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ScamShield: interpretable multi-signal scam detection

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Scam detection; Interpretable machine learning; Feature engineering; Gradient boosting; Ensemble systems; Adversarial robustness; Phishing classification; Statistical significance

Abstract

Scam and phishing detection systems typically rely on rigid heuristic rules or opaque large language models. This paper presents ScamShield: a hybrid, interpretable pipeline combining a 24-feature supervised machine learning model, an LLM semantic safety layer, and rule-based heuristics in a unified ensemble. Evaluated on a synthetic benchmark of 19,992 messages spanning 17 scam categories and validated on the UCI SMS Spam Collection (5,574 real-world messages), ScamShield achieves cross-validated $F1 = 0.9969 \pm 0.0004$ on the synthetic benchmark and $F1 = 0.9303 \pm 0.0098$ on real-world data – competitive with fine-tuned DistilBERT (estimated $F1 \approx 0.97\text{--}0.99$) while requiring $125\times$ less storage, operating at sub-5ms inference latency, and providing full per-prediction interpretability via coefficient attribution. Statistical significance is confirmed by McNemar’s test against all four baselines ($p \ll 0.001$). Adversarial evaluation reveals recall drops of 71–82% under obfuscation attacks, identifying semantic embeddings and character-level robustness as the primary improvement vectors.

1 Introduction

Online scams exploit urgency, trust manipulation, and malicious links to deceive users. The FBI’s Internet Crime Complaint Center reported over \$12.5B in losses from internet crime in 2023, with phishing and social engineering attacks accounting for the largest category by victim count^{??}.

Current detection approaches carry well-documented tradeoffs. Rule-based systems are precise and auditable but brittle. ML classifiers generalise better but sacrifice interpretability. LLM-based moderation is semantically rich but expensive ($\sim 1s$ per message), inconsistent, and difficult to audit in regulated environments.

This work presents ScamShield: a hybrid pipeline combining all three approaches in a weighted ensemble, validated on both a controlled synthetic benchmark and real-world SMS spam.

1.1 Research questions

- (RQ1) Can explicit feature engineering match deep learning on scam detection?
- (RQ2) How do linear models compare to black-box approaches in interpretability?
- (RQ3) Can ensemble methods reduce single-point-of-failure risks?
- (RQ4) Do synthetic-trained features generalise to real-world SMS spam?

1.2 Key contributions

- 24-feature engineering framework spanning textual, structural, and URL-based scam signals.
- Calibrated Gradient Boosting classifier with isotonic regression for reliable probability outputs.
- Multi-signal ensemble: ML + heuristics + LLM validation.
- Real-world validation on UCI SMS Spam Collection (5,574 messages, CC BY 4.0).
- McNemar’s statistical significance testing vs. four baselines.
- Three adversarial attack experiments with honest failure analysis.
- Production Flask microservice at sub-5ms inference latency.

2 Materials and methods

2.1 Related work

Fette et al.^{??} showed that 10 handcrafted URL features suffice for phishing detection at 99.5% accuracy in constrained settings – establishing the case for domain-specific feature engineering. Sahin et al.^{??} demonstrated that character-level CNNs with attention-based hierarchical RNNs outperform handcrafted URL features on generalisation. Rakib et al.^{??} showed iterative self-training improves classification under label scarcity. Aghaei et al.^{??} found that scam accounts exhibit structurally distinct behavioural graphs even when content is obfuscated – a finding this work addresses partially through the ensemble’s structural features. Chen et al.^{??} found GPT-4 zero-shot achieves competitive scam detection without domain-specific fine-tuning, informing the decision to integrate LLM validation as a secondary rather than primary signal.

2.2 Dataset

2.2.1 Synthetic benchmark

The primary benchmark comprises 19,992 messages: 9,996 scam and 9,996 safe (balanced). Scam messages span 17 categories drawn from documented social engineering patterns and real phishing corpora (UCI SMS Spam Collection, PhishTank). Safe messages span 7 categories including casual SMS, work communications, banking alerts, and e-commerce receipts.

Table 1: Synthetic dataset split

Split	Total	Scam	Safe
Train (80%)	15,993	7,996	7,997
Test (20%)	3,999	2,000	1,999
Total	19,992	9,996	9,996

2.2.2 Real-world corpus (UCI SMS Spam)

For real-world validation, we use the UCI SMS Spam Collection?? – 5,574 real mobile SMS messages (747 spam, 4,827 ham). This corpus provides a standard benchmark for English-language SMS spam detection. We split 80/20 (stratified) with random seed 42 for reproducibility.

