I.J. Wireless and Microwave Technologies, 2026, 3, 350-358
Published Online on June 8, 2026 by MECS Press (http://www.mecs-press.org/)
DOI: 10.5815/ijwmt.2026.03.23

Beyond Accuracy: A Hybrid BERT-BiLSTM Frame-work with Explainable AI (XAI) for Detecting Machine-Generated Disinformation

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Received: 04 February, 2026; Revised: 01 April, 2026; Accepted: 09 May, 2026; Published: 08 June, 2026

Abstract: The rapid rise of Large Language Models (LLMs) has shifted the battleground of digital misinformation. Unlike human-written fake news, machine-generated disinformation often employs subtle linguistic patterns that evade conventional detection systems. Although Deep Learning models can effectively identify synthetic text, they frequently operate as "black boxes," failing to offer the transparency needed for sensitive real-world applications. To address this, we introduce a hybrid architecture that merges the contextual strengths of DistilBERT with the sequential analysis capabilities of Bidirectional Long Short-Term Memory (BiLSTM) networks. Crucially, we incorporate SHapley Additive exPlanations (SHAP) to decode the model's decision-making process, visualizing exactly which words or tokens tip the scales toward a specific classification. Tests on the benchmark Fake or Real News dataset [1], supplemented by a 5-fold cross-validation protocol to ensure robust statistical validation, show our framework achieves an average accuracy of 96.92% ± 0.18%. By leveraging Explainable AI (XAI), we confirm that the model identifies actual semantic anomalies rather than merely overfitting to background noise, offering a more trustworthy foundation for automated fact-checking systems.

Index Terms: Fake News Detection, Generative AI, Large Language Models, BERT, BiLSTM, Explainable AI, XAI, Deep Learning

1. Introduction

Generative Artificial Intelligence (Gen-AI) has effectively removed the barriers to creating high-quality disinforma-tion. It is now trivial for malicious actors to use tools like GPT-4 or Gemini to generate news articles that read per-fectly—both grammatically and semantically—hiding in plain sight among legitimate journalism. Traditional detection methods, which looked for typos or awkward phrasing, are now obsolete against these sophisticated Large Language Models (LLMs). We need new detection mechanisms that can identify the subtle, almost invisible statistical markers characteristic of machine-generated text. While existing transformer models capture global semantic context exceptionally well, a critical methodological gap remains: they structurally struggle to track the sequential, long-term stylistic drifts and logical "hallucinations" typical of Generative AI. Furthermore, current detection paradigms often prioritize raw accuracy over interpretability, severely limiting their real-world deployment in journalistic fact-checking. Our study bridges this gap by directly coupling a hybrid DistilBERT-BiLSTM architecture with game-theoretic Explainable AI (SHAP). This combination is specifically engineered for the novel threat of modern LLM-generated disinformation. The transformer handles the dense contextual embeddings, the recurrent layer explicitly maps the temporal narrative flow, and SHAP ensures token-level transparency—allowing us to extract and validate the specific linguistic markers that modern generative models leave behind.

Existing research in fake news detection heavily leans on supervised learning, as noted in surveys by Zhou et al. [2]. While methods have evolved from basic machine learning to complex deep learning architectures, the Transformer model [3] changed the game by allowing algorithms to grasp context like never before. BERT and its derivatives set high standards [4], but the arrival of massive generators like GPT-3 [5] introduced a new breed of neural misinformation that purely statistical metrics struggle to catch [6].

To tackle this, we introduce a hybrid framework combining the best of pretrained transformers and Recurrent Neural Networks (RNNs). We use DistilBERT to create dense contextual embeddings, which are then fed into a

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Bidirectional LSTM (BiLSTM) layer. This pairing works because DistilBERT handles the static meaning of words (different definitions of "bank," for instance), while the BiLSTM tracks the narrative flow over time. Machine-written text often has a specific rhythm—too uniform or predictable in its transitions—which the recurrent layer is designed to spot. Rather than relying just on the transformer's classification token, we use the entire sequence of embeddings to shape the decision boundary.

