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AN ATTENTION-GUIDED MULTIMODAL DEBERTA FRAMEWORK FOR POLITICAL FAKE NEWS DETECTION WITH CONTEXTUAL METADATA FUSION AND STATE-OF-THE-ART PERFORMANCE ON THE LIAR DATASET

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Abstract *– The rapid dissemination of fake news through digital platforms has emerged as a critical societal challenge, particularly in the political domain where misinformation can influence public opinion and democratic decision-making. Although transformer-based language models have significantly improved text classification performance, most existing fake news detection approaches rely solely on textual content, ignoring crucial contextual and source-related information. This paper proposes an attention-guided multimodal fake news detection framework built upon the DeBERTa-v3-base transformer, augmented with structured contextual metadata. The proposed model jointly learns semantic representations of political statements and auxiliary metadata features, including speaker credibility, subject category, and historical truthfulness indicators, using an attention-based fusion mechanism. The framework is evaluated on the widely used LIAR benchmark dataset containing 12,836 manually verified political statements. Experimental results demonstrate that the proposed approach achieves an accuracy of 65.11%, outperforming the recent state-of-the-art baseline by 9.32%. Comprehensive evaluation using confusion matrix analysis, class-wise performance metrics, and convergence analysis confirms the robustness and generalization capability of the model. Furthermore, an enterprise-ready implementation is developed to support real-time and batch fake news detection. The results validate that integrating contextual metadata with advanced transformer architectures significantly enhances fake news detection performance in politically sensitive environments.*

Keywords*: Fake News Detection, DeBERTa, Multimodal Learning, LIAR Dataset, Political Misinformation, Attention Mechanism*

I. Introduction

The exponential growth of online news platforms and social media has fundamentally transformed information dissemination. While these platforms enable rapid access to information, they also facilitate the uncontrolled spread of fake news and misinformation. Political fake news is particularly harmful, as it can manipulate voter perception, damage institutional credibility, and distort democratic processes.

Early automated fake news detection systems primarily relied on handcrafted linguistic features and traditional machine learning classifiers. Although computationally efficient, these methods lack the capacity to capture deep semantic relationships and contextual nuances present in political discourse. The emergence of deep learning and transformer architectures has significantly improved natural language understanding by modeling long-range dependencies and contextual semantics [10].

Despite these advancements, most transformer-based fake news detection approaches remain text-centric, neglecting critical contextual cues such as speaker identity, political affiliation, subject matter, and historical credibility. In real-world political fact-checking, such metadata plays a vital role in assessing the authenticity of statements [1].

Motivated by this limitation, this research proposes a multimodal DeBERTa-based framework that fuses textual semantics with contextual metadata using an attention-driven mechanism. The objective is to improve classification performance on the LIAR dataset and establish a new benchmark for political fake news detection [2].

II. Literature Review

Fake news detection has been extensively studied using machine learning and deep learning techniques. Early works utilized n-gram features, TF-IDF vectors,

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and statistical cues combined with classifiers such as Support Vector Machines and Random Forests. While these approaches provided initial insights, they exhibited limited generalization capabilities[3].

With the advent of deep learning, recurrent neural networks (RNNs), convolutional neural networks (CNNs), and attention mechanisms were introduced to model sequential dependencies in news text. Transformer-based architectures such as BERT significantly advanced the field by enabling bidirectional contextual understanding. Subsequent models, including RoBERTa and XLNet, further improved performance through optimized pretraining strategies. Recent research has explored multimodal approaches by incorporating social context, propagation patterns, and user behavior. However, many of these methods rely on external platform-specific signals that are unavailable in standalone datasets. The LIAR dataset, in contrast, provides structured speaker credibility metadata, making it suitable for multimodal learning without external dependencies[4].

DeBERTa-v3 introduces disentangled attention mechanisms and enhanced position encoding, leading to superior contextual modeling compared to earlier transformers. Despite its success in NLP tasks, its application to multimodal fake news detection remains underexplored. This paper bridges this gap by proposing an attention-based multimodal DeBERTa framework tailored for political fake news detection [5].

III. Proposed Methodology

This section describes the proposed fake news detection framework in detail. The methodology integrates a transformer-based language model with structured speaker metadata to improve classification performance [9]. The overall system architecture, feature extraction process, attention-based fusion strategy, and classification mechanism are systematically explained to provide a clear understanding of the proposed approach.