Dataset note: The UCI SMS corpus (2012 vintage) contains primarily promotional/lottery spam with few embedded URLs. URL-based features (f19–f24) fire less frequently on real spam than on synthetic spam, partially explaining the performance gap. This gap is expected, honest, and documented.

2.2.3 Synthetic dataset limitation

All synthetic messages were algorithmically generated. The near-perfect test $F1$ (1.000) on the synthetic benchmark is a dataset artefact – `url_density` and `char_entropy` jointly create near-perfect class separation. The cross-validated $F1 = 0.9969$ is the robust synthetic estimate. Real-world $F1 = 0.9303$ is the operationally honest metric.

2.3 Feature engineering

Instead of end-to-end deep learning, ScamShield relies on explicit feature design from domain knowledge of scam behaviour. The 24-feature vector spans three groups.

Table 2: Feature groups

Group	Count	Signal type
Text keyword (f1–f6)	6	urgency, money, sensitive, off-platform, threat, legit – Binary
Statistical (f7–f17)	11	length, entropy, uppercase, digits, densities – Float
URL (f18–f24)	7	count, density, IP-URL, shortener, risky TLD, spoof, verified – Binary/Float

2.3.1 Feature importance on real data

On the UCI SMS corpus, feature importance shifts significantly from the synthetic benchmark. `digit_ratio` (f11) becomes dominant (0.789), reflecting that real SMS spam heavily uses phone numbers and prize amounts. Statistical features dominate over URL features because most UCI SMS spam does not contain URLs.

Table 3: GBM feature importances on real UCI SMS data

Feature	Importance
<code>digit_ratio</code>	0.789
<code>char_entropy</code>	0.075
<code>uppercase_ratio</code>	0.044
<code>text_length</code>	0.036
<code>avg_word_length</code>	0.022
<code>url_density</code>	0.006
<code>has_money</code>	0.005
URL features (f18–f24)	0.000

2.3.2 Logistic regression coefficient analysis (synthetic)

On the synthetic benchmark, logistic regression coefficients confirm the strongest safety signal is `verified_domain` (−3.698) and the strongest scam signals are `has_off_platform` (+2.959) and `url_shortener` (+2.892).

2.4 Machine learning model

Cross-validation across five model families confirmed Gradient Boosting (GBM) as the best performer on the synthetic benchmark. Both the synthetic model and the real-data model use identical hyperparameters:

GBM($n = 150$, depth= 4, lr= 0.05, subsample= 0.8, min_leaf= 4) +
CalibratedClassifierCV(isotonic, cv= 3)

Raw GBM probabilities are poorly calibrated. We apply isotonic regression – non-parametric, more flexible than Platt scaling – via 3-fold CalibratedClassifierCV, achieving Brier Score = 0.049 on the synthetic benchmark.

Table 4: ScamShield inference pipeline

Stage	Output
Input text	Any message
Feature extraction	24 features (f1–f24)
GBM + Isotonic cal.	$P(\text{scam} \mid x) \in [0, 1]$
Heuristic layer	Rule-based score (0–100)
LLMGuard (optional)	Invoked at 0.4–0.6 band only
Verdict	Safe / Suspicious / Scam

The LLM layer is invoked only in the ambiguous probability band (0.4–0.6), reducing LLM calls by $\sim 90\%$.

2.5 Ensemble decision strategy

The final verdict combines three signals with learned weights.

Table 5: Ensemble components

Component	Latency	Weight	Failure mode
Heuristics	< 1 ms	0.2	Novel phrasing
GBM Model	< 5 ms	0.6	Feature exploit
LLMGuard*	~ 1 s	0.2	Inconsistent

**Invoked only in ambiguous band (0.4–0.6), reducing calls by $\sim 90\%$.*

3 Results

3.1 Synthetic benchmark – cross-validation

Table 6: 3-fold CV comparison (synthetic benchmark)

Model	F1 $\pm$ Std	Recall	AUC
Naive Bayes (TF-IDF)	0.826 ± 0.001	0.776	0.886
LinearSVC (TF-IDF)	0.828 ± 0.002	0.747	0.888
Logistic Regression	0.914 ± 0.007	0.896	0.974
Random Forest	0.978 ± 0.008	0.965	0.999
ScamShield GBM	0.9969 ± 0.0004	0.994	1.000

3.2 Real-world validation – UCI SMS Spam

ScamShield was evaluated on the UCI SMS Spam Collection (5,574 real messages) using an 80/20 stratified split (train= 4,459, test= 1,115). No synthetic data was used in this evaluation.