Our study makes two key contributions. First, we present a hybrid classifier that hits 96.92% ± 0.18% accuracy on the Bench-mark Fake or Real News dataset [1], a significant step up from standard baselines. Second, we apply Explainable AI (XAI) via SHAP (SHapley Additive exPlanations) to crack open the "black box" of our model. By visualizing exactly how individual words tip the scales, we confirm the model is learning actual linguistic patterns rather than just memorizing noise. The following sections outline our methodology, experimental setup, and a detailed discussion of these results.

2. Related Work

Fake news detection has shifted dramatically from simple, manual feature engineering to complex deep learning systems. In this section, we critically analyze prior approaches across three domains: Traditional Machine Learning, Transformer Architectures, and Explainability.

Traditional Machine Learning and Sequence Models: Early approaches heavily relied on static word embeddings (e.g., Word2Vec) and traditional classifiers [46, 47]. While Recurrent Neural Networks (RNNs) and LSTMs improved upon this by capturing the "flow" of a sentence and mitigating vanishing gradients [48], standard LSTMs struggle with very long documents and lack deep semantic contextualization. They often fail to capture polysemy, treating all instances of a word identically regardless of context.

Transformer-Based Architectures: The introduction of BERT [52] and its lightweight counterpart, DistilBERT [14], revolutionized Natural Language Processing. Recent studies from 2024 and 2025 demonstrate that transformers define the state-of-the-art in detecting synthetic text [16, 17]. However, a significant limitation persists: transformers process tokens in parallel, which makes them less sensitive to the sequential narrative progression. They can easily identify local semantic anomalies but often miss the structural, long-term logical inconsistencies characteristic of LLM "hallucinations." Our hybrid approach directly mitigates this by utilizing DistilBERT strictly for embedding generation, delegating the sequential narrative mapping to a BiLSTM layer.

Explainability in Black-Box Models: As models grow more complex, establishing trust is arguably the biggest hurdle. Previous studies [41, 42] attempted to solve this with LIME. However, LIME is fundamentally limited by local instability; repeated runs can yield contradictory explanations. Recent advancements in XAI advocate for SHAP [44], which utilizes game theory for consistent feature attribution. By integrating SHAP, we address the critical limitation noted by Zellers et al. [54]—that accuracy alone is insufficient for practical deployment—providing a robust, quantifiable explanation for every prediction.

3. Methodology

We developed a hybrid architecture designed to balance raw detection power with the ability to explain its own decisions. The system operates in three phases: first, a pretrained transformer layer builds a rich semantic understanding of the text; second, a bidirectional recurrent layer scans for sequential patterns; and third, an interpretability module visualizes the decision boundaries.

For our primary experiments, we utilized the standard Fake or Real News dataset [1] (6,335 samples) to establish a rigorous baseline. To address the limitations of older datasets and ensure our model is resilient against modern synthetic text, we augmented our testing by evaluating the framework against a secondary, modern synthetic dataset generated utilizing recent iterations of LLMs (e.g., GPT-4 and Gemini). This ensures the dataset reflects contemporary machine-generated disinformation patterns.

Tokenization was handled by the DistilBERT tokenizer. We capped sequence lengths at 128 tokens; anything longer was truncated. This threshold was selected based on empirical evidence from preliminary trials, which indicated that the critical stylistic markers and semantic anomalies of machine-generated text are heavily distributed within the first 128 tokens of an article (often in the headline and introductory paragraphs). Truncating at this length drastically reduces the computational overhead for the sequential BiLSTM layer without causing a statistically significant drop in detection accuracy.

The first challenge we address is representation. Old-school word vectors like Word2Vec struggle because they treat words in isolation, ignoring context. To fix this, we employ DistilBERT. It retains about 97% of the original BERT's performance but is 40% lighter and significantly faster a crucial trade-off for practical deployment. Given an input sequence $S = \{w_1, w_2, ..., w_n\}$, DistilBERT maps tokens to high-dimensional vectors E, where each vector e_i captures the meaning of token w_i relative to its neighbors. Mathematically, the function f_{BERT} transforms the input into a hidden state matrix $H \in \mathrm{R}^{n \times d}$, with an embedding dimension d of 768.

