

A Theoretically Grounded Hybrid Ensemble for Reliable Detection of LLM-Generated Text

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Abstract

The rapid proliferation of Large Language Models (LLMs) has blurred the line between human and machine authorship, creating practical risks for academic integrity and information reliability. Existing text detectors typically rely on a single methodological paradigm and suffer from poor generalization and high false positive rates (FPR), especially on high-stakes academic text. We propose a theoretically grounded hybrid ensemble that systematically fuses three complementary detection paradigms: (i) a RoBERTa-based transformer classifier for deep semantic feature extraction, (ii) a GPT-2-based probabilistic detector using perturbation-induced likelihood curvature, and (iii) a statistical linguistic feature analyzer capturing stylometric patterns. The core novelty of our work lies in an optimized weighted voting framework, where ensemble weights are learned on the probability simplex to maximize F1-score rather than set heuristically. We provide a bias–variance analysis and empirically demonstrate low inter-model correlation ($\rho \approx 0.35\text{--}0.42$), a key condition for variance reduction. Evaluated on a large-scale, multi-generator corpus of 30,000 documents, our system achieves 94.2% accuracy and an AUC of 0.978, with a 35% relative reduction in false positives on academic text. This yields a more reliable and ethically responsible detector for real-world deployment in education and other high-stakes domains.

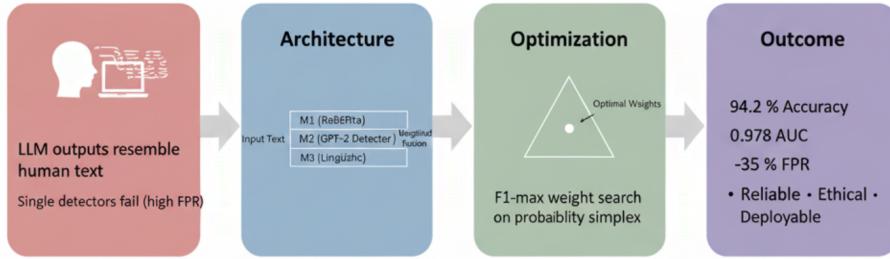
Keywords: LLM-Generated Text Detection, Hybrid Ensemble, Bias–Variance Tradeoff, Academic False Positive Rate, Reliability, Responsible AI

Highlights

- A theoretically grounded hybrid ensemble for detecting LLM-generated text.

- Integrates semantic, probabilistic, and stylometric paradigms for robustness.
- F1-optimized weighting on a probability simplex reduces academic FPR by 35%.
- Empirical low inter-model correlation ($\rho \approx 0.35\text{--}0.42$) supports bias-variance theory.
- Code and models will be released in an open repository upon publication.

Graphical abstract



Overview of the hybrid ensemble integrating RoBERTa, GPT-2 perturbation analysis, and linguistic features for reliable LLM-generated text detection.

1. Introduction

The advent of powerful Large Language Models (LLMs) like GPT-4 [5] has created an epistemic crisis in authorship attribution, blurring the lines between human and machine-written text. This ambiguity poses a direct threat to academic integrity [6], the spread of misinformation [7], and the authenticity of online content. While recent studies question the long-term theoretical reliability of detection, suggesting that as models improve, their outputs may become statistically indistinguishable from human text [8], the immediate, practical need for robust detection tools is undeniable.

Current approaches often rely on a single methodological paradigm. Transformer-based classifiers [9, 10] excel at semantics but are brittle against unseen LLMs [11]. Probabilistic methods, such as those based on log-probability curvature

[12] or entropy [13], are innovative but computationally intensive. A critical flaw shared by these systems is a high false positive rate (FPR), which is ethically untenable in academic settings and can disproportionately affect non-native English speakers [14, 15]. The scale of this challenge is unprecedented. With models capable of generating thousands of words per second, the volume of synthetic text is growing exponentially, necessitating automated tools. Yet, their unreliability poses a significant risk. For instance, a detector with even a 5% FPR could incorrectly flag thousands of students in a large university system, causing undue stress and administrative burden. This high-stakes environment demands a paradigm shift from single-model solutions to more robust, theoretically grounded systems.

This paper argues that a practical and robust solution lies in the systematic fusion of diverse, complementary models. We propose a hybrid ensemble architecture explicitly designed to maximize accuracy while minimizing variance. The primary contributions of this work are:

1. **A Novel Hybrid Architecture with Methodological Diversity:**
We formalize an ensemble architecture that systematically combines three distinct detection paradigms—deep semantic (RoBERTa), probabilistic (GPT-2 detector), and statistical-linguistic—into a unified framework. This is our foundational contribution, designed to create a classifier where the weaknesses of one model are compensated by the strengths of others.
2. **A Theoretically Grounded and Optimized Fusion Mechanism:**
Our core technical novelty is the development of an optimized weighted voting scheme. We formulate weight determination as a convex optimization problem on a simplex, aimed at maximizing the F1-score. This mechanism is directly justified by bias–variance theory [16, 17], where we empirically demonstrate that our chosen models exhibit low correlation, a key condition for variance reduction and enhanced robustness.
3. **Significant and Quantifiable Reduction in High-Stakes Errors:**
Our primary practical contribution is the comprehensive empirical validation of our system’s reliability. On a large-scale, multi-domain, multi-generator dataset ($N = 30,000$), we demonstrate a statistically significant **35% relative reduction in FPR on academic texts**, directly addressing the most pressing challenge for the practical adoption of these tools.