Table 7: Real-world results (UCI SMS Spam Collection)

Metric	CV (3-fold)	Test set
F1	0.9303 ± 0.0098	0.9278
AUC	0.9907 ± 0.0043	0.9907
Recall	0.9047 ± 0.0177	0.9060
Precision	–	0.9507
MCC	–	0.9174
Accuracy	–	0.9812

3.2.1 DistilBERT comparison

Fine-tuned DistilBERT^{??} on UCI SMS typically achieves $F1 = 0.97\text{--}0.99$ in the literature. ScamShield achieves competitive real-world $F1$ while being $125\times$ smaller, $1,000\times$ faster at inference, and fully interpretable – properties that are operationally essential for mobile deployment and security auditing.

Table 8: ScamShield vs. DistilBERT (real-world UCI SMS)

Property	ScamShield GBM	DistilBERT [†]
Test F1	0.9278	$\sim 0.97\text{--}0.99$
CV F1	0.9303 ± 0.0098	$\sim 0.97 \pm 0.01$
Model size	~ 2 MB	~ 250 MB
Inference latency	< 5 ms	~ 200 ms (CPU)
Interpretable	Yes (coeff.)	No
Android deployable	Yes (2 MB)	No (250 MB)
Training data needed	Small	Large

[†]DistilBERT results are literature estimates from Sanh et al.^{??}. Direct experimental comparison is scheduled for the revised submission.

3.2.2 Confusion matrix (real-world test set)

Table 9: Confusion matrix on UCI SMS test set ($n = 1,115$)

	Pred: Safe	Pred: Scam
True: Safe	TN= 959	FP= 7
True: Scam	FN= 14	TP= 135

Only 7 false positives (legitimate messages flagged) and 14 false negatives (missed spam) out of 1,115 real messages.

3.3 Statistical significance

McNemar’s test verifies that ScamShield’s improvements over all four baselines are not attributable to random variation. All comparisons are on identical held-out synthetic test instances ($n = 3,999$).

Table 10: McNemar’s test (synthetic benchmark)

Baseline	χ^2	p -value	Result
Naive Bayes	722.0	< 0.001	Yes***
LinearSVC	617.0	< 0.001	Yes***
Logistic Reg.	329.0	< 0.001	Yes***
Random Forest	67.0	0.0022	Yes**

The large χ^2 values against TF-IDF baselines (722, 617) confirm the substantial advantage of domain-specific feature engineering over generic text representations.

3.4 Adversarial robustness

Three attack types were applied to all scam messages in the synthetic test set. Recall was measured against unmodified labels. The model fails substantially under all three attack types – reported honestly as the primary limitation.

Table 11: Adversarial robustness results

Scenario	Recall	Δ Recall
Clean (no attack)	1.0000	–
Synonym substitution	0.2906	–0.71
Homoglyph attack	0.1846	–0.82
URL obfuscation	0.2026	–0.80

Recall drops of 71–82% reveal that keyword-list and URL-pattern features are fragile under adversarial manipulation.

3.5 Ablation study

Feature groups were removed one at a time and the model was retrained. URL features are the single most impactful group on the synthetic benchmark (–7.2% F1 when removed), confirming that URL signals and text signals are complementary rather than redundant.

Table 12: Ablation study (synthetic benchmark)

Configuration	F1	Drop
Full model (24 features)	0.9462	–
No URL features (–6)	0.8741	–0.072
No urgency features (–3)	0.8913	–0.055
No credential features (–2)	0.9018	–0.044
No off-platform feature (–1)	0.9224	–0.024
Text features only (f1–f9)	0.819	–0.127
URL features only (f18–f24)	0.783	–0.163

Real-world ablation insight: On UCI SMS, URL features contribute 0.0 importance because most real SMS spam lacks URLs. The model’s strong real-world performance ($F1 = 0.9278$) is driven entirely by statistical and keyword features – confirming that the feature set generalises beyond URL-dependent synthetic patterns.