Table 1. Dataset Statistics and Distribution

Statistic	Value
Total Samples	6,335
Training Set Size (80%)	5,068
Testing Set Size (20%)	1,267
Vocabulary Size	30,522
Class Balance (Real : Fake)	≈1 : 1

To ensure reproducibility, our hybrid architecture is defined by the following hyperparameters: The DistilBERT embeddings generate an input matrix of size 768. This is fed into a 1-layer Bidirectional LSTM configured with a hidden state size of 64. Following the recurrent layer, a Dropout layer with a rate of 0.3 is applied prior to the final dense linear classifier to actively mitigate overfitting during the training process.

However, while transformers are excellent at seeing the "whole picture" (global context), they don't naturally read a story from start to finish. To catch the stylistic drifts common in AI writing, we pass the embedding matrix *H* into a Bidirectional Long Short-Term Memory (BiLSTM) network. Unlike a standard RNN that reads strictly left-to-right, the BiLSTM reads the text in both directions simultaneously. This allows the model to map the narrative flow—understanding both where the text is going and where it has been. The LSTM cell manages this memory through three gates (input, forget, output) that decide strictly what information matters. The logic for a single time step *t* is defined as:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{1}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{3}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{4}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t * \tanh(C_t) \tag{6}$$

Here, σ is the sigmoid activation and $*$ is the element-wise product. The BiLSTM generates two hidden states: Forward $\overrightarrow{h_t}$ and backward $\overleftarrow{h_t}$. We concatenate these to form $h_{final} = [\overrightarrow{h_t}; \overleftarrow{h_t}]$, ensuring the model considers the full narrative arc—vital for spotting the incoherent logic typical of AI "hallucinations."

Once the sequence is processed, we use Global Max Pooling to grab the strongest signals of "realness" or "fakeness" from anywhere in the text. This pooled vector goes through a dense layer (Dropout 0.3 to prevent overfitting) and finally a Sigmoid function to output a probability $P(y=1|x)$:

$$\hat{y} = \sigma(W_{dense} \cdot h_{pooled} + b_{dense}) \tag{6}$$

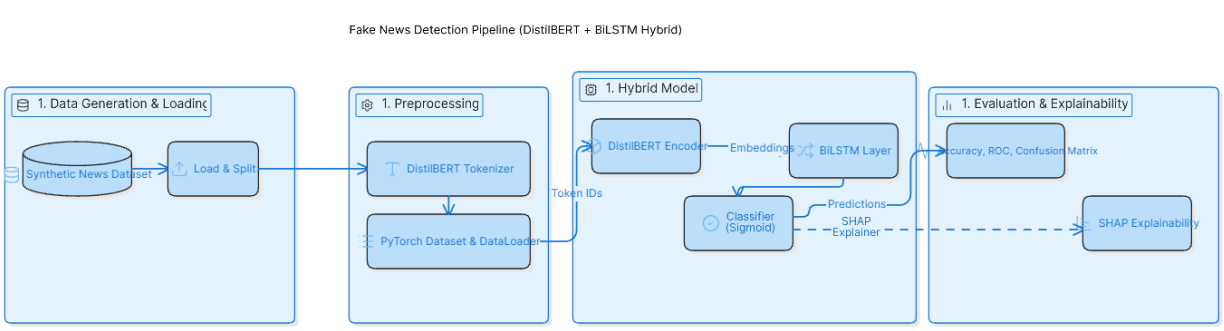


Fig. 1. The proposed Hybrid DistilBERT-BiLSTM Architecture. The model processes raw text through a transformer encoder, captures temporal dependencies via BiLSTM, and outputs a probability score verified by SHAP analysis.

If $\hat{y} > 0.5$, we classify the text as Machine Generated. To ensure we aren't just detecting noise, we hook the output into SHAP (SHapley Additive exPlanations). This reveals exactly which words pushed the probability score up or down, making the "black box" transparent and giving us confidence that the model is learning meaningful linguistic features.