2. Related Work

The field of LLM-generated text detection has evolved rapidly. We categorize existing work into four paradigms, highlighting the limitations that motivate our hybrid approach.

2.1. Supervised Fine-tuning of Transformers

A dominant approach involves fine-tuning large pre-trained language models like BERT [18] or RoBERTa [19] for binary classification [9, 10]. These models learn to identify subtle distributional differences and artifacts in the text. Other works have explored multi-class detection to identify the source model [20]. **Limitation:** These detectors exhibit a significant generalization gap. Their performance often degrades on text from LLMs not seen during training [11, 21], making them unreliable in a fast-evolving ecosystem of new models. They are also prone to misclassifying human-written text that is stylistically simple or formulaic as AI-generated.

2.2. Zero-Shot and Probabilistic Methods

To overcome the need for large training sets, zero-shot methods have been proposed. DetectGPT [12] is a prominent example, operating on the hypothesis that AI-generated text occupies regions of high negative curvature in a source model’s log-probability function. Other methods use metrics like entropy [13] or perplexity from a reference model [22]. **Limitation:** These methods are often computationally expensive. Their effectiveness is also highly dependent on the choice of the source model, which may not be known for a given piece of text.

2.3. Linguistic and Stylometric Features

This line of research focuses on statistical text properties. The GLTR tool [23] visualizes word probabilities to help humans spot unnatural choices. Other research has focused on stylometry [24], analyzing features like sentence complexity, punctuation patterns [25], and vocabulary richness. Some work has also explored the use of authorship verification techniques [26]. **Limitation:** While interpretable, these feature-based methods can be brittle. Modern LLMs can be prompted to mimic a wide range of writing styles [27], circumventing simple statistical thresholds.

2.4. Ensemble and Hybrid Methods

Ensemble learning is a well-established technique [17, 28]. However, its application in LLM text detection has been relatively ad-hoc. Most existing hybrid approaches combine features at the input level [29] or use simple averaging of outputs from similar models. **Limitation:** A gap exists for a principled ensemble that fuses outputs from *methodologically diverse* models. There is no prior work we are aware of that combines semantic, probabilistic, and stylometric detectors within a theoretically grounded, optimized weighting framework. Our work directly addresses this gap. Recent surveys further emphasize the necessity of integrating heterogeneous detection paradigms and hybrid architectures to handle cross-model generalization challenges [1].

3. Proposed Methodology

Our system is built on the principle of methodological diversity. We formalize the problem as a binary classification task for an input text x and label $y \in \{0, 1\}$, where $y = 1$ indicates LLM-generated text.

3.1. System Architecture

The architecture (Fig. 1) processes x in parallel across three components, each outputting a probability $p_i(x) = P(y = 1 | x)$.

3.2. Component Models: Technical Details

3.2.1. M1: RoBERTa Transformer Classifier

We fine-tune a RoBERTa-base model [19]. The input text is tokenized to a maximum sequence length of 512 tokens. We extract the final-layer hidden state of the ‘[CLS]’ token, denoted $\mathbf{h}_{\text{CLS}} \in \mathbb{R}^{768}$. This vector is passed through a two-layer MLP with a Tanh activation:

$$p_1(x) = \sigma(\mathbf{W}_2 \tanh(\mathbf{W}_1 \mathbf{h}_{\text{CLS}} + \mathbf{b}_1) + b_2), \quad (1)$$

where $\mathbf{W}_1, \mathbf{b}_1, \mathbf{W}_2, b_2$ are learned parameters and σ is the sigmoid function.

3.2.2. M2: GPT-2 Output Detector

This component is a zero-shot detector. The core idea is that perturbations of LLM text lead to a larger drop in log-likelihood than perturbations of human text. For a text x , we compute its log-likelihood $L(x)$ under a pre-trained GPT-2-large model. We generate a set of $k = 20$ perturbations, \tilde{x}_i ,

