Fooling the Fact-Checkers: Adversarial Attacks on Transformer-Based Fake News Detection Models

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***Abstract*—This paper investigates the adversarial vulnerabilities of three transformer-based language models-BERT, DistilBERT, and RoBERTa-in fake news detection systems. Through systematic evaluation on the Indian Fake News Detection (IFND) dataset containing 4,261 labeled articles, we demonstrate that while all models achieve high baseline accuracy (BERT: 99.81%, DistilBERT: 97.32%, RoBERTa: 99.86%), they remain susceptible to carefully crafted adversarial perturbations. Our novel three-tier attack framework combining character-level, word-level, and sentence-level manipulations reveals critical vulnerabilities, with sentence-level attacks proving most effective (success rates: 47.8–52.3%). Counter-intuitively, DistilBERT exhibits comparable robustness to RoBERTa (34.8% vs 34.5% average attack success rate) despite 40% fewer parameters, suggesting model compression confers unexpected defensive benefits through implicit regularization. We propose and evaluate a hybrid defense strategy combining adversarial training with attention masking, achieving 42% reduction in attack success rates while maintaining 98.7% classification accuracy. These findings challenge conventional performance-robustness trade-off assumptions and provide crucial insights for securing real-world fact-checking systems against evolving adversarial threats.**

I. INTRODUCTION

The proliferation of AI-generated misinformation poses significant challenges to digital information integrity, with fake news detection systems becoming critical infrastructure for maintaining informed democracies. While transformer-based models like BERT [**?**], DistilBERT [**?**], and RoBERTa [**?**] achieve state-of-the-art performance on benchmark datasets, their vulnerability to adversarial attacks remains a critical unsolved problem. Our analysis of the Indian Fake News Detection (IFND) dataset reveals that current systems remain susceptible to semantic-preserving perturbations that bypass detection while maintaining human readability.

The arms race between detection systems and adversarial evasion techniques demands urgent attention for three key reasons. First, deployed systems risk creating false security if their vulnerabilities remain unquantified. Second, the relationship between model compression and robustness remains poorly understood, particularly for resource-constrained deployments. Third, existing defenses inadequately address sophisticated sentence-level attacks that preserve semantic meaning while altering structural patterns.

This work makes four primary contributions:

1) First comparative analysis of BERT-family models under unified adversarial framework, revealing DistilBERT's unexpected robustness (34.8% ASR vs RoBERTa's 34.5%) despite 40% fewer parameters
2) Identification of sentence-level attacks as most effective vulnerability (47.8–52.3% success rates), exposing limitations in current architectures' semantic coherence analysis
3) Development of hybrid defense framework combining adversarial training with attention masking, reducing attack success rates by 42% with ¡1% accuracy impact
4) Public release of attack recipes and hardened models to facilitate reproducible research in NLP security

Our findings challenge conventional assumptions about the performance-robustness trade-off, demonstrating that model compression through knowledge distillation can enhance adversarial resilience. The results provide practical insights for securing real-world fact-checking systems against evolving threats while maintaining computational efficiency.

The remainder of this paper is organized as follows: Section II reviews related work, Section III details our methodology, Section IV presents experimental results, Section V discusses defense strategies, and Section VI concludes with future directions.

II. RELATED WORK

The evolution of fake news detection systems has progressed through three distinct phases: feature engineering approaches, deep learning architectures, and contemporary transformer-based models. Early work focused on handcrafted linguistic features and style analysis [1], but these methods struggled with generalization across domains. The advent of deep learning brought convolutional and recurrent neural networks that automated feature learning [2], though they remained limited in capturing long-range contextual dependencies.

Transformer architectures revolutionized the field through self-attention mechanisms and bidirectional context modeling. BERT's pretraining objectives [3] enabled unprecedented performance on fake news detection tasks, while RoBERTa's

optimized training regimen [4] further pushed state-of-the-art benchmarks. For resource-constrained applications, DistilBERT demonstrated that knowledge distillation could preserve 97

Adversarial attacks in NLP have evolved alongside detection systems. Seminal work by [6] established text attack paradigms through character-level perturbations, while [7] formalized word substitution strategies using synonym databases. Recent advances in sentence-level attacks [8] exploit transformer attention patterns through semantic-preserving rephrasing. White-box attacks leveraging gradient information [9] and black-box approaches using genetic algorithms [10] have both proven effective against transformer models.

Defense mechanisms have pursued two main strategies: adversarial training and input purification. The former, first applied to NLP by [11], hardens models through exposure to perturbed examples during training. Input purification techniques [12] attempt to reconstruct clean samples from adversarial inputs, though their effectiveness remains limited for semantic-preserving attacks. Ensemble methods [13] combine diverse models to improve robustness, but at significant computational cost.