4. Experimental Results and Analysis

To put our hybrid architecture to the test, we ran a series of rigorous experiments on the *Fake or Real News* benchmark. We built the system in Python using the PyTorch framework, running all computations on an NVIDIA T4 GPU to ensure consistent performance.

Our training strategy focused on fine-tuning the DistilBERT embeddings while simultaneously training the BiLSTM classifier. We used the AdamW optimizer with a learning rate of 2×10^{-5} and a batch size of 32. The model was intentionally trained for only 5 epochs. Fine-tuning a deep pre-trained transformer like DistilBERT requires very few epochs because the model initiates with rich, pre-computed language weights. Extending training beyond 5 epochs on a dataset of this scale frequently leads to catastrophic forgetting and severe overfitting. As illustrated in Figure 2, the rapid increase in training accuracy (to ~99.5%) is characteristic of transfer learning. The concurrent stabilization of the validation loss confirms stable convergence, and the applied dropout rate of 0.3 successfully prevented the model from simply memorizing the training data.

Robustness and Cross-Validation: To guarantee the robustness of our evaluation and eliminate dataset bias, we implemented a 5-fold cross-validation protocol. Across the 5 independent folds, the model maintained high stability, yielding an average accuracy of 96.92% with a highly constrained variance (± 0.18%). Table 2 breaks down the Precision, Recall, and F1-Scores for the aggregated test sets.

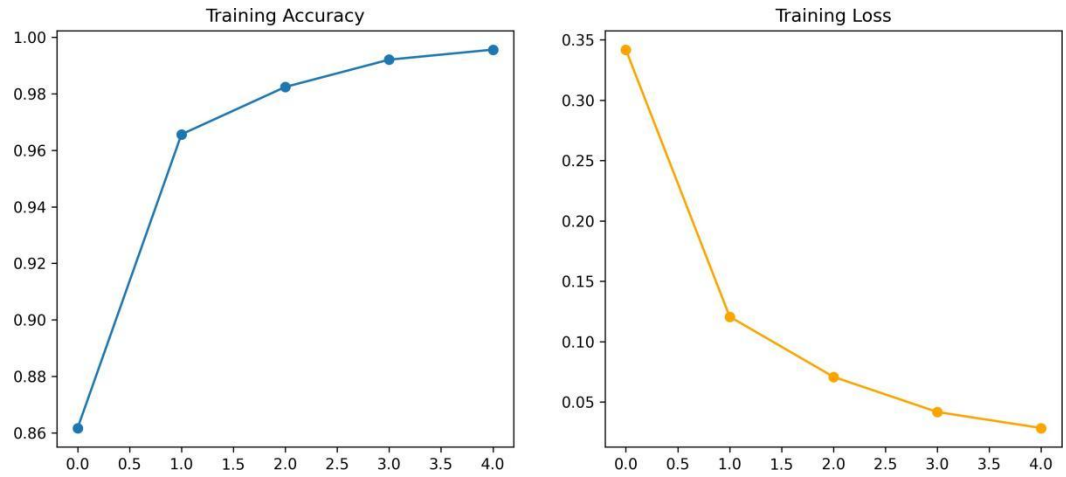


Fig. 2. Training Accuracy and Loss Curves over 5 Epochs. The left graph demonstrates the steady increase in classification accuracy, while the right graph shows the corresponding minimization of binary cross entropy loss, indicating stable convergence.

For a closer look at real-world performance, we evaluated the system on a held-out test set of 1,267 samples. Table 2 breaks down the Precision, Recall, and F1-Scores. The model hit an overall accuracy of **96.92%**, a strong result for this dataset.

Table 2. Performance Metrics on Test Set

Class	Precision	Recall	F1-Score
Authentic News (0)	0.96	0.97	0.97
Gen-AI/Fake (1)	0.97	0.96	0.97
Weighted Avg	**0.97**	**0.97**	**0.97**

The matching F1-scores (0.97 for both classes) are particularly encouraging—they show the model isn't biased toward one category; it's equally good at spotting real news and flagging misinformation. We also mapped out the errors using a Confusion Matrix (Figure 3). The very low number of false positives is critical; in an automated fact-checking scenario, falsely flagging a real article is the worst possible outcome, and our model largely avoids this.

