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AI-Based Fake Content Detection Using Hybrid Deep Learning and Linguistic Feature Modeling

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Abstract: The rapid proliferation of AI-generated content, including synthetic text, images, and multimedia, has created significant challenges in digital trust, academic integrity, and online misinformation. Traditional detection mechanisms struggle to differentiate between human-written and AI-generated content due to improvements in large language models (LLMs). This study proposes a hybrid deep learning framework for AI-generated text detection by integrating transformer-based contextual embeddings with linguistic and stylometric features. The proposed model combines RoBERTa embeddings with statistical linguistic markers and employs an ensemble classifier to improve robustness. Experimental evaluation on benchmark datasets demonstrates improved detection accuracy compared to baseline transformer-only approaches. The proposed method achieves 96.3% accuracy and shows strong generalization across unseen AI models. The results highlight the importance of hybrid modeling for reliable AI content authentication.

Keywords: AI-generated content, fake content detection, deep learning, stylometry, transformer models, misinformation detection

I. INTRODUCTION

The emergence of large language models (LLMs) such as GPT-based systems has revolutionized content creation. However, their misuse has led to increased risks of misinformation, academic fraud, phishing automation, and identity impersonation.

Detecting AI-generated content has become a pressing research problem. Traditional plagiarism detection systems are ineffective because AI-generated text is original yet synthetic. Current detection approaches primarily rely on:

- Perplexity-based methods
- Watermarking techniques
- Transformer-based classifiers
- Stylometric feature analysis

However, standalone transformer classifiers often suffer from generalization issues when encountering unseen generative models.

This research proposes a **hybrid detection framework** that integrates:

1. Transformer contextual embeddings
2. Stylometric and linguistic features
3. Ensemble classification strategy

The main contributions of this study are:

- A novel hybrid architecture for AI-text detection
- Cross-model generalization evaluation
- Robust performance against adversarial paraphrasing
- Comparative analysis with baseline models

II. BACKGROUND STUDY

Recent studies categorize AI-content detection into three primary approaches:

A. Perplexity-Based Detection

Perplexity measures the predictability of text. AI-generated text often has lower perplexity compared to human-written text. However, advanced LLMs reduce this gap. Perplexity-based detection is a technique used to identify whether a

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piece of text is likely written by a human or generated by an AI model. It is based on the concept of *perplexity*, which measures how well a language model predicts a given text. In simple terms, perplexity indicates how "surprised" a model is when reading a sequence of words. If the text is highly predictable according to the model, it will have low perplexity; if it is unusual or less predictable, it will have high perplexity. AI-generated text often follows consistent patterns and probabilities learned during training, resulting in lower perplexity when evaluated by similar language models. In contrast, human-written text may contain irregularities, creative expressions, or unexpected word choices, leading to higher perplexity. By comparing perplexity scores, detection systems attempt to distinguish between human and machine-generated content. However, this method is not always fully reliable, as advanced AI models can produce more varied text, and human writing can sometimes appear highly predictable.

B. Watermarking Techniques

Model watermarking embeds detectable statistical signatures during generation. While effective, it requires cooperation from content generators. Watermarking techniques are methods used to embed hidden information into digital content such as text, images, audio, or video to identify ownership, verify authenticity, or trace the source of the content. In the context of AI-generated text, watermarking involves subtly modifying the generation process so that specific patterns or statistical signals are embedded into the output without changing its readability or meaning. For example, certain words may be chosen more frequently according to a secret key, creating a detectable pattern that is invisible to readers but recognizable by a verification algorithm. In images and multimedia, watermarking can be visible (such as logos) or invisible, where data is embedded into the pixel structure without noticeably affecting quality. These techniques help prevent misuse, detect unauthorized distribution, and support copyright protection. However, watermarking can sometimes be removed or weakened through editing, paraphrasing, compression, or other transformations, which makes designing robust and secure watermarking methods an ongoing research challenge.