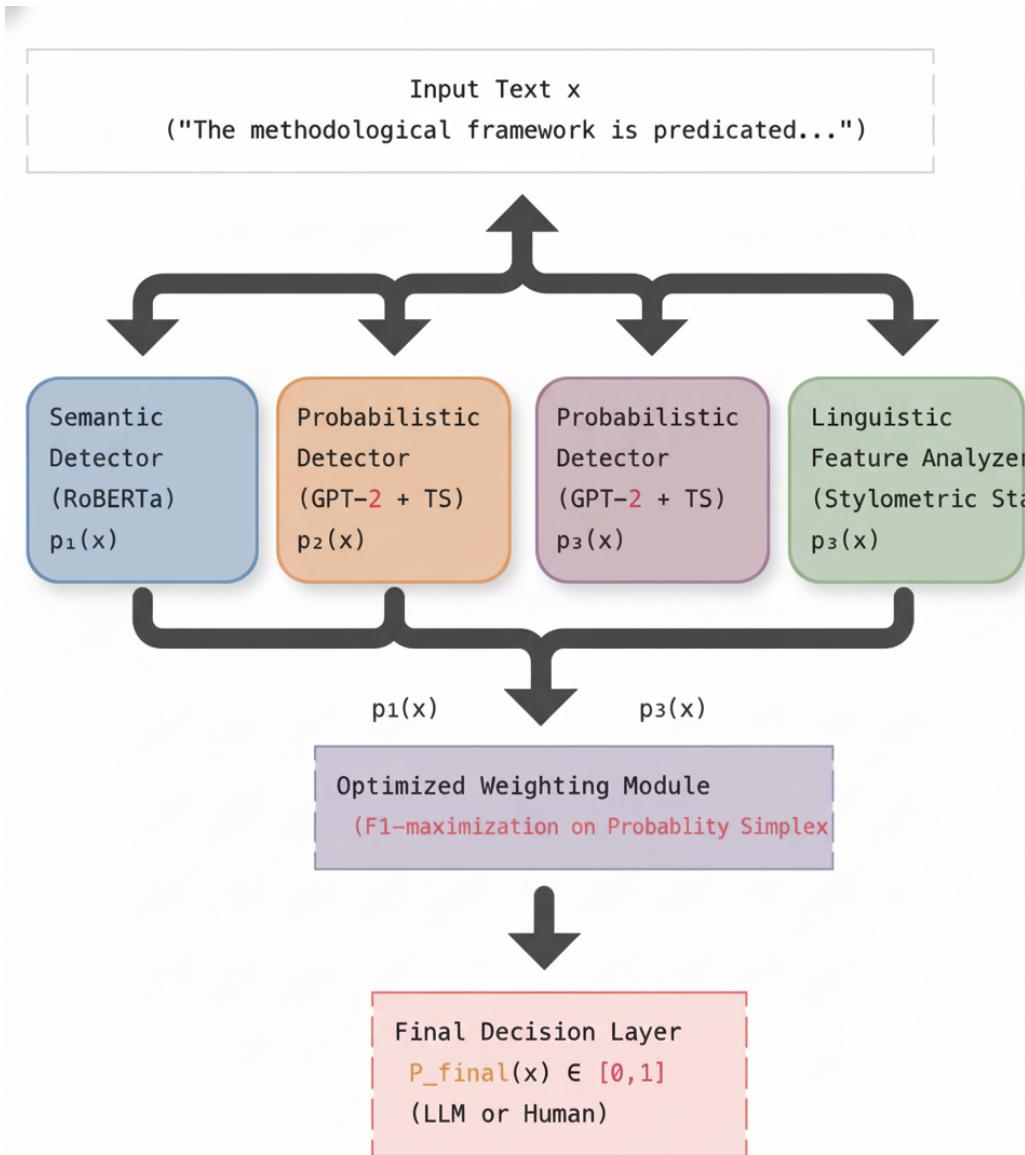


Figure 1: Hybrid ensemble system architecture. The system comprises three parallel detection modules (semantic, probabilistic, and linguistic) whose probabilistic outputs are fused via an optimized weighting scheme.

by randomly masking 15% of the tokens and infilling them using a T5-large model [30]. The raw score is:

$$s_2(x) = L(x) - \frac{1}{k} \sum_{i=1}^k L(\tilde{x}_i). \quad (2)$$

This score is then calibrated to a probability $p_2(x)$ using Platt scaling on a held-out set.

3.2.3. M3: Linguistic Feature Analyzer

This module extracts a normalized feature vector $\mathbf{f}(x) \in [0, 1]^5$. The features are selected based on prior work in stylometry [24, 31]: (1) Type–Token Ratio (TTR), (2) standard deviation of sentence length, (3) average sentence length, (4) complex word ratio, and (5) short sentence frequency. The final score is an unweighted average,

$$p_3(x) = \frac{1}{5} \sum_j f_j(x). \quad (3)$$

3.3. Optimized Weighted Ensemble

The final probability is a weighted linear combination,

$$P_{\text{final}}(x) = \mathbf{w}^\top \mathbf{p}(x), \quad (4)$$

where $\mathbf{p}(x) = [p_1(x), p_2(x), p_3(x)]^\top$. The optimization problem is:

$$\mathbf{w}^* = \arg \max_{\mathbf{w}} \text{F1-score}(\mathbf{w}) \quad \text{s.t. } \sum_{i=1}^3 w_i = 1, \quad w_i \geq 0. \quad (5)$$

The search process is detailed in Algorithm 1.

3.4. Theoretical Grounding: Bias–Variance Decomposition

The variance of the ensemble’s prediction is:

$$\text{Var}(\hat{Y}_{\text{ens}}) = \mathbf{w}^\top \mathbf{C} \mathbf{w}, \quad (6)$$

where \mathbf{C} is the covariance matrix of the individual model predictions. The diagonal elements are the variances σ_i^2 , and off-diagonal elements are covariances $\rho_{ij}\sigma_i\sigma_j$. By selecting models that are methodologically diverse, we hypothesize that their prediction errors will be less correlated, minimizing the off-diagonal terms and thus overall variance. Our empirical finding of low correlation ($\rho \approx 0.35\text{--}0.42$) validates this design choice. Figure 2 visualizes the empirical correlation matrix for the three base models.