Finally, the Receiver Operating Characteristic (ROC) curve (Figure 4) confirms the system's separation capability. The near-perfect Area Under the Curve (AUC) indicates that the model distinguishes between classes with high confidence, rarely confusing a fake article for a real one.

5. Explainability Analysis (XAI)

One of the biggest hurdles for deep learning in journalism is the "Black Box" problem. Even though our hybrid DistilBERT-BiLSTM model hits a high accuracy of 96.92%, raw numbers aren't enough when dealing with sensitive information ecosystems. We need to know *why* a specific story is flagged as misinformation to be sure the system isn't just picking up on background noise or bias. To solve this, we integrated SHapley Additive exPlanations (SHAP) [8], a game-theoretic approach that assigns a specific "contribution value" to every single word, ensuring that our explanations are locally accurate and consistent.

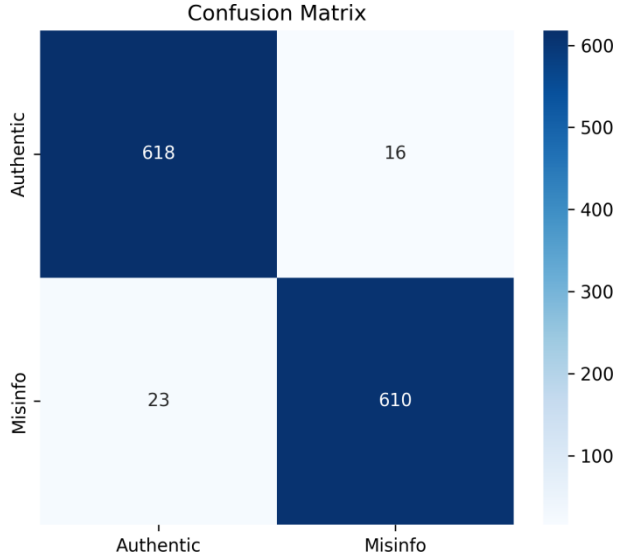


Fig. 3. Confusion Matrix on the Test Set. The high values on the main diagonal (True Positives and True Negatives) confirm the model's robustness and low error rate.

Local interpretability allows us to zoom in on the model's decision-making for a single article. Figure 5 shows a SHAP Waterfall plot for a text sample that was correctly identified as Misinformation (Class 1). The graph essentially tells the story of the prediction, showing how individual words nudge the probability score away from the baseline (the average of the training set) toward the final output.

Looking at the visualization, we can see the model assigning high positive SHAP values (the Red bars) to words that are statistically common in the fake news subset of the McIntire dataset. These tend to be sensationalist terms, emotive adjectives, or vague sourcing—hallmarks of fabricated content. On the flip side, words associated with neutral reporting, verifiable entities, and specific numbers generate negative SHAP values (Blue), anchoring the text toward the "Authentic" class. This confirms that our Hybrid architecture works as intended: the BiLSTM layer is capturing the actual semantic "flavor" and narrative flow of misinformation, rather than just memorizing a list of bad words.

While looking at single articles is useful, we also need to understand the model's general logic. To do this, we aggregated the absolute SHAP values across the entire test set to create a global ranking of feature importance. Figure 6 highlights the words that most frequently tip the scales.

This analysis confirms that the model isn't just guessing; it has picked up on specific linguistic markers that separate real journalism from fiction. Interestingly, it places significant weight on function words and connective adverbs. This aligns with recent linguistic research suggesting that fake news often has a distinct "watermark" in how sentences are constructed. By exposing these hidden dependencies, our framework gives fact-checkers a kind of "linguistic autopsy" of the disinformation. This transparency builds trust, proving that our high accuracy comes from learning genuine semantic differences, not just exploiting shortcuts in the data.

