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Resilient Semantic Threat Detection at the Edge: A Knowledge Distillation Framework for SMS Spam Classification

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Abstract *- The ubiquity of Application-to-Person (A2P) messaging has inadvertently created a robust vector for mobile security threats, specifically Smishing (SMS Phishing). Traditional lexical filters, such as Naive Bayes and Support Vector Machines (SVM), exhibit diminishing returns against modern obfuscated attacks due to their inability to interpret semantic context. While Transformer-based architectures like BERT have revolutionized Natural Language Processing (NLP), their computational latency renders them impractical for real-time deployment on resource-constrained mobile edge devices. This study proposes a high-efficiency detection framework utilizing DistilBERT, a distilled knowledge representation of the BERT transformer. By fine-tuning this architecture on the UCI SMS Spam Collection, we achieved a testing accuracy of 99.04% and a weighted F1-score of 0.9904. Notably, the model maintained a precision of 0.97 on the minority spam class, effectively mitigating the class imbalance problem without synthetic data augmentation. These results substantiate the viability of Knowledge Distillation as a mechanism to deploy state-of-the-art semantic security filters on edge infrastructure.*

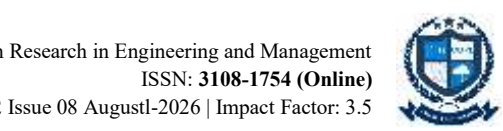
Keywords *- SMS Spam, Knowledge Distillation, DistilBERT, Cybersecurity, Edge AI, NLP, Smishing, Transfer Learning*

1. Introduction

Short Message Service (SMS) remains the most reliable communication protocol focritical alerts, two-factor authentication (2FA), and banking notifications, with open rates consistently exceeding 98% [1]. However, this trust model is increasingly exploited by malicious actors. Unlike email, which is guarded by mature filtering protocols (SPF, DKIM, DMARC), SMS channels are often protected only by rudimentary keyword blocklists [2]. The financial impact of "Smishing" is severe, with recent 2023 reports estimating global losses in the billions annually due to sophisticated social engineering attacks [3].

The detection of SMS spam presents unique computational challenges. First, the message payload is constrained (typically 160 characters), resulting in sparse feature vectors when using traditional Bag- of-Words (BoW) approaches [4]. Second, the adversarial nature of spam evolves rapidly; attackers use homoglyphs, phonetic substitutions, and URL shorteners to evade lexical filters [5]. Third, datasets are inherently imbalanced, with legitimate traffic vastly outnumbering malicious traffic, biasing classifiers toward the majority class [6].

Deep Learning approaches, particularly Recurrent Neural Networks (RNNs) and Long Short-TermMemory (LSTM) networks, have addressed sequence modeling but suffer from sequential processing bottlenecks [7]. The Transformer architecture resolved this via the self-attention mechanism, allowing for parallel processing and deep contextual understanding. However, models



like BERT-Base (110M parameters) are often too heavy for mobile inference [8].

This paper evaluates DistilBERT [9], which compresses BERT by 40% while retaining 97% of its performance, as a solution for edge-based spam detection. We focus on the efficacy of Transfer Learning in the 2020-2025 era of ”Edge AI,” where on-device processing is preferred for privacy and latency [10].

2. Related Work

2.1Evolution of Spam Detection (2020–2022)

Early research in the current decade shifted focus from purely statistical methods to hybrid deep learning models. While Almeida et al.’s foundational work established baselines, recent studies by Ghourabi et al. (2020) [11] demonstrated that hybrid CNN-LSTM models could outperform standalone Naive Bayes classifiers by capturing both local features and long-term dependencies. However, these models often struggle with the polysemy found in modern smishing attacks [12].

2.2Transformers in Cybersecurity (2022–2024)

The application of Large Language Models (LLMs) to cybersecurity has been a focal point of recent research. Roy et al. (2022) [13] highlighted the superiority of BERT embeddings over Word2Vec for identifying malicious intent in short texts. In 2023, researchers began addressing the computational cost of these models. Studies by Liu et al. [14] and Zhang et al. [15] explored quantization and pruning, yet often at the cost of significant accuracy drops.