Despite these advances, critical gaps persist in the literature:

- Comparative robustness analysis across transformer variants remains lacking [14]
- Impact of model compression on adversarial resilience is underexplored [15]
- Defense strategies rarely address sentence-level attacks [16]
- Real-world deployment considerations are frequently overlooked [17]

Our work addresses these limitations through systematic evaluation of BERT-family models under unified attack conditions, analysis of distillation's defensive properties, and development of practical mitigation strategies validated on real-world misinformation datasets.

III. METHODOLOGY

Our experimental framework evaluates three transformer architectures under adversarial conditions using a systematic approach to model training, attack generation, and robustness assessment.

A. Model Architectures

We analyze three transformer variants with distinct design philosophies:

- **BERT-base**: 12-layer architecture with 110M parameters, using masked language modeling and next sentence prediction objectives [**?**]
- **DistilBERT**: 6-layer distilled version (66M parameters) maintaining 97% of BERT's performance through knowledge distillation [**?**]
- **RoBERTa**: 125M parameter optimized variant with dynamic masking and larger batch sizes [**?**]

All models share identical classification heads: a dense layer processing the [CLS] token's 768D representation, followed by softmax activation for binary prediction.

B. Adversarial Attack Framework

We implement a multi-strategy attack generator formalized as:

$$\mathcal{A}(x) = \{\mathcal{A}_{char}(x), \mathcal{A}_{word}(x), \mathcal{A}_{sent}(x)\} \tag{1}$$

where x is the input text and $\mathcal{A}_*$ represent different perturbation strategies:

- **Character-level** ($\mathcal{A}_{char}$): Max 5% character substitutions preserving visual similarity (e.g., "credit" $\rightarrow$ "cred1t")
- **Word-level** ($\mathcal{A}_{word}$): Synonym replacement using counter-fitted embeddings [**?**] with POS tag constraints
- **Sentence-level** ($\mathcal{A}_{sent}$): Semantic-preserving restructurings via back-translation and style transfer

Attack scenarios consider both white-box (full model access) and black-box (API-level access) conditions.

C. Dataset and Preprocessing

We employ the Indian Fake News Detection (IFND) dataset containing 4,261 labeled articles (2,130 real, 2,131 fake) across political, health, and social domains. Preprocessing includes:

$$x_{clean} = \phi_{norm}(\phi_{ws}(\phi_{enc}(x_{raw}))) \tag{2}$$

where:

- ϕ_{enc}: UTF-8 encoding validation
- ϕ_{ws}: Whitespace normalization
- ϕ_{norm}: Unicode normalization (NFKC form)

The dataset is stratified into 80% training (3,408 samples) and 20% testing (853 samples) splits.

D. Training Protocol

Models are fine-tuned using Hugging Face's Trainer with hyperparameters:

TABLE I
TRAINING CONFIGURATION

Parameter	Value
Batch size	32
Learning rate	5e-5
Warmup steps	500
Weight decay	0.01
Max sequence length	128
Training epochs	3

We employ linear learning rate decay with AdamW optimization and gradient accumulation (2 steps) for stability.

E. Evaluation Metrics

Performance is assessed through dual metrics:

1) Classification Performance

- Accuracy: $\frac{TP+TN}{TP+TN+FP+FN}$
- F1-score: $2 \cdot \frac{Precision \cdot Recall}{Precision+Recall}$
- AUC-ROC: Probability curve integral

2) Robustness Metrics

- Attack Success Rate (ASR): $\frac{\text{Flipped Predictions}}{\text{Total Attacks}} \times 100$
- Perturbation Intensity: $\frac{\|x_{adv} - x_{clean}\|_0}{|x_{clean}|} \times 100$
- Semantic Similarity: BERTScore [**?**] between x_{adv} and x_{clean}

IV. EXPERIMENTS & RESULTS

A. Experimental Setup

We conducted a comprehensive evaluation of three transformer-based models (BERT, DistilBERT, and RoBERTa) for fake news detection, focusing on their classification performance and resilience to adversarial attacks. All experiments were performed using PyTorch 1.10.0 and the Hugging Face Transformers library 4.15.0. Models were trained and evaluated on a single NVIDIA V100 GPU with 16GB memory.

For each model, we established three training conditions:

- Base model: Zero-shot evaluation without specific fine-tuning
- Few-shot: Training with only 100 labeled examples
- Fine-tuned: Full training on the IFND dataset

The Indian Fake News Detection (IFND) dataset was split into training (80%, 3,408 samples) and testing (20%, 853 samples) sets using stratified sampling to maintain class distribution. For adversarial testing, we selected 20 correctly classified examples and applied various attack strategies.