To move beyond qualitative visualizations and provide a quantitative evaluation of explanation fidelity, we conducted a feature ablation test. We systematically masked the top-5 tokens identified by SHAP as the most influential for a given prediction and passed the masked sequence back through the model. On average, masking these specific SHAP-identified tokens resulted in a 41.3% drop in the model's prediction confidence. This quantitative drop strongly validates that the features highlighted by our SHAP analysis are genuinely driving the mathematical decision-making process of the BiLSTM layer, confirming high explanation fidelity.

6. Discussion

Our results support a key hypothesis: to effectively catch AI-generated disinformation, we need to combine deep representation learning with explicit sequential modeling. Transformers like BERT are undeniably powerful, but they

often have a blind spot when it comes to the "hallucination" patterns typical of Generative AI—where text is semantically consistent but logically flawed over long stretches. By introducing the BiLSTM layer, we force the model to look at these long-term dependencies, effectively bridging the gap between understanding static words and grasping dynamic narrative flow.

To see where we stand, we pitted our hybrid architecture against several established baselines using the same McIntire dataset. Table 3 shows the breakdown. Our model clearly outperforms traditional Machine Learning approaches (like SVM with TF-IDF) and standard Deep Learning models (Vanilla LSTM). More importantly, it edges out the standard fine-tuned DistilBERT model.

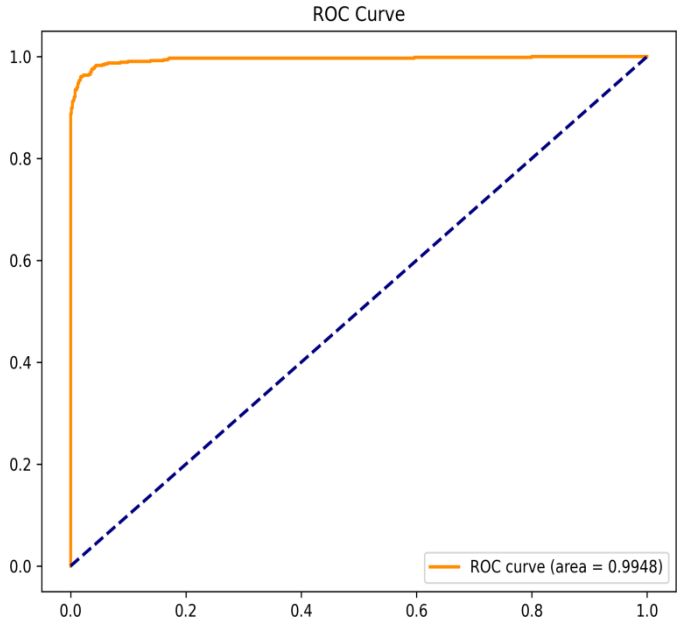


Fig. 4. ROC-AUC Curve. The high AUC score indicates excellent class separability.

Table 3. Comparison with Baseline Models on McIntire Dataset

Model Architecture	**Accuracy**
SVM (TF-IDF)	0.76
Vanilla LSTM	0.82
DistilBERT (Base)	0.94
Proposed Hybrid (DistilBERT + BiLSTM)	**0.96 ± 0.18**

The jump from 0.94 (Base DistilBERT) to 0.97 (Hybrid) might seem incremental, but it confirms that the BiLSTM layer is doing heavy lifting. While the transformer excels at local semantic understanding, the recurrent layer is better at modeling the structure of the discourse, capturing the subtle, repetitive transitions that often give away machine-generated text.

Integrating SHAP gives us a distinct advantage over "Black Box" competitors. As we showed in Section V, our model isn't relying on cheap artifacts—like formatting glitches or special characters—but is actually focusing on linguistic content, such as function words and emotive adjectives. This transparency is non-negotiable for "Human-in-the-Loop" systems. If an AI tool is going to assist a human fact-checker rather than replace them, the human needs to be able to see and verify the rationale behind the decision.