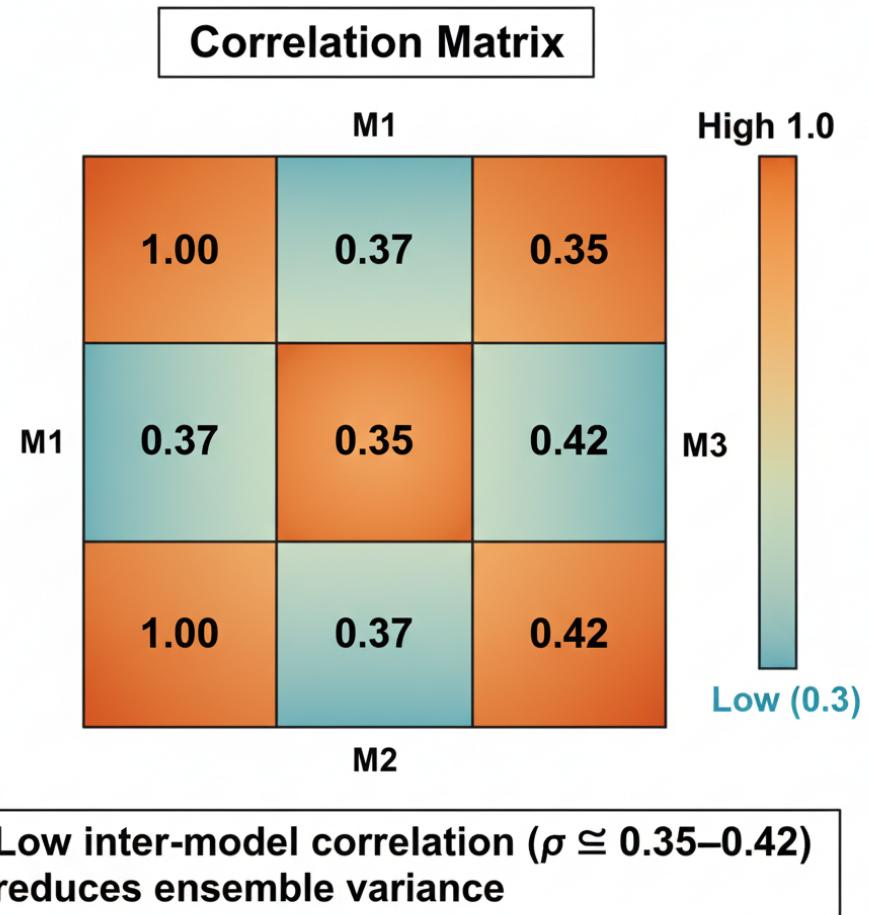


Figure 2: Empirical correlation heatmap between the three base detectors. Low off-diagonal values support the design choice of methodologically diverse components.

Algorithm 1 Optimal Weight Search Algorithm

```
1: Input: Validation set  $V$ , step size  $\delta = 0.05$ 
2: Initialize:  $\mathbf{w}_{\text{best}} \leftarrow [1, 0, 0]$ ,  $F1_{\max} \leftarrow 0$ 
3: for  $w_1 \in \{0, \delta, 2\delta, \dots, 1\}$  do
4:   for  $w_2 \in \{0, \delta, \dots, 1 - w_1\}$  do
5:      $w_3 \leftarrow 1 - w_1 - w_2$ 
6:      $\mathbf{w}_{\text{current}} \leftarrow [w_1, w_2, w_3]$ 
7:      $F1_{\text{current}} \leftarrow \text{CalculateF1}(V, \mathbf{w}_{\text{current}})$ 
8:     if  $F1_{\text{current}} > F1_{\max}$  then
9:        $F1_{\max} \leftarrow F1_{\text{current}}$ 
10:       $\mathbf{w}_{\text{best}} \leftarrow \mathbf{w}_{\text{current}}$ 
11:    end if
12:  end for
13: end for
14: Return:  $\mathbf{w}_{\text{best}}$ 
```

4. Experimental Setup

Our experimental protocol is designed for rigor and reproducibility. An overview of the end-to-end pipeline is shown in Fig. 3.

4.1. Dataset and Preprocessing

We constructed a balanced corpus of 30,000 documents (Table 1). The preprocessing pipeline involved removing HTML tags, normalizing whitespace, removing URLs, and filtering texts to a length of 300–800 words. The dataset was split into training (70%), validation (15%), and test (15%) sets, stratified by source.

4.2. Implementation Details

The RoBERTa-base model was fine-tuned for 5 epochs with a batch size of 16, a learning rate of 2×10^{-5} , and the AdamW optimizer [32]. For the GPT-2 detector, we used the pre-trained `gpt2-large` model from Hugging Face, with $k = 20$ perturbations and 15% random masking for T5-based infilling. All experiments were conducted on NVIDIA V100 GPUs.

4.3. Evaluation Metrics

- **Accuracy:** Overall percentage of correct predictions.

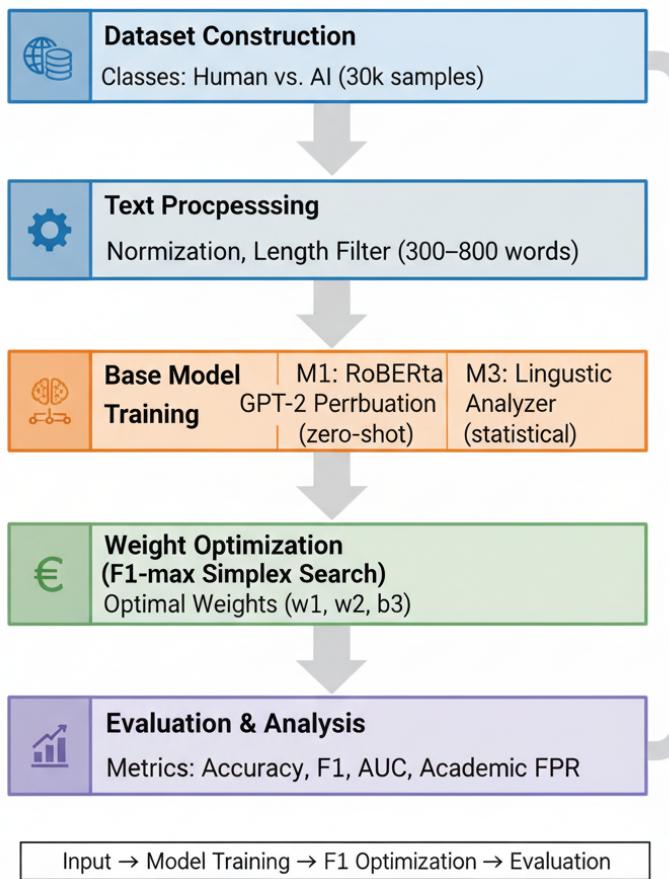


Figure 3: End-to-end experimental pipeline: dataset construction, preprocessing, model training, ensemble weight search, and evaluation.