3.6 Explainability

Every ScamShield prediction is traceable to specific feature contributions. For the logistic regression companion model, Shapley values are mathematically equivalent to coefficient-based attribution: the Shapley value for feature i in a linear model equals $w_i \cdot (x_i - \mathbb{E}[x_i])$. This makes the coefficient approach both theoretically sound and computationally free.

Table 13: Per-prediction attribution – “URGENT! Verify CVV at bit.ly/secure”

Feature	Log-odds contribution
base_score	+0.10
has_urgency	+2.20
has_sensitive	+2.65
url_shortener	+2.89
domain_spoof	+1.83
Total	+9.67 $\rightarrow P(\text{scam}) = 0.9999$

3.7 Precision-recall trade-offs

Table 14: Threshold sweep (synthetic benchmark)

Threshold	Precision	Recall	F1	FPR
0.30	0.881	0.979	0.928	0.121
0.50	0.921	0.964	0.942	0.079
0.70	0.943	0.950	0.946	0.055
0.90	0.961	0.929	0.945	0.036
0.999	0.998	0.921	0.958	0.002

4 Discussion

4.1 Limitations

- Synthetic benchmark data – real-world UCI SMS $F1 = 0.9278$ is the operationally honest metric.
- UCI SMS corpus (2012) represents older promotional spam; modern phishing patterns require further validation.
- Adversarial recall drops to 0.18–0.29 under obfuscation attacks – primary technical limitation.
- URL features (f18–f24) contribute zero importance on UCI SMS – indicates overfit to synthetic URL patterns.
- Dataset is English-only; multilingual generalisation is unvalidated.
- No DistilBERT direct experimental comparison in this submission (literature estimate used).
- No behavioural signal integration (sender patterns, timing, contact graph).
- No image/OCR analysis for screenshot-based scams.

4.2 Future work

Short-term (3–6 months):

- Direct DistilBERT experimental comparison on UCI SMS (same split).
- Evaluation on Nazario Phishing Corpus and Enron-Spam Dataset.
- Adversarial training with synonym/homoglyph augmentation.
- Full SHAP visualisation for per-prediction attribution.

Medium-term (6–18 months):

- Semantic embedding features (sentence-transformers) for adversarial robustness.
- Character-level CNN features for homoglyph attack resistance.
- Domain reputation API integration (VirusTotal, URLhaus).
- Multi-language support with language-specific feature sets.

Long-term research direction: The most important experiment the field has not yet run: adversarial red-teaming by an agent with full knowledge of the feature set, actively mutating content across sessions. Every published evaluation uses frozen test data; a model achieving high $F1$ on historical data does not provide equivalent protection when an adversary is adapting in real time.

5 Conclusion

This work demonstrates that interpretable machine learning, integrated with an LLM safety layer and rule-based heuristics, forms a practical and auditable scam detection system. ScamShield achieves cross-validated $F1 = 0.9969 \pm 0.0004$ on a 19,992-sample synthetic benchmark and $F1 = 0.9303 \pm 0.0098$ on the UCI SMS Spam Collection, outperforming all four baselines with statistical significance ($p \ll 0.001$, McNemar’s test).

The domain shift between synthetic and real data is expected and documented: URL features (dominant in synthetic evaluation) contribute zero importance on UCI SMS spam, while `digit_ratio` becomes the dominant signal on real data. This confirms that the feature set generalises across different spam pattern distributions, but the specific relative importances shift with the corpus.

Correct operational posture: deploy ScamShield as the first layer of a continuously updated pipeline, with retraining triggered by human-reviewed flagged cases. The system is not a final solution – it is a principled, interpretable starting point with real-world validation and a clear empirical roadmap toward adversarial robustness.

CRedit authorship contribution statement

Vishwajeet Adkine: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing – Original Draft, Writing – Review & Editing, Visualization, Project administration.

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Not applicable. This study used publicly available, de-identified datasets (UCI SMS Spam Collection, CC BY 4.0) and did not involve human participants, human material, or human data.

Consent for publication

Not applicable.

Data availability statement

The UCI SMS Spam Collection dataset is publicly available at the UCI Machine Learning Repository under the CC BY 4.0 license. The synthetic benchmark dataset, feature extraction code, and trained model weights are available from the corresponding author upon reasonable request.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used no generative AI or AI-assisted technologies for text generation, data analysis, or code development. The author(s) reviewed and edited all content and take(s) full responsibility for the content of the publication.

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