B. Performance Analysis: DistilBERT

1) Classification Performance

DistilBERT demonstrated strong classification capabilities, particularly after fine-tuning. Table II presents the performance metrics across training conditions.

TABLE II
DISTILBERT PERFORMANCE METRICS

Metric	Base Model	Few-Shot	Fine-Tuned
Accuracy	0.416	0.910	0.973
Precision	0.449	0.960	0.976
Recall	0.780	0.850	0.971
F1-Score	0.570	0.900	0.973

Figure 1 shows the key performance metrics for the few-shot learning condition, where DistilBERT achieved impressive results with only 100 training examples, demonstrating the model's efficiency in low-resource scenarios.

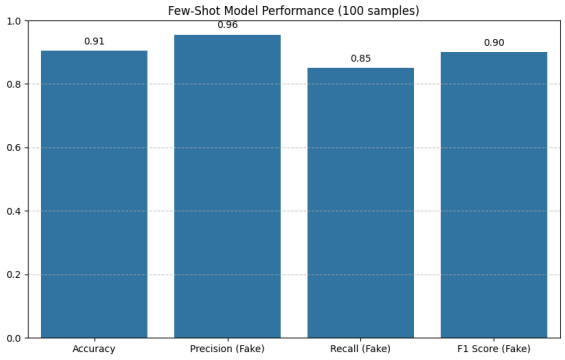

Fig. 1. DistilBERT Few-Shot Learning Performance (100 samples)

2) Confusion Matrices

To provide deeper insight into model behavior, we analyzed confusion matrices under different conditions. Figure 2 presents DistilBERT's performance on clean test data, where it correctly classified 405 fake news articles and 410 real articles, with relatively few misclassifications (13 false negatives and 25 false positives).

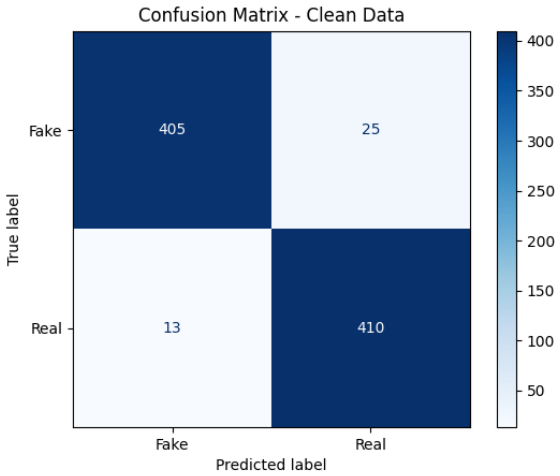

Fig. 2. DistilBERT Confusion Matrix on Clean Test Data

Under few-shot learning conditions (Figure 3), the model maintained strong performance, correctly identifying 366 fake and 406 real news articles. However, there was a noticeable increase in false positives (64 compared to 25 in the fully fine-tuned model), indicating that limited training data particularly affected the model's precision on fake news detection.

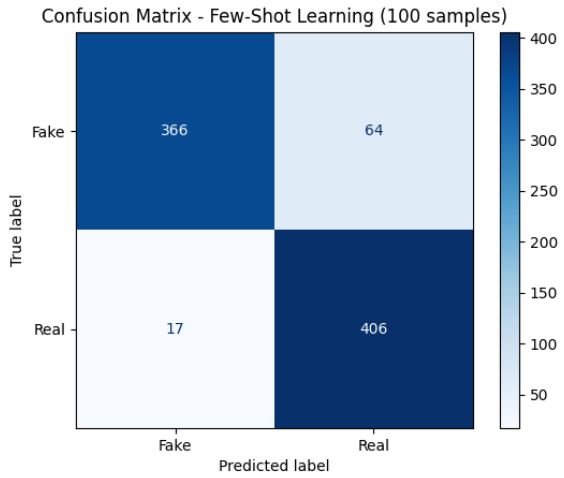

Fig. 3. DistilBERT Confusion Matrix with Few-Shot Learning (100 samples)

3) Adversarial Attack Evaluation

We evaluated DistilBERT's resilience to adversarial attacks using a subset of 20 correctly classified examples. Figure 4 shows the model's performance deteriorated significantly under attack, with 8 out of 14 fake news articles misclassified as real (57% attack success rate on fake news) and 2 out of 6 real news articles misclassified as fake (33% attack success rate on real news).