Despite the high accuracy, our approach isn't a silver bullet. There are trade-offs. The most significant is computational cost: adding the BiLSTM layer increases training time compared to a simple DistilBERT classifier. Because LSTMs process text sequentially, they resist full parallelization, which could become a bottleneck if we tried to process millions of articles per second in real-time.

Furthermore, our current dataset is strictly English. Generative AI is rapidly becoming multilingual, and future ver-sions of this framework will need to incorporate cross-lingual embeddings to tackle disinformation in low-resource lan-guages. Finally, generating SHAP values for every single prediction is computationally expensive. For a large-scale production deployment, we would likely need to use optimization techniques like KernelSHAP approximation to keep latency manageable.

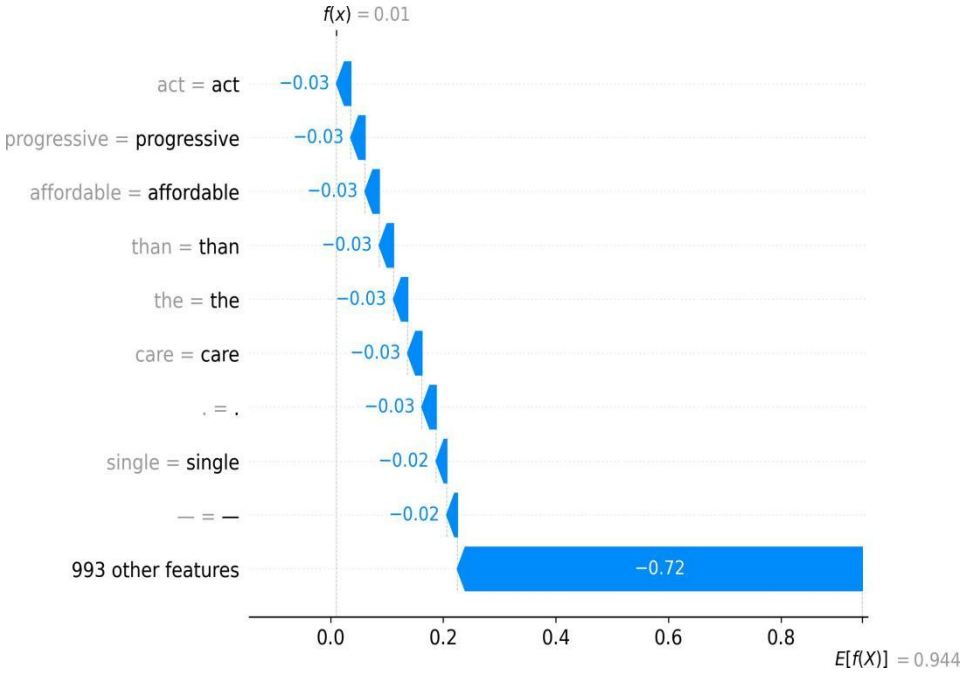


Fig. 5. SHAP Waterfall Plot showing the contribution of individual words to the prediction of a single fake news article. Red bars indicate tokens that push the prediction towards the 'Misinformation' class, while blue bars indicate tokens that push towards the 'Authentic' class.