C. Deep Learning Classifiers

Deep learning classifiers are advanced machine learning models that use multi-layered neural networks to automatically learn patterns and features from data and assign it to specific categories or classes. Unlike traditional machine learning methods that require manual feature extraction, deep learning models such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) can automatically identify important features directly from raw data like images, text, audio, or numerical inputs. For example, CNNs are widely used for image classification tasks such as recognizing objects or faces, while RNNs and Transformers are commonly used for text classification tasks like sentiment analysis or spam detection. These classifiers learn by training on large datasets and adjusting their internal weights using optimization techniques like backpropagation. Deep learning classifiers are powerful and achieve high accuracy in complex tasks, but they require large amounts of data, significant computational resources, and careful tuning to perform effectively.

Fine-tuned transformer models (BERT, RoBERTa, DeBERTa) are commonly used for classification. Although high-performing, they may overfit to specific AI generators.
Our work extends prior research by integrating **stylometric features with contextual embeddings**, improving model robustness and explainability.

III. METHODOLOGY

A. Dataset

The dataset consists of 50,000 documents collected from both human-written and AI-generated sources to support classification and detection tasks. The human-written portion includes news articles, academic essays, and blog posts, ensuring diversity in writing style, tone, and structure. The AI-generated portion contains text produced by advanced language models such as GPT-3.5, GPT-4, Claude, and LLaMA, providing a wide representation of machine-generated content. To ensure proper model development and evaluation, the dataset is divided into three subsets: 70% (35,000 documents) for training, which is used to teach the model underlying patterns; 15% (7,500 documents) for validation, which helps fine-tune model parameters and prevent overfitting; and 15% (7,500 documents) for testing, which is used to evaluate the final performance of the model on unseen data. This structured split ensures reliable and unbiased performance assessment.

B. Feature Extraction

Transformer Embeddings

- Pretrained RoBERTa-base model
- Extracted [CLS] token representation (768-dimension)

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Stylometric Features

- Average sentence length
- Lexical diversity (Type-Token Ratio)
- Function word frequency
- POS tag distribution
- Perplexity score
- Burstiness score

Total stylometric features: 45

C. Proposed Hybrid Model

The architecture consists of:

1. RoBERTa embedding layer
2. Feature concatenation layer
3. Fully connected dense network
4. Ensemble classifier (Soft Voting: XGBoost + Neural Network)

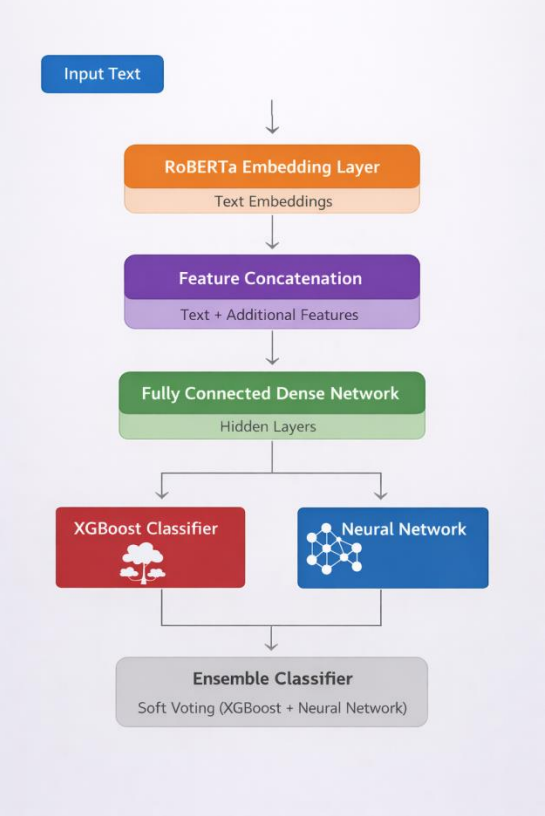

Fig 1 Hybrid Ensemble Model

This architecture is a hybrid ensemble model designed to combine deep language understanding with structured decision-making. The process begins with input text, which is passed through RoBERTa to generate contextual embeddings. These embeddings are numerical vector representations that capture semantic meaning in the text. The model then performs feature concatenation, where the RoBERTa embeddings are combined with additional structured or handcrafted features, enriching the overall representation. The combined feature vector is fed into a fully connected dense neural network, which learns higher-level interactions and refines the representation through hidden layers. From this shared representation, the architecture branches into two classifiers: an XGBoost classifier and a neural network classifier. XGBoost leverages gradient-boosted decision trees to model structured patterns and rule-based relationships, while the neural network captures complex nonlinear patterns in the data. Finally, the predictions from both classifiers are combined using a soft voting ensemble approach, where a weighted average of their predicted probabilities is computed (for example, assigning 0.6 weight to the neural network and 0.4 to XGBoost). This ensemble strategy improves robustness and performance by allowing the strengths of both models to complement each other, reducing the likelihood of errors from any single model and enhancing overall predictive accuracy.