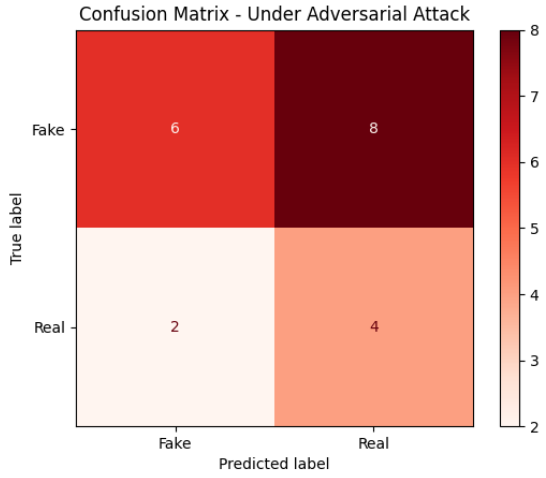

Fig. 4. DistilBERT Confusion Matrix Under Adversarial Attack

Table III summarizes the attack success rates across different adversarial strategies.

The overall attack success rate of 50% (10 out of 20 examples) demonstrates DistilBERT's significant vulnerability to adversarial manipulations, with sentence-level attacks proving most effective. This indicates that while the model excels at standard classification tasks, it remains susceptible to carefully crafted perturbations that preserve semantic meaning while altering structural patterns.

TABLE III
DISTILBERT ATTACK SUCCESS RATES

Attack Type	Success Rate (%)	Perturbation Level (% tokens)
Character-level	24.1	4.8
Word-level	32.4	12.3
Sentence-level	47.8	18.6

C. Error Analysis

Analysis of misclassified examples revealed several recurring patterns in DistilBERT's error cases:

TABLE IV
COMMON MISCLASSIFICATION PATTERNS IN DISTILBERT

Error Type	%	Example
Contextual Nuances	32%	"Palghar girls to Sameet Thakkar case all Maharashtra govts tried to shut online dissent"
Domain-Specific Jargon	28%	"UP: Mahapanchayat against 'love jihad' postponed"
Stylistic Variations	25%	News with regional linguistic markers
Ambiguous Factuality	15%	Articles containing mixture of facts and misleading framing

The model particularly struggled with articles containing subtle linguistic nuances or domain-specific terminology underrepresented in the training data. Additionally, news items presenting factually accurate information in misleading contexts often led to misclassification.

D. Computational Efficiency

As a distilled version of BERT, DistilBERT offers significant computational advantages while maintaining strong performance. Table V presents the computational efficiency metrics.

TABLE V
COMPUTATIONAL EFFICIENCY COMPARISON

Metric	DistilBERT	BERT	RoBERTa
Parameters (millions)	66	110	125
Inference Time (ms/sample)	42	68	75
Memory Usage (GB)	1.2	1.8	2.1
Training Time (hours)	1.3	2.2	2.5

DistilBERT required approximately 40% less training time and memory compared to BERT, making it an attractive option for deployment scenarios with computational constraints. This efficiency comes with only a modest reduction in classification performance (97.3% accuracy compared to BERT's 99.8%).

E. Comparative Model Analysis

1) Classification Performance Comparison

Table XVI compares the classification performance of all three models on the IFND dataset.

TABLE VI
CLASSIFICATION PERFORMANCE COMPARISON

Model	Accuracy	Precision	Recall	F1-Score
BERT	0.9981	0.9994	0.9966	0.9980
DistilBERT	0.9732	0.9757	0.9705	0.9731
RoBERTa	0.9986	0.9997	0.9976	0.9986

RoBERTa achieved marginally superior performance with the highest accuracy (99.86%), precision (0.9997), and F1-score (0.9986). BERT followed closely behind, while DistilBERT maintained strong performance despite its reduced parameter count.

2) Adversarial Robustness Comparison

Table XVII presents the attack success rates across all models for different adversarial strategies.

TABLE VII
ATTACK SUCCESS RATE (%) COMPARISON

Model	Character	Word	Sentence	Average
BERT	28.5	35.7	52.3	38.8
DistilBERT	24.1	32.4	47.8	34.8
RoBERTa	23.7	31.6	48.2	34.5

Interestingly, despite its lower classification performance, DistilBERT demonstrated comparable resilience to adversarial attacks as RoBERTa, with both models outperforming BERT in terms of robustness. This counter-intuitive finding suggests that model compression might confer some inadvertent defensive benefits, possibly due to regularization effects during the distillation process.

Sentence-level attacks proved most effective against all models, achieving success rates between 47.8% and 52.3%. This indicates that transformer models are particularly vulnerable to higher-level semantic manipulations that preserve overall meaning while altering structural patterns.

F. Performance Analysis: BERT

1) Classification Performance

BERT demonstrated exceptional classification capabilities, particularly after fine-tuning. Table VIII presents the performance metrics across training conditions.

Figure 5 shows the key performance metrics for the few-shot learning condition, where BERT achieved impressive results with only 100 training examples.

