, and Material-UI and communicates with the fine-tuned BERT model through an application programming interface (API). It returns classification labels (fake or real) and confidence scores. The system was deployed using a microservices architecture and achieved inference latency of less than 400 ms,

Figure 7: Language-selection interface.

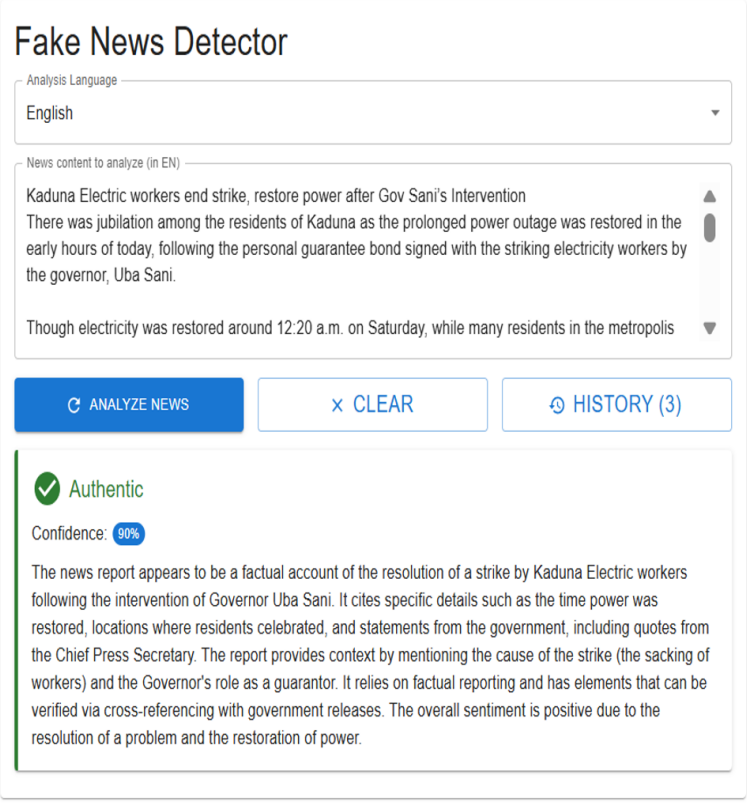


Figure 8: Real-news output.

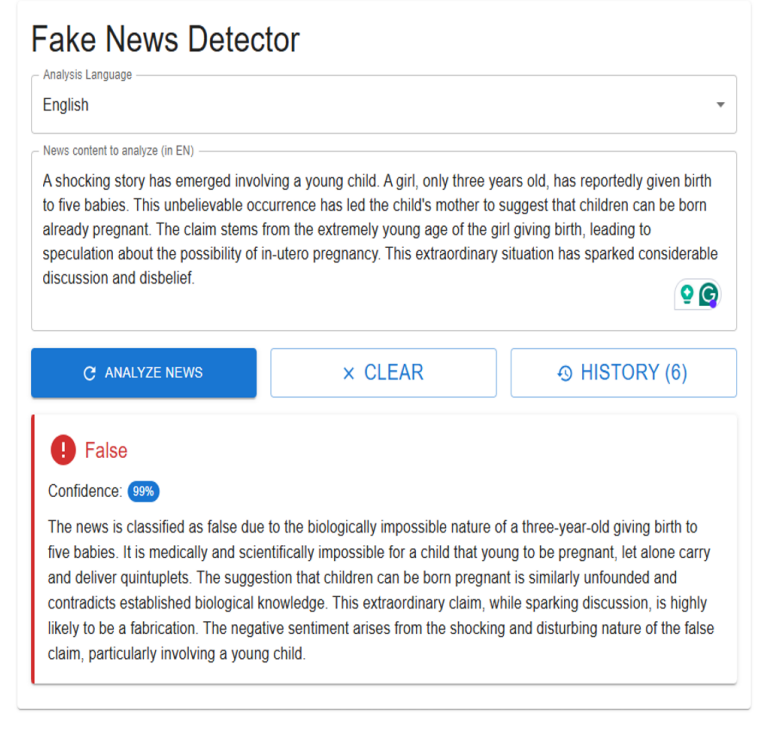


Figure 9: Fake-news output.

supporting high-traffic environments. The responsive layout makes it usable on desktop, tablet, and mobile devices. The live system is available at https://real-time-fake-news-detection2.vercel.app/.

5. Discussion

The proposed culturally aware BERT model achieved 91.3% accuracy, outperforming the traditional ML models tested for fake-news detection in the Nigerian context. The system addresses multilingual and regulatory issues in Nigeria and achieved a precision of 90.8%, representing a conservative and ethically compatible approach to misinformation detection in politically sensitive and ethnically diverse settings. Language-adaptive fine-tuning supported consistent performance across indigenous languages, while the slight reduction in recall reflects a preference for reliability over aggressive detection. Incorporating regulatory language during annotation, rather than during inference, oriented the model toward compliance-aware learning without adding rule-based bias or reducing transparency.

6. Conclusion

This study presents a culturally aware NLP framework that uses BERT to detect fake news in Nigerian digital media. By combining regulatory-guided annotation, language-adaptive fine-tuning, and rigorous evaluation across multiple Nigerian languages, the system achieved strong cross-language performance and high overall accuracy. The findings suggest that transformer-based designs can help mitigate misinformation in low-resource and multilingual settings when they are localized and systematically evaluated. The dashboard interface demonstrates the practical applicability of the framework for journalists, scholars, policymakers, and the public. Future research should develop explainability tools, expand indigenous-language corpora, and integrate multimodal data to improve transparency and recall in AI-based fake-news detection in Nigeria.

Data availability

The dataset links provided by the authors are available as a dataset file and a dataset spreadsheet. The code link provided by the authors is available as a Google Colab notebook.

Declaration of competing interest

The authors declare no competing interests.

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