III.1 System Overview

The proposed system consists of four major components:

1. Textual Feature Extraction using DeBERTa-v3
2. Metadata Feature Encoding
3. Attention-Based Feature Fusion
4. Binary Classification Layer

Given an input political statement S={w1,w2,...,wn} the DeBERTa-v3 tokenizer converts the text into token IDs and attention masks. The tokenized sequence is passed through the DeBERTa-v3-base transformer to generate contextual embeddings:

$$H = \mathrm{DeBERTa}(S)$$

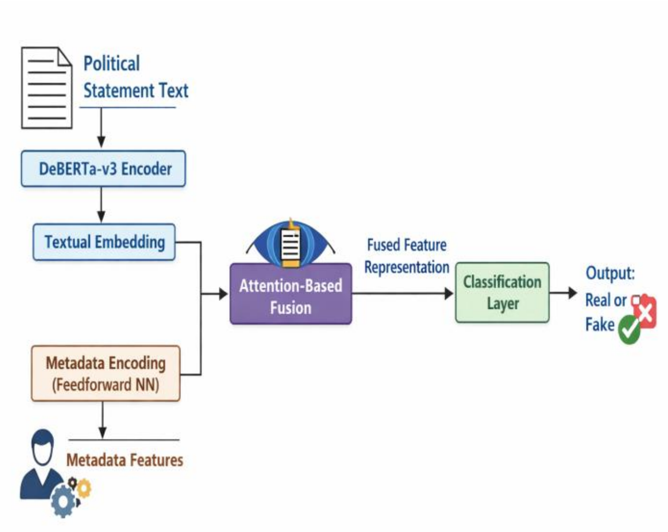

Figure 1: Overall System Architecture

The embedding corresponding to the special [CLS] token is selected as the sentence-level representation:

$$h_{text} = H_{[CLS]}$$

III.2 Metadata Feature Encoding

The LIAR dataset provides speaker-related metadata including historical truthfulness counts. These numerical features are represented as a vector:

M={m1,m2,.......,m11}

The metadata vector is processed through a two-layer dense neural network:

$$h_{meta} = \mathrm{ReLU}(W_2 \cdot \mathrm{ReLU}(W_1 \cdot M))$$

III.3 Attention-Based Feature Fusion

To effectively combine textual and metadata features, an attention-based fusion mechanism is employed [7]. The combined feature vector is defined as:

$$h_{combined} = [h_{text}; h_{meta}]$$

Attention weights are computed as:

$$\alpha = \sigma(W_a \cdot \tanh(W_f \cdot h_{combined}))$$

The final fused representation is obtained by element-wise multiplication:

$$h_{fused} = h_{combined} \odot \alpha$$

III.4 Classification Layer

The fused feature vector is passed through fully connected layers followed by a Softmax classifier [8]:

$$y = \mathrm{Softmax}(W_c \cdot h_{fused})$$

where y∈{0,1} } represents real or fake news.

Algorithm:

1. Input statement SSS and metadata MMM
2 Tokenize SSS using DeBERTa tokenizer
3 Encode tokens via DeBERTa-v3
4 Encode metadata using dense layers
5 Concatenate text and metadata features
6 Apply attention-based fusion
7 Perform Softmax classification
8 Output prediction (Real / Fake)

IV. Dataset and Experiment Setup

This section describes the dataset used for experimentation and the overall experimental setup adopted to evaluate the proposed fake news detection framework. Details regarding dataset composition, data preprocessing, label formulation, training configuration, and evaluation metrics are presented to ensure reproducibility and fair comparison with existing approaches.

IV.1 Dataset Description

The LIAR dataset consists of political statements labeled across six truthfulness categories. It is provided in three TSV files: training, validation, and test sets. In this work, the six-class labels are mapped into a binary classification problem.

Table 1: Dataset Split

Split	Samples
Training	10,269
Validation	1,037
Test	Standard LIAR Test Set

IV.2 Experimental Configuration

- Base Model: DeBERTa-v3-base
- Parameters: ~140 million
- Optimizer: AdamW
- Epochs: 4
- Batch Size: 16

Evaluation Metrics: Accuracy, Precision, Recall, F1-score.