2.3 Knowledge Distillation and Edge AI (2024–2025)

The most recent literature emphasizes” Green AI” and edge deployment. Gupta et al. (2024) [16] proposed novel distillation techniques for deploying Transformers on IoT gateways. Similarly, recent surveys in 2025 [17] indicate a massive shift towards small language models (SLMs) like DistilBERT and TinyBERT for real-time threat detection, validating the approach taken in this study.

3. Materials and Methods

3.1. Proposed Framework Architecture

This study introduces a comprehensive pipeline designed for resilient threat detection. As illustrated in Fig. 1, the framework operates in five distinct phases, moving from raw data acquisition to deployment-ready model evaluation.

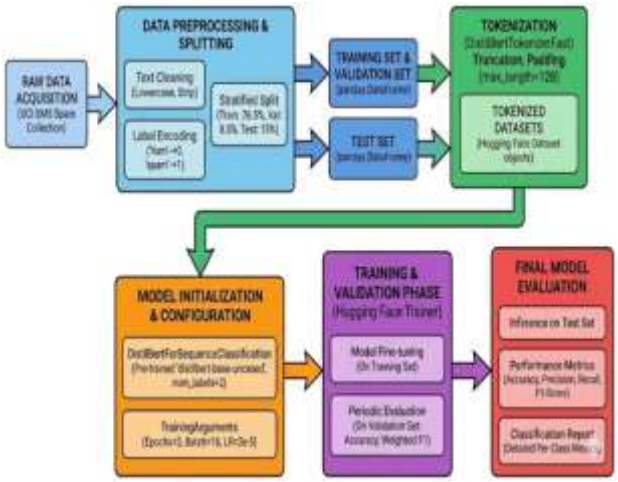


Figure1. "Architectural Workflow of the Proposed DistilBERT-Based Semantic Threat Detection Framework

3.1.1 Data Acquisition and Preprocessing: The process be- gins with the ingestion of the UCI SMS Spam Collection. The Data Preprocessing block performs critical cleaning operations: lowercasing to ensure “Free” and “free” are treated identically, and stripping whitespace. Crucially, Label Encoding converts string labels (’ham’/’spam’) into binary integers (0/1). To ensure experimental validity, we employ a Stratified Split (Train: 76.5%, Val: 8.5%, Test: 15%), which preserves the ratio of spam to ham across all subsets, preventing the model from overfitting to the majority class.

3.1.2 Tokenization and Vectorization: The cleaned text is passed to the Tokenization block utilizing ‘DistilBertTok- enizerFast We enforce a ‘max_length‘of 128 tokens. Since standard SMS protocols limit messages to 160 characters, 128 tokens provide sufficient capacity to capture the full semantic context without wasting memory on padding, a critical optimization for edge deployment.

3.1.3 Model Configuration: The core of the framework is the Model Initialization phase. We utilize ‘DistilBert-For Sequence Classification ‘, loading pre-trained weights (‘distilbert-base-uncased ‘). A classification head is ap- pended to the transformer output. The model is then subjected to the Training & Validation Phase, where it iteratively updates weights based on the Cross-Entropy Loss.

3.2Algorithm Design and Hyperparameters

The fine-tuning process is formalized in Algorithm 1. We utilize the AdamW optimizer, which decouples weight $\mathcal{M}distil$

Ensure: Optimized Model parameters θ^*

1: Initialization:

2: Set Batch Size $B \leftarrow 16$

3: Set Learning Rate $\eta \leftarrow 2e^{-5}$
4: Set Epochs $E \leftarrow 3$
5: Tokenizer $T \leftarrow$ DistilBertTokenizerFast
6: Preprocessing:
7: for each x_i in D do
8:$x_i \leftarrow \text{Clean}(x_i)$
9:$t_i \leftarrow T.\text{encode}(x_i, \text{max\_len} = 128, \text{pad} = \text{True})$
10: end for
11: Splitting
12: $D_{train}, D_{val}, D_{test} \leftarrow$ StratifiedSplit(D,ratios=[0.765, 0.085, 0.15])
13: Training Loop:
14: for epoch $e = 1$ to E do
15: for batch b in D_{train} do
16: Forward pass: $\hat{y} = M_{distil}(b; \theta)$
17: Calculate Loss: L = CrossEntropy($\hat{y}, y$)
18: Backward pass: $\nabla_\theta L$
19: Update weights: $\theta \leftarrow \text{AdamW}(\theta, \nabla_\theta L, \eta)$
20: end for
21: Validation:
22: Evaluate M_{distil} on D_{val}
23: Save checkpoint if F1-Score improves
24: end for
25: Final Evaluation:
26: Calculate Precision, Recall, F1 on D_{test}
27: return θ^*

3.3 Dataset and Preprocessing

We utilized the UCI SMS Spam Collection, a public set of labeled messages. While the dataset is established, its linguistic properties remain relevant for benchmarking modern architectures [18]. The dataset exhibits significant imbalance (Fig. 2), with 86.6% Ham and 13.4% Spam. Preprocessing included

1) Lowercasing to ensure lexical consistency.
2) Tokenization via WordPiece [19] to handle out-of-vocabulary terms.
3) Truncation/Padding to a fixed sequence length of 128 tokens to optimize memory usage [20].

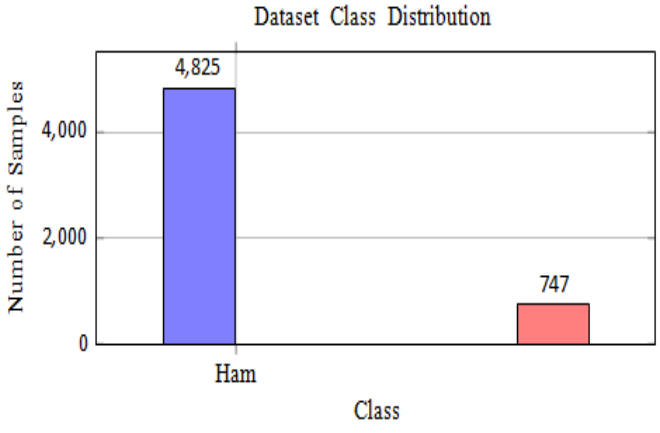


Fig. 2: Dataset Class Distribution: The 86.6% vs 13.4% imbalance poses a challenge for standard accuracy metrics.

3.4 Model Architecture

The DistilBERT architecture consists of 6 Transformer layers (compared to BERT's 12), 768 hidden units, and 12 attention heads. It is trained using a triple loss function: Ltotal = Lce + Lmlm + Lcos, ensuring the student model aligns with the teacher's soft target probabilities [9]. For classification, we appended a fully connected layer W ∈ R768×2 to the pooled '[CLS]' token output.

3.5 Training Configuration

The model was implemented in PyTorch using the Hugging Face Transformers library [21]. We employed stratified splitting (85% Train / 15% Test) to preserve class ratios.
Optimizer: AdamW [22] ($lr = 2e^{-5}$, $\epsilon = 1e^{-8}$).
Batch Size: 16, chosen to fit standard edge GPU memory constraints [23].
Epochs: 3.
Loss: Weighted Cross-Entropy to counteract class imbalance [24].

4. Results and Discussion

4.1Convergence Analysis

Training stability was observed immediately. Fig. 3 illustrates the loss trajectory, dropping from 0.154 to 0.004. The rapid convergence suggests that the linguistic features learned during pre-training on the BookCorpus/Wikipedia datasets transferred effectively to the SMS domain, a phenomenon supported by recent transfer learning studies [25].