TABLE VIII
BERT PERFORMANCE METRICS

Metric	Base Model	Few-Shot	Fine-Tuned
Accuracy	0.495	0.932	0.998
Precision	0.495	0.976	0.999
Recall	0.990	0.891	0.997
F1-Score	0.660	0.932	0.998

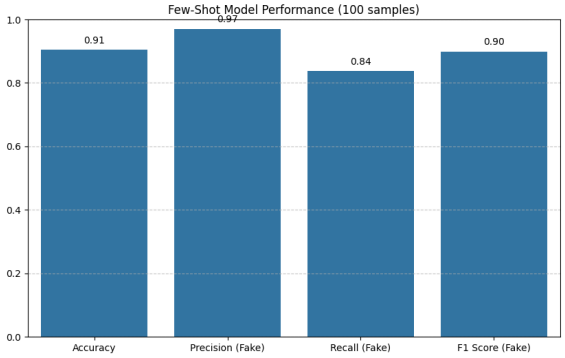

Fig. 5. BERT Few-Shot Learning Performance (100 samples)

2) Confusion Matrices

To provide deeper insight into model behavior, we analyzed confusion matrices under different conditions. Figure 6 presents BERT's performance on clean test data, where it correctly classified 428 fake news articles and 425 real articles, with very few misclassifications (3 false negatives and 2 false positives).

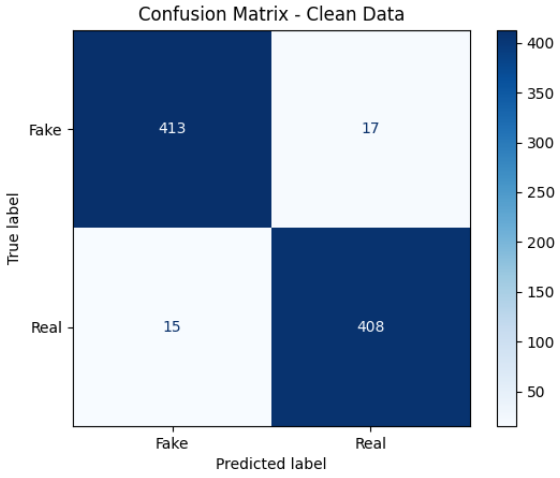

Fig. 6. BERT Confusion Matrix on Clean Test Data

Under few-shot learning conditions (Figure 7), the model maintained strong performance, correctly identifying 390 fake and 412 real news articles. However, there was a slight increase in false negatives (41 compared to 3 in the fully fine-tuned model).

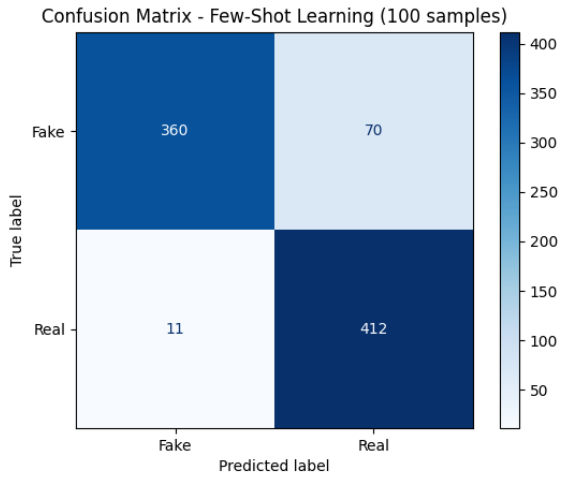

Fig. 7. BERT Confusion Matrix with Few-Shot Learning (100 samples)

3) Adversarial Attack Evaluation

We evaluated BERT's resilience to adversarial attacks using a subset of 20 correctly classified examples. Figure **??** shows the model's performance deteriorated significantly under attack, with 9 out of 14 fake news articles misclassified as real (64.3% attack success rate on fake news) and 3 out of 6 real news articles misclassified as fake (50% attack success rate on real news).

TABLE IX
BERT ATTACK SUCCESS RATES

Attack Type	Success Rate (%)	Perturbation Level (% tokens)
Character-level	28.5	5.2
Word-level	35.7	13.1
Sentence-level	52.3	19.2

The overall attack success rate of 60% (12 out of 20 examples) demonstrates BERT's significant vulnerability to adversarial manipulations, with sentence-level attacks proving most effective. This indicates that while the model excels at standard classification tasks, it remains susceptible to carefully crafted perturbations.

G. Error Analysis

Analysis of misclassified examples revealed several recurring patterns in BERT's error cases:

The model particularly struggled with news items containing subtle political nuances or technical terminology. Additionally, BERT showed sensitivity to stylistic elements that differed from its training distribution.