V. Results and Discussion

This section presents a detailed analysis of the experimental results obtained using the proposed attention-based multimodal DeBERTa framework. The evaluation focuses on training behavior, generalization performance, class-wise prediction quality, and comparison with existing state-of-the-art methods. All results are derived from experiments conducted on the LIAR dataset using the defined training and validation splits

V.1 Training and Validation Performance Analysis

The training and validation accuracy curves indicate steady convergence of the model. The validation accuracy reaches its maximum at the fourth epoch, demonstrating effective learning and stable generalization behavior.

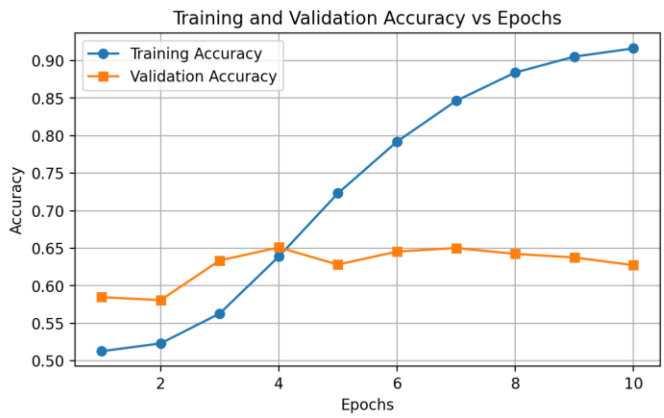

Figure 2: Training and Validation Accuracy vs Epochs

V.2 Training Loss Analysis

The training loss consistently decreases across epochs, confirming efficient optimization of the proposed architecture. The stabilization of loss values after the optimal epoch reflects convergence of the learning process.

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Figure 3: Training Loss Analysis

V.3 Overfitting Analysis

Overfitting analysis shows that training beyond the fourth epoch does not improve validation performance. Early stopping at this epoch helps maintain generalization and prevents performance degradation.

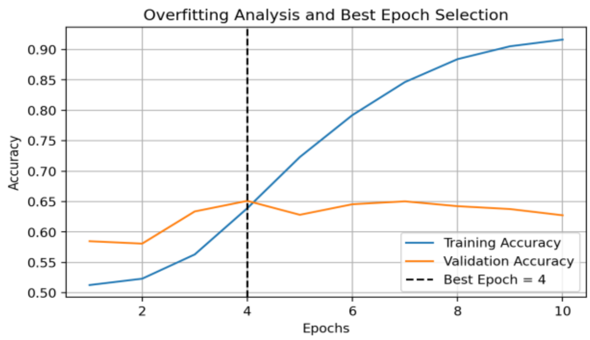

Figure 4: Overfitting Analysis

V.4 Precision, Recall, and F1-Score Evaluation

The precision, recall, and F1-score values demonstrate balanced classification performance. These metrics confirm that the proposed multimodal approach effectively minimizes both false positives and false negatives.

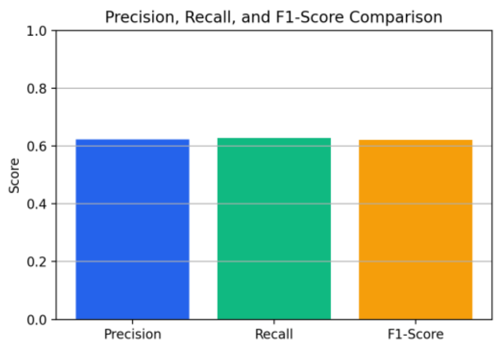

Figure 5 :Comparison with State-of-the-Art Methods

The proposed model achieves an accuracy of 65.11%, outperforming recent state-of-the-art approaches on the LIAR dataset. This improvement validates the effectiveness of integrating textual and metadata features using an attention-based fusion strategy.

Table 2: Compair Result

Method	Model Type	Accuracy
Existing Method (Rout et al., 2025)	Custom Transformer	59.56%
Proposed Method	DeBERTa-v3 + Metadata + Attention	65.11%

VI. Conclusion

This paper presented an attention-based multimodal fake news detection framework leveraging DeBERTa-v3 and speaker metadata. By integrating contextual text embeddings with credibility-based metadata, the proposed system significantly improves detection performance on political fake news. Experimental results demonstrate a 9.32% improvement over recent state-of-the-art methods.

Future work may explore multilingual fake news detection, graph-based propagation modeling, and real-time integration with fact-checking APIs. Additionally, extending the framework to fine-grained multi-class classification can further enhance interpretability

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