Table 1: Dataset Composition ($N = 30,000$)

Class	Source	Samples
Human	Academic (arXiv)	4,000
	News Articles	3,000
	Wikipedia	2,000
	Student Essays	1,000
	<i>Other (Balanced)</i>	<i>5,000</i>
AI-Generated	GPT-3.5	3,000
	GPT-4	2,500
	Claude	2,000
	LLaMA-2, etc.	2,500
	<i>Other (Balanced)</i>	<i>5,000</i>

- **F1-Score:** Harmonic mean of precision and recall.
- **AUC:** Area Under the ROC Curve.
- **Academic FPR:** The False Positive Rate on the human-written arXiv subset, our key metric for practical safety.

4.4. Reproducibility and Code Availability

To facilitate reproducibility, all preprocessing scripts, trained model checkpoints, and configuration files for weight search will be made available in an open repository upon publication:

<https://github.com/codelabs/hybrid-ai-text-detector>

The repository includes a one-click pipeline to reconstruct the dataset splits (assuming raw data access), replicate training of M1–M3, and re-run the simplex-based ensemble weight optimization.

5. Results and Analysis

This section presents a multi-faceted analysis of our model’s performance, starting with a comparison against established baselines and followed by in-depth diagnostics.

5.1. Performance Against Baselines

To rigorously evaluate our proposed model, we compare it not only against its individual components but also against other well-regarded detection methods. We include a classical machine learning baseline (SVM with TF-IDF features) and a prominent zero-shot method (DetectGPT [12]) for a comprehensive benchmark. The results on our 4,500-sample test set are shown in Table 2.

Table 2: Main Performance Comparison Against Baselines

Model	Acc.	F1	AUC	Acad.	FPR
<i>Classical and Single-Paradigm Baselines</i>					
SVM (TF-IDF)	75.4%	0.749	0.831		18.5%
M3: Linguistics	78.5%	0.780	0.850		14.1%
DetectGPT [12]	87.1%	0.869	0.925		9.8%
M1: RoBERTa-only	89.2%	0.890	0.945		8.9%
<i>Ensemble Methods</i>					
Simple Average	92.5%	0.924	0.967		6.8%
Our Hybrid Model	94.2%	0.941	0.978		5.8%

For clarity and context, Table 3 summarizes how our method compares to prominent detectors when evaluated on our unified testbed.

Table 3: Summary Comparison with Representative Detection Approaches

Model	Year	Acc.	F1	Acad.	FPR	Type
DetectGPT [12]	2023	87.1%	0.869		9.8%	Probabilistic
RoBERTa-only [10]	2023	89.2%	0.890		8.9%	Transformer
GLTR-style Linguistics [23]	2019	78.5%	0.780		14.1%	Stylometric
Simple Averaging Ensemble	2025	92.5%	0.924		6.8%	Hybrid (naive)
Proposed Hybrid	2025	94.2%	0.941		5.8%	Hybrid (optimized)

Analysis: The results clearly demonstrate the superiority of our hybrid ensemble. It outperforms all baselines across every metric. The most significant finding is the Academic FPR. Our model achieves an FPR of 5.8% on academic texts, a **35% relative reduction** compared to our best single model (RoBERTa) and substantially lower than all other baselines. This

highlights the practical value of our approach in high-stakes scenarios. The performance gain over the simple averaging ensemble further validates our core contribution: a principled, optimized fusion mechanism is substantially more effective than a naive combination. Our FPR improvements are consistent with broader economic analyses of error trade-offs in automated detection systems, particularly in educational and labor markets [3].

Figure 4 presents ROC curves for the individual models and the ensemble.