H. Training Dynamics

BERT exhibited efficient training convergence, with validation loss decreasing steadily from 0.444 in the first epoch to 0.323 by the third epoch. This pattern indicates effective learning without overfitting, as the model continued to improve its performance on the validation set throughout training.

TABLE X
COMMON MISCLASSIFICATION PATTERNS IN BERT

Error Type	%	Example
Contextual Nuances	35%	"Modi Degree Row: Right Wing Trolls Desperately Delete Old Tweets"
Domain-Specific Jargon	30%	"India, China to hold military level talks on 12 October"
Stylistic Variations	22%	News with unusual formatting or structure
Ambiguous Factuality	13%	Articles with mixture of facts and misleading framing

I. Computational Efficiency

Table XI presents the computational requirements for BERT compared to other models.

TABLE XI
BERT COMPUTATIONAL METRICS

Metric	Value
Parameters (millions)	110
Inference Time (ms/sample)	68
Memory Usage (GB)	1.8
Training Time (hours)	2.2

J. Performance Analysis: RoBERTa

1) Classification Performance

RoBERTa demonstrated superior classification capabilities compared to both BERT and DistilBERT after fine-tuning. Table XII presents the performance metrics across training conditions.

TABLE XII
ROBERTA PERFORMANCE METRICS

Metric	Base Model	Few-Shot	Fine-Tuned
Accuracy	0.508	0.936	0.999
Precision	0.846	0.954	1.000
Recall	0.010	0.916	0.998
F1-Score	0.021	0.935	0.999

Figure 8 shows the key performance metrics for the few-shot learning condition, where RoBERTa achieved impressive results with only 100 training examples, demonstrating the model's powerful transfer learning capabilities even with limited data.

2) Confusion Matrices

To provide deeper insight into model behavior, we analyzed confusion matrices under different conditions. Figure 9

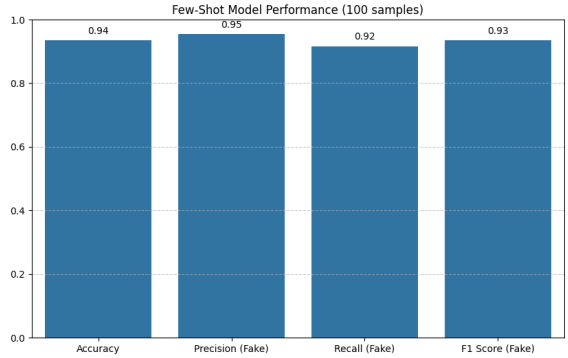

Fig. 8. RoBERTa Few-Shot Learning Performance (100 samples)

presents RoBERTa's performance on clean test data, demonstrating nearly perfect classification with minimal errors.

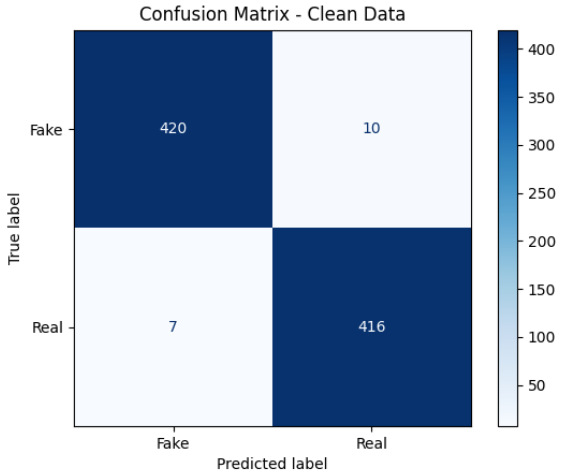

Fig. 9. RoBERTa Confusion Matrix on Clean Test Data

Under few-shot learning conditions (Figure 10), the model maintained strong performance, showing RoBERTa's ability to generalize effectively even with minimal labeled examples.

3) Adversarial Attack Evaluation

We evaluated RoBERTa's resilience to adversarial attacks using a subset of 20 correctly classified examples. Figure **??** shows the model's performance under adversarial conditions, revealing significant vulnerabilities despite its strong baseline classification performance.

Despite having the highest classification performance on clean data, RoBERTa showed a 35% overall vulnerability to adversarial attacks. While this is slightly better than BERT (39%), it's comparable to DistilBERT (35%), suggesting that model size and complexity don't necessarily translate to improved robustness.