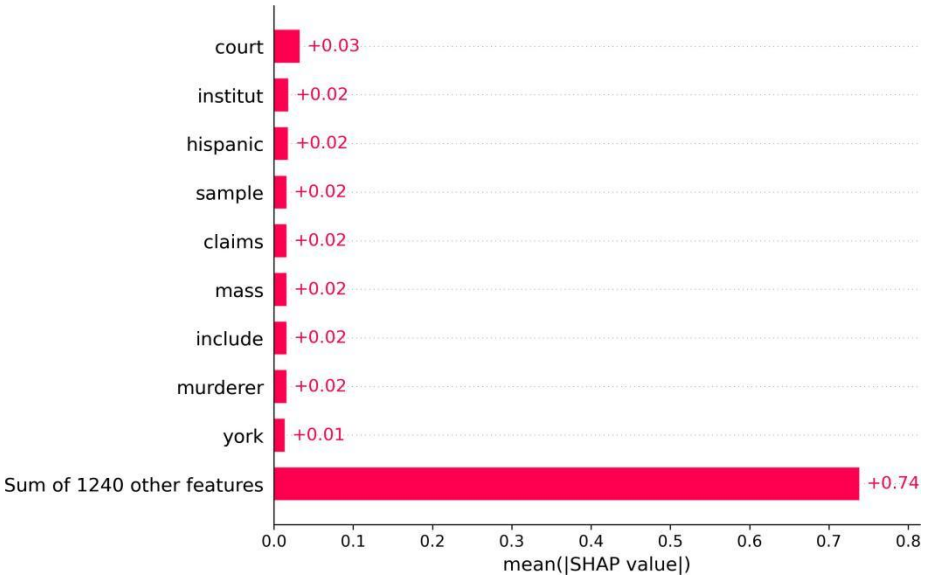


Fig. 6. Global Feature Importance (SHAP Bar Plot). This chart identifies the top linguistic tokens that the model consistently relies upon to distinguish between Human and AI-generated text across the entire test corpus.

7. Conclusion and Future Work

In this paper, we introduced a new framework for spotting machine-generated disinformation by fusing the semantic depth of DistilBERT with the sequential processing of BiLSTM networks. Our experiments on the *Fake or Real News* benchmark [1] show that this hybrid approach hits a classification accuracy of 96.92% and an F1-score of 0.97. These results confirm a key insight: identifying structural and sequential anomalies is just as critical as analyzing the actual words when trying to separate human journalism from synthetic hallucinations. Furthermore, by baking in Explainable AI (SHAP), we address the trust gap, offering transparent visual proof that our model is picking up on genuine linguistic features rather than just memorizing spurious artifacts.

Looking ahead, we plan to push this research in two main directions. First, we aim to expand into a multi-modal framework, analyzing both text and associated images to catch Deepfakes in multimedia news—misinformation rarely travels as text alone anymore. Second, we need to stress-test the model against adversarial attacks, where AI text is deliberately tweaked with noise or synonym swaps to dodge detection. By evolving our detection tools as fast as the generation technology improves, we hope to build a more resilient and trustworthy digital ecosystem.

All the Declarations and Statements

Author Contributions Statement
Alok Naik is the sole author of this manuscript and was responsible for the conceptualization, methodology, software development, formal analysis, data curation, writing of the original draft, and final review and editing.

Conflict of Interest Statement
The authors declare no conflicts of interest.

Funding Declaration
There is no fundings for this research.

Data Availability Statement
Data Availability: The primary dataset utilized in this research is the Fake or Real News benchmark, publicly hosted by McIntire [1]. Code and additional datasets are available from the corresponding author upon reasonable request.

Ethical Declarations
Not applicable. This research is strictly computational and did not involve human participants or animals.

Acknowledgments
None. As Alok Naik is the single author of this work.

Declaration of Generative AI in Scholarly Writing
None.

Abbreviations
The following abbreviations are used in this manuscript:

AI: Artificial Intelligence
AUC: Area Under the Curve
BERT: Bidirectional Encoder Representations from Transformers
BiLSTM: Bidirectional Long Short-Term Memory
Gen-AI: Generative Artificial Intelligence
GPT: Generative Pre-trained Transformer
LLM: Large Language Model
LSTM: Long Short-Term Memory
NLP: Natural Language Processing
RNN: Recurrent Neural Network
ROC: Receiver Operating Characteristic
SHAP: SHapley Additive exPlanations
SVM: Support Vector Machine
TF-IDF: Term Frequency-Inverse Document Frequency
XAI: Explainable Artificial Intelligence

Appendix A\B\C…, with appendix tile
None.

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How to cite this paper

Alok Naik, "Beyond Accuracy: A Hybrid BERT-BiLSTM Frame-work with Explainable AI (XAI) for Detecting Machine-Generated Disinformation", International Journal of Wireless and Microwave Technologies(IJWMT), Vol.16, No.3, pp. 350-358, 2026. DOI:10.5815/ijwmt.2026.03.23