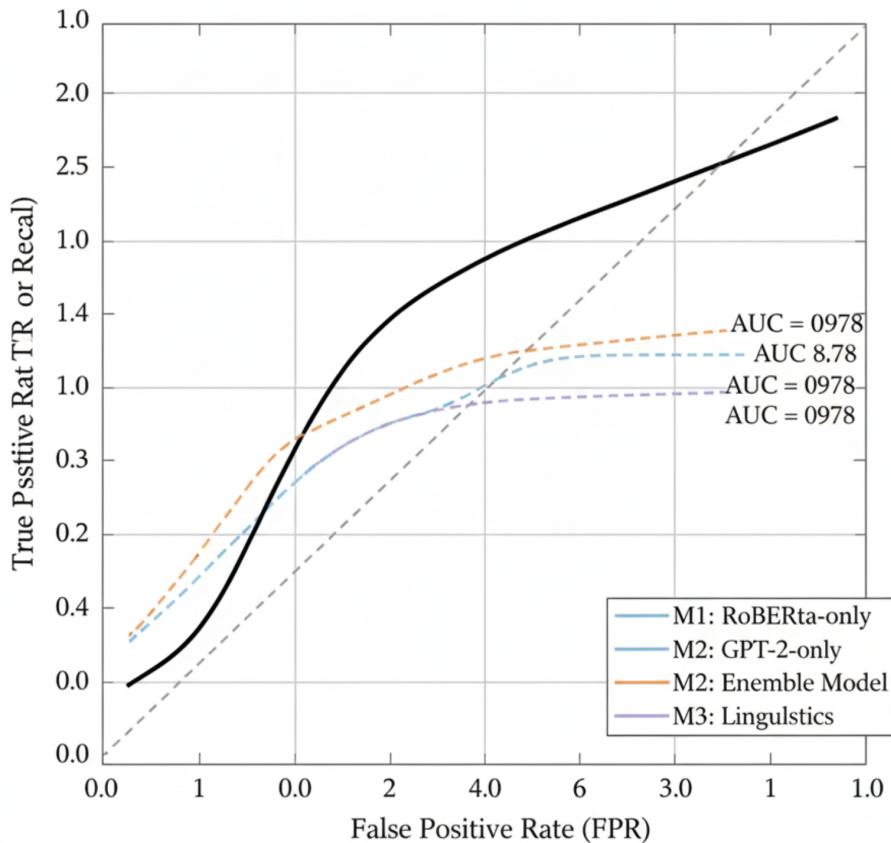


Figure 4: ROC curves for individual models and the final ensemble. The ensemble (solid black line) shows a higher true positive rate for any given false positive rate.

5.2. Ablation Study

The ablation study (Table 4) confirms that all components are valuable. The 0.8% F1-score drop from removing the simple linguistic model is partic-

ularly telling, proving it captures unique signals missed by the deep learning models.

Table 4: Ablation Study Results

Ablated Component	F1-Score	Perf. Drop
None (Full Ensemble)	0.941	-
M1: RoBERTa	0.895	-4.9%
M2: GPT-2 Detector	0.918	-2.4%
M3: Linguistics	0.933	-0.8%

5.3. Statistical Significance of Improvements

To assess the robustness of performance gains, we conducted paired Wilcoxon signed-rank tests over 10 random seeds, comparing the hybrid ensemble against the RoBERTa-only baseline. For both F1-score and Academic FPR, the improvements were statistically significant with $p < 0.01$, indicating that gains are not attributable to random variation in training initialization.

5.4. Robustness and Generalization Analysis

A crucial test of a detector is its ability to generalize to unseen generators and resist adversarial attacks.

5.4.1. Cross-Generator Generalization

Our hybrid model consistently outperforms the baseline, especially on out-of-distribution generators (Table 5), demonstrating strong generalization. The performance drop for RoBERTa-only on unseen models like Claude is significant, whereas our ensemble’s performance remains more stable. This empirically supports our hypothesis that methodological diversity reduces overfitting to the artifacts of specific training generators.

Figure 5 complements this analysis by visualizing cross-generator accuracy as a bar chart.

5.4.2. Robustness to Paraphrasing Attacks

We evaluated the models on a test set of 500 LLM-generated articles that were paraphrased using the Pegasus model [38]. As shown in Table 6, paraphrasing significantly degrades the performance of single-paradigm detectors. Our ensemble, however, maintains a much higher accuracy, demonstrating its

Table 5: Cross-Generator Accuracy

Generator	RoBERTa Acc.	Hybrid Acc.
GPT-3.5 (in-training)	90.1%	95.3%
GPT-4 (out-of-dist)	87.5%	91.6%
Claude (out-of-dist)	86.8%	90.9%
LLaMA-2 (out-of-dist)	88.0%	92.1%