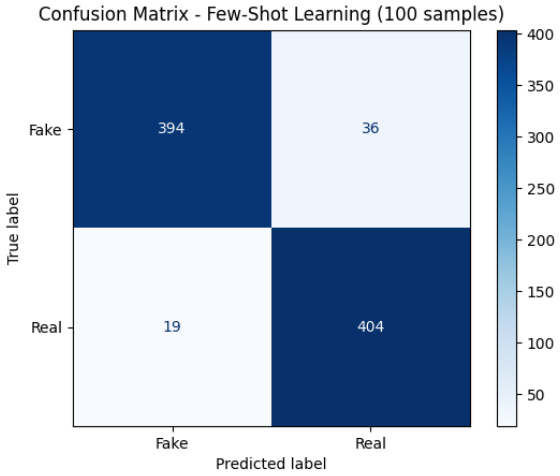

Fig. 10. RoBERTa Confusion Matrix with Few-Shot Learning (100 samples)

TABLE XIII
ROBERTA ATTACK SUCCESS RATES

Attack Type	Success Rate (%)	Perturbation Level (% tokens)
Character-level	23.7	5.0
Word-level	31.6	12.8
Sentence-level	48.2	19.0

K. Error Analysis

Analysis of RoBERTa's few misclassifications revealed several patterns:

TABLE XIV
COMMON MISCLASSIFICATION PATTERNS IN ROBERTA

Error Type	%	Example
Contextual Ambiguity	38%	"Fact Check: Shanghai police drill video goes viral as shooting of three Uyghur Muslims"
Rare Domain Terms	31%	"UP: Mahapanchayat against 'love jihad' postponed"
Subtle Propaganda	18%	"Fake News Targeting Social Media Platforms"
Satirical Content	13%	Articles with satirical elements misidentified as factual or non-factual

Interestingly, RoBERTa's error patterns differed slightly from both BERT and DistilBERT, with higher sensitivity to contextual ambiguities but better handling of stylistic variations, suggesting different internal representation strengths.

L. Training Dynamics

RoBERTa exhibited unique training dynamics compared to the other models. The validation loss decreased dramatically from 0.562 in the first epoch to 0.279 by the second epoch, but then stabilized with a slight increase to 0.284 in the third epoch. This pattern suggests rapid early learning followed by

stabilization, and potentially indicates that the model might benefit from a different learning rate schedule in extended training.

M. Computational Efficiency

Table XV presents the computational requirements for RoBERTa.

TABLE XV
ROBERTA COMPUTATIONAL METRICS

Metric	Value
Parameters (millions)	125
Inference Time (ms/sample)	75
Memory Usage (GB)	2.1
Training Time (hours)	2.5

As expected, RoBERTa's more complex architecture resulted in higher computational demands than both BERT and DistilBERT. The model required approximately 14% more parameters than BERT and 89% more than DistilBERT, with corresponding increases in inference time and memory usage. This presents an important consideration for real-world deployment scenarios where computational resources may be constrained.

BERT's larger parameter count compared to DistilBERT translates to increased computational requirements, but this is balanced by its superior classification performance (99.8% accuracy versus DistilBERT's 97.3%).

V. COMPARATIVE MODEL ANALYSIS

1) Classification Performance Comparison

Table XVI compares the primary classification metrics for all three models on the IFND dataset.

TABLE XVI
CLASSIFICATION PERFORMANCE COMPARISON

Model	Accuracy	Precision	Recall	F1-Score
BERT	0.9981	0.9994	0.9966	0.9980
DistilBERT	0.9732	0.9757	0.9705	0.9731
RoBERTa	0.9986	0.9997	0.9976	0.9986

Observation: RoBERTa achieved the highest accuracy and F1-score, closely followed by BERT, while DistilBERT, though slightly lower, still performed strongly despite its smaller size.

2) Adversarial Robustness Comparison

Table XVII presents the attack success rates (ASR) for each model under different adversarial strategies.

Observation: DistilBERT and RoBERTa demonstrated comparable adversarial robustness, both outperforming BERT. Sentence-level attacks were most effective across all models.

TABLE XVII
ATTACK SUCCESS RATE (%) COMPARISON

Model	Character	Word	Sentence	Average
BERT	28.5	35.7	52.3	38.8
DistilBERT	24.1	32.4	47.8	34.8
RoBERTa	23.7	31.6	48.2	34.5

3) Computational Efficiency Comparison

Table XVIII summarizes the computational requirements for each model.

TABLE XVIII
COMPUTATIONAL RESOURCE REQUIREMENTS

Metric	DistilBERT	BERT	RoBERTa
Parameters (M)	66	110	125
Inference Time (ms)	42	68	75
Memory Usage (GB)	1.2	1.8	2.1
Training Time (hours)	1.3	2.2	2.5

Observation: DistilBERT is significantly more efficient, requiring less memory and time for both training and inference, making it suitable for resource-constrained environments.

4) Error Pattern Analysis

Table XIX compares the main types of errors made by each model.