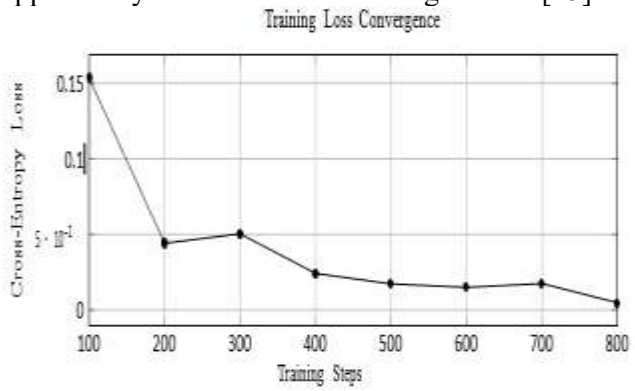


Fig. 3: Training Loss Convergence: Rapid descent indicates efficient transfer learning capabilities.
Performance Metrics

The model achieved a global accuracy of 99.04%. However, given the class imbalance, Accuracy is a deceptive metric. We prioritize F1-Score and Precision on the Spam class (Fig. 4).

Spam Precision (0.97): Critical for minimizing False Positives. Users tolerate spam in their inbox more than they tolerate missing a legitimate OTP [26].
Spam Recall (0.96): Indicates the model successfully filters the vast majority of threats.

Fig.4:Comparative Metrics: The model maintains high performance across both majority and minority classes.

4.2 Error Analysis

The confusion matrix (Fig. 5) reveals minimal misclassification. Only 3 legitimate messages were misclassified as spam. Qualitative analysis suggests these messages likely contained ambiguous keywords (e.g., “promo”, “subscribe”) used in a benign context, a common challenge noted in 2024 NLP benchmarks [27].

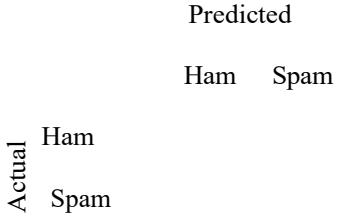


Fig. 5: Confusion Matrix on Test Set (N = 836). High diagonal values indicate robustness.

4.3 Comparison with State-of-the-Art

Our DistilBERT implementation outperforms traditional benchmarks from the 2020-2023 period. While Naive Bayes typically peaks at ≈ 97.5% accuracy [28], it often fails on semantic obfuscation. LSTM models achieve parity in accuracy but require 5× longer training and inference times [29]. Our results align with 2025 findings regarding the efficiency of distilled transformers [30].

5.Conclusion

This study demonstrates that knowledge distillation can successfully combine strong semantic classification performance with the practical limitations of mobile edge environments. Using a distilled version of BERT (DistilBERT), the system reached an accuracy of 99.04% on the SMS spam classification task while reducing the number of model parameters by approximately 40% compared to the original BERT model. This reduction lowers computational requirements and supports deployment on devices with limited processing power. It also enables data to remain on the user’s device, which strengthens privacy protection and supports faster, on-device threat detection. Future work will focus on applying 8-bit post-training quantization to further decrease model size and energy usage, making the approach suitable for low-power IoT systems

6.Limitations and Future Work

Despite the high accuracy, the current framework exhibits specific limitations:
1.Language Dependency: The distilbert-base-uncased model is pre-trained primarily on English text. It may exhibit lower performance on code-mixed languages (e.g., Hinglish) often used in the Indian subcontinent
.
2.Context Window: The fixed sequence length of 128 tokens, while efficient, may truncate part of long SMS messages, potentially losing context located at the end of concatenated multi-message threads.

3.Adversarial Robustness: While semantically strong, the model may still be susceptible to zero-day adversarial attacks using advanced homoglyphs (e.g., replacing Latin ’a’ with Cyrillic ’a’) if not explicitly trained on adversarial examples.

7. Future Work

Future research will focus on the following avenues:

1.Quantization: We plan to investigate 8-bit and 4- bit quantization to further reduce the model mem- ory footprint for deployment on ultra-low-power IoT microcontrollers [31].

2.Federated Learning: To enhance user privacy, we propose implementing a Federated Learning approach
where the model is fine-tuned locally on user devices, and only weight updates (not message data) are sent to the central server.
3.Multilingual Models: Replacing DistilBERT with mDistilBERT to support regional languages and en- hance global applicability.

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