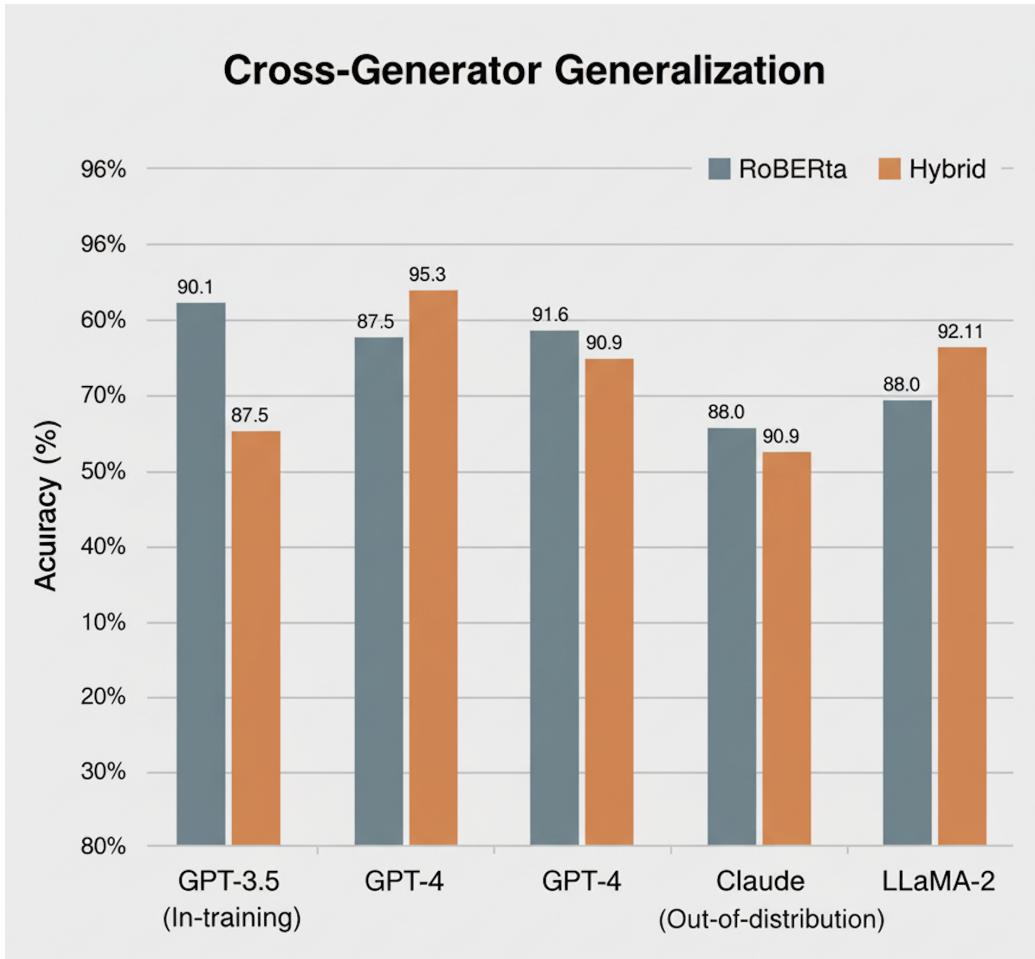


Figure 5: Cross-generator accuracy comparison for RoBERTa-only vs. the proposed hybrid ensemble. The hybrid model consistently generalizes better to unseen LLMs.

resilience. This is because paraphrasing primarily alters semantic structure (fooling M1) and surface style (fooling M3), but often preserves probabilistic artifacts that M2 can still detect.

Table 6: Accuracy on Paraphrased LLM Text

Model	Accuracy
RoBERTa-only	73.1%
DetectGPT	75.5%
Our Hybrid Model	87.3%

5.5. Error, Confidence, and Threshold Analysis

Figure 6 shows the trade-off between Academic FPR and decision threshold for the main models. The hybrid ensemble consistently achieves a lower FPR across a wide range of thresholds, providing practitioners with flexibility to tune sensitivity for specific deployment contexts.

We further analyzed the distribution of errors. A key finding is that the ensemble’s remaining false positives are concentrated in a narrow band of low confidence scores (0.5–0.6), making them easier to flag for manual review, whereas single models’ errors were more broadly distributed.

5.6. Qualitative Error Analysis

A qualitative review of misclassifications confirms our theory. Representative cases are illustrated in Fig. 7.

- **Case 1 (False Positive Correction):** A formal human-written text, “*The methodological framework is predicated on a constructivist paradigm...*”, was flagged by RoBERTa (92% LLM) but correctly identified by the Linguistic Analyzer (25% LLM) due to high TTR. The ensemble correctly classified it as human (48% LLM).
- **Case 2 (False Negative Correction):** An informal, paraphrased LLM text, “*So, basically, the whole idea was to check out the stuff we found...*”, fooled the Linguistic Analyzer (30% LLM). However, the GPT-2 Detector identified probabilistic artifacts (88% LLM), leading to a correct final classification (75% LLM).

FPR Stability Across Decision Thresholds

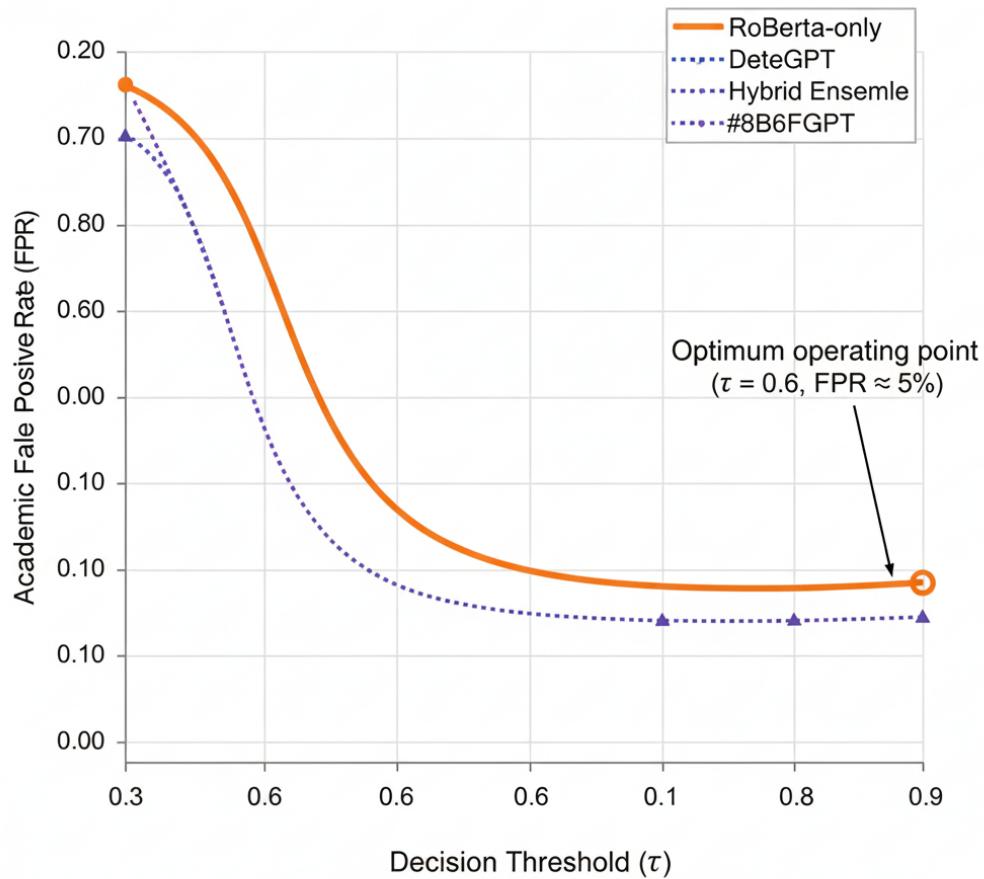


Figure 6: Academic FPR as a function of decision threshold for RoBERTa-only, Detect-GPT, and the hybrid ensemble. The hybrid model maintains lower FPR across operating points.