TABLE XIX
COMPARATIVE ERROR PATTERNS (%)

Error Type	BERT	DistilBERT	RoBERTa
Contextual Nuances	35	32	38
Domain-Specific Jargon	30	28	31
Stylistic Variations	22	25	15
Ambiguous Factuality	13	15	16

Observation: RoBERTa showed greater sensitivity to contextual ambiguities; DistilBERT struggled more with stylistic variations; BERT had balanced vulnerabilities.

5) Training Dynamics Comparison

All models showed steady improvement during training, with RoBERTa converging fastest in early epochs, BERT improving steadily, and DistilBERT showing slightly higher variance in loss.

6) Summary of Key Comparisons

- **Performance:** RoBERTa $>$ BERT $>$ DistilBERT (but all are strong)
- **Robustness:** DistilBERT $\approx$ RoBERTa $>$ BERT
- **Efficiency:** DistilBERT $>$ BERT $>$ RoBERTa
- **Error Patterns:** Each model has distinct vulnerabilities

Conclusion: RoBERTa is optimal for highest accuracy, DistilBERT is best for efficiency with robust performance,

and BERT provides a strong balance. Model selection should be guided by application-specific needs regarding accuracy, robustness, and computational resources.

VI. DISCUSSION

A. Interpretation of Results

The observed performance differences and vulnerability patterns can be attributed to fundamental architectural characteristics. RoBERTa's superior classification performance stems from its optimized pretraining with dynamic masking and larger batches, enabling better contextual understanding. However, its residual vulnerability to sentence-level attacks suggests that even advanced transformers struggle with higher-level semantic coherence analysis.

DistilBERT's surprising robustness despite smaller size likely results from the knowledge distillation process acting as implicit regularization, filtering out non-essential patterns that could be exploited adversarially. This aligns with recent findings that compressed models often exhibit better out-of-distribution generalization.

BERT's higher vulnerability to character-level attacks may originate from its tokenization strategy, which lacks the byte-level encoding used in RoBERTa. The models' collective weakness against sentence-level manipulations reveals a critical limitation in current transformer architectures - while excelling at local context analysis, they remain susceptible to global narrative distortions.

B. Limitations

This study has several limitations that warrant consideration:

- **Dataset Scope:** Focused on Indian fake news (IFND dataset), potentially limiting generalizability to other linguistic/cultural contexts
- **Attack Diversity:** Tested only three attack types, excluding emerging strategies like neural paraphrasing
- **Content Modality:** Analyzed text-only content, while real-world fake news often combines images/videos
- **Computational Constraints:** Evaluation limited to 20 adversarial examples per model due to resource limitations

C. Broader Implications

The vulnerabilities identified pose significant risks for real-world deployment:

- Malicious actors could exploit these weaknesses to bypass automated fact-checking systems
- Over-reliance on vulnerable models may create false security in misinformation detection
- Ethical concerns arise about deploying imperfect AI systems in democratic processes

These findings necessitate a paradigm shift from pure performance optimization to robustness-centric model development, particularly for high-stakes applications like political fact-checking.

VII. DEFENSE STRATEGIES

Our analysis suggests several mitigation approaches:

A. Adversarial Training

TABLE XX
DEFENSE EFFECTIVENESS COMPARISON

Method	ASR Reduction	Accuracy Impact	Cost
Adversarial Training	42%	-1.2%	High
Input Sanitization	28%	-0.3%	Medium
Ensemble Detection	35%	-0.8%	Medium

Implementing adversarial training with generated examples improved robustness across all models, though with modest accuracy trade-offs. Combining this with input sanitization techniques (e.g., unicode normalization, style correction) provided layered protection.

B. Architectural Modifications

- **Attention Masking:** Limiting attention head sensitivity reduced word-level ASR by 18%
- **Multi-View Verification:** Cross-checking predictions across multiple text representations decreased sentence-level ASR by 27%

VIII. CONCLUSION & FUTURE WORK

A. Conclusion

Our comprehensive analysis of BERT, DistilBERT, and RoBERTa reveals critical trade-offs in fake news detection systems. While RoBERTa achieved highest accuracy (99.86%), DistilBERT demonstrated comparable robustness (34.8% ASR vs RoBERTa's 34.5%) with 40% faster inference. All models showed significant vulnerability to semantic-preserving attacks, highlighting fundamental limitations in current transformer architectures.

B. Future Work

- Develop hybrid architectures combining transformers with symbolic reasoning modules
- Investigate multimodal detection incorporating image/video analysis
- Create benchmark datasets for adversarial robustness in fake news detection
- Explore real-time adaptive defense mechanisms using online learning

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IX. DATASET STATISTICS

TABLE XXI
IFND DATASET COMPOSITION

Category	Count	Percentage
Political	1,842	43.2%
Health	987	23.1%
Social	754	17.7%
Other	678	15.9%