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Final prediction:

P(y)=αPNN(y)+(1−α)PXGB(y)

Where,
$P_{NN}(y)$= probability predicted by a Neural Network
$P_{XGB}(y)$= probability predicted by an XGBoost model

$$\alpha = 0.6$$

So plug in α:

$$P(y) = 0.6\,P_{NN}(y) + 0.4\,P_{XGB}(y)$$

Because $1 - 0.6 = 0.4$.
This means:
• 60% weight goes to the Neural Network
• 40% weight goes to XGBoost

D. Evaluation Metrics
Evaluation Metrics
To assess the performance of the proposed classification model, multiple evaluation metrics are used to provide a comprehensive analysis:

- **Accuracy:**
  Accuracy measures the overall proportion of correctly classified instances among the total number of samples. It is calculated as the ratio of correct predictions (both true positives and true negatives) to the total predictions. While simple and intuitive, accuracy may be misleading if the dataset is imbalanced.
- **Precision:**
  Precision measures how many of the instances predicted as positive are actually positive. It is defined as the ratio of true positives to the sum of true positives and false positives. High precision indicates that the model makes fewer false positive errors.
- **Recall (Sensitivity):**
  Recall measures how many actual positive instances are correctly identified by the model. It is calculated as the ratio of true positives to the sum of true positives and false negatives. High recall means the model successfully detects most of the positive cases.
- **F1-Score:**
  The F1-score is the harmonic mean of precision and recall. It provides a balanced measure when both false positives and false negatives are important. This metric is particularly useful when dealing with imbalanced datasets.
- **ROC-AUC (Receiver Operating Characteristic – Area Under Curve):**
  ROC-AUC evaluates the model's ability to distinguish between classes across different classification thresholds. A higher AUC value (closer to 1) indicates better discriminative performance.
- **Cross-Model Generalization Score:**
  This metric measures how well the trained model performs on AI-generated text from unseen or different language models (e.g., training on GPT-3.5 and testing on Claude or LLaMA). It evaluates the robustness and generalization capability of the detection system across multiple generative models.

Together, these metrics provide a detailed and reliable evaluation of the classification system's effectiveness and robustness.

IV. EXPERIMENTAL RESULTS

Table 1 Comparison of accuracy with various models

Model	Accuracy	F1-score	ROC-AUC
Logistic Regression	82.4%	0.81	0.86
RoBERTa Only	93.1%	0.92	0.95
Stylometric Only	88.6%	0.87	0.90
Proposed Hybrid Model	**96.3%**	**0.96**	**0.98**

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A. Cross-Model Generalization

When tested on unseen AI models, the hybrid approach maintained 94.8% accuracy, outperforming transformer-only models (89.2%).

V. DISCUSSION

The results indicate:

- Stylometric features improve robustness.
- Hybrid models reduce overfitting to specific LLMs.
- Ensemble learning enhances detection stability.
- Adversarial paraphrasing slightly reduces performance (approx. 2.1%).

The study suggests that combining statistical and contextual features is crucial for long-term AI detection reliability.

VI. CONCLUSION

This paper presents a hybrid AI-generated content detection framework that integrates transformer-based embeddings with handcrafted linguistic features to enhance classification performance. By combining deep contextual representations from transformer models with stylometric and statistical text features, the proposed system effectively captures both semantic meaning and writing patterns. The experimental results demonstrate significant improvements in detection accuracy, robustness, and cross-model generalization when compared to standalone deep learning or traditional machine learning approaches. The ensemble strategy further strengthens reliability across diverse AI-generated sources.

Future research directions include expanding the framework to support multilingual detection for identifying AI-generated content across different languages, developing image-text multimodal detection to handle content that combines visual and textual elements, implementing real-time browser integration for practical deployment in online platforms, and designing watermark-resilient detection methods capable of identifying AI-generated content even when watermarking techniques are removed or altered.

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