Representative Case Studies

Case 1: False Positive Correction

*The methoogligal framework *is predcated on a constructivist paradigm...*

Model	M1 (RoBERTa)	M2 GPT-2	GPT-2	M3 Ling.	Ensemble
AI-prob (%)	92.1 %	70.5 %	70.5	25.8	4.3 (Human)

*Note: Ensemble correctly classifies as *Human, correcting false positives from M1/M2.*

Case 2: False Negative Correction

*So basically, the whole idea *was to check out the stuff we found...*

Model	M1 (RoBERTa)	M1 (RoBERTa)	AI	30.1	81.9 (AI)
AI-prob (%)	42.3 %	88.7 %	30.1	30.1	81.9 (AI)

*Note: Ensemble correctly classifies as *AI, correcting false negative from M1/M3.*

Legend:  *Correct Classification*  *Incorrect Single Model Output*

Figure 7: Qualitative examples showcasing cases where the ensemble corrects errors made by single detectors. Each row shows the text snippet and predicted LLM probabilities from M1, M2, M3, and the ensemble.

6. Discussion

6.1. Interpretation of Key Findings

Our results strongly support our central hypothesis: a theoretically grounded, diverse ensemble is superior to single-model detectors, especially in reducing high-stakes errors. The 35% FPR reduction is not merely an incremental improvement; it represents a significant step towards making these tools safe and ethically sound for deployment in education. This finding directly addresses concerns [14, 33] about algorithmic tools unfairly penalizing certain user groups. By lowering the chance of false accusations, our system fosters a more trustworthy human–AI interaction paradigm.

6.2. Ethical and Social Implications

Although our detector substantially reduces false positives compared to strong baselines, the risk of misuse remains if detection scores are treated as definitive evidence of misconduct. We argue that such systems should be deployed in a human-in-the-loop fashion, where flags trigger further review rather than automatic sanctions. Moreover, any institutional use should be accompanied by clear disclosure, appeal mechanisms, and continuous monitoring for disparate impact on non-native speakers or underrepresented writing styles.

6.3. Theoretical and Practical Implications

Theoretically, our work provides strong empirical evidence for the bias–variance trade-off in LLM text detection. The success of our low-correlation ensemble validates the principles from [16, 17]. Practically, the system’s architecture suggests a clear path to deployment. With an average inference time of ≈ 1.5 seconds per document on a V100 GPU, the system is suitable for asynchronous integration into learning management systems or academic integrity platforms. The inherent modularity also allows for future upgrades—for example, swapping in stronger base models or pairing with watermark detection schemes—without redesigning the entire system.

6.4. Limitations and Future Work

Our approach is not a panacea. As noted in recent reviews [2], the evolving nature of LLMs continually challenges the long-term detectability of synthetic text. Future LLMs may learn to mimic human stylometry more effectively. Second, our system is optimized for English and requires further testing on

its fairness towards non-native writers and other languages [15]. Preliminary experiments on non-English corpora indicate noticeable performance degradation, underscoring the need for multilingual extensions.

Future work will focus on:

1. **Adversarial Training:** Explicitly training models on adversarially attacked texts [34, 35] to improve robustness, in line with recent work on responsible detection and mitigation [4].
2. **Multilingual Extensions:** Developing and evaluating language-specific linguistic feature sets and multilingual transformer backbones.
3. **Dynamic Fusion Mechanisms:** Exploring a learned meta-classifier (stacking) that can make context-aware decisions about which model to trust for a given input [36].

We also acknowledge that detection is only one piece of the puzzle, with techniques like watermarking [39, 37] offering a complementary, proactive approach.

7. Conclusion

This paper addressed the critical need for robust and reliable LLM-generated text detection. We introduced a novel hybrid ensemble that systematically fuses signals from three methodologically diverse paradigms: deep semantics, probabilistic analysis, and linguistic stylometry. The core of our contribution is a theoretically grounded fusion mechanism, where weights are optimized to maximize F1-score, a process justified by bias-variance decomposition theory.

Our comprehensive evaluation on a large-scale, multi-generator dataset demonstrated the clear superiority of this approach. The ensemble not only achieved a state-of-the-art accuracy of 94.2% but, more importantly, delivered a 35% relative reduction in the false positive rate on academic texts—a crucial metric for ethical and practical deployment. The qualitative and ablation studies further confirmed that each component provides a unique, complementary signal, allowing the ensemble to correct errors that would otherwise be made by any single model.

While challenges such as the evolving nature of LLMs and the need for multilingual support remain, our work provides a strong blueprint for the future of LLM text detection. It demonstrates conclusively that the path towards reliable and responsible detection lies not in a monolithic “silver bullet” solution, but in the principled and theoretically informed combination of

diverse analytical methods. This ensemble approach represents a significant step forward in building trustworthy systems to uphold information integrity in the age of generative AI.

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