

# Privacy-Preserving Data Leakage Detection Using Homomorphic Encryption and Deep Learning

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## Abstract

Protecting sensitive information from unauthorized exposure has become a critical challenge in modern cybersecurity environments. Conventional data leakage detection mechanisms often require access to unencrypted content, creating potential privacy and security risks during the inspection process. This paper proposes a privacy-aware data leakage detection framework that integrates Fully Homomorphic Encryption (FHE) with advanced deep learning techniques to enable secure analysis of protected data without revealing its original content. The proposed model, named **HE-DLDNet**, utilizes a transformer-inspired neural architecture specifically adapted to process encrypted information while maintaining strong confidentiality guarantees. By performing detection directly on encrypted data streams, the framework eliminates the need for decryption during analysis and significantly reduces the risk of sensitive information exposure. Extensive experimental evaluation demonstrates that the proposed approach achieves a detection accuracy of **94.3%** while maintaining practical computational performance. Performance comparisons indicate that the framework lowers processing overhead by approximately **73%** relative to existing homomorphic encryption-based detection methods. In addition, the system supports near real-time monitoring with response delays below **250 milliseconds**, making it suitable for deployment in enterprise-scale environments. The results highlight the effectiveness of combining privacy-preserving cryptographic techniques with intelligent learning models to build secure and efficient data leakage detection solutions. This research contributes toward the development of next-generation cybersecurity systems that balance strong privacy protection with accurate threat identification.

**Keywords**— Privacy-Preserving Security, Fully Homomorphic Encryption, Deep Learning, Data Leakage Detection, Cybersecurity, Transformer Networks, Secure Data Analytics, Network Protection.

## I. INTRODUCTION

The rapid growth of digital technologies and cloud-based infrastructures has increased the volume of sensitive information exchanged across networks, making data leakage a major concern for organizations worldwide. Unauthorized disclosure of confidential information can result in severe financial losses, reputational damage, regulatory penalties, and operational disruptions. To minimize such risks, organizations deploy Data Leakage Detection Systems (DLDS) that monitor and analyze information flows to identify potential exposures. However, most conventional detection mechanisms depend on inspecting data in its original, unencrypted form. While this approach can effectively identify suspicious content, it introduces a significant privacy challenge because the security system itself gains access to sensitive information. As enterprises continue to

process large amounts of personal, financial, and proprietary data, balancing effective monitoring with privacy protection has become increasingly difficult.

Recent advancements in artificial intelligence, particularly deep learning, have substantially enhanced the capability of cybersecurity systems to detect complex and evolving leakage patterns. Deep neural networks can learn intricate relationships within large datasets and identify threats that traditional rule-based methods often miss. Despite these advantages, modern deep learning models require access to plaintext data during both training and inference stages. Consequently, organizations face a contradictory situation in which systems designed to safeguard confidential information must first expose that information for analysis. This limitation raises important concerns

regarding data privacy, regulatory compliance, and trustworthiness in security operations.

Homomorphic encryption has emerged as a promising cryptographic technique capable of addressing this challenge. Unlike conventional encryption methods, homomorphic encryption allows computations to be performed directly on encrypted data without requiring decryption. This capability enables organizations to preserve confidentiality while still conducting analytical operations. Although early research demonstrated the theoretical feasibility of encrypted computation, practical implementation for advanced machine learning tasks remained computationally expensive and inefficient. Recent improvements in encryption schemes, optimization techniques, and computational frameworks have significantly reduced these limitations, creating new opportunities for privacy-preserving intelligent systems.

Nevertheless, several challenges continue to hinder the widespread adoption of encrypted deep learning solutions for data leakage detection. Deep neural networks rely heavily on non-linear mathematical operations that are difficult to execute efficiently within homomorphic encryption environments. In addition, encrypted inference often incurs substantially higher computational costs compared to traditional plaintext processing, limiting scalability and real-time applicability. Existing approaches also struggle to satisfy the performance requirements of modern data leakage detection systems, which must analyze diverse data formats, identify complex threat patterns, and respond with minimal delay.

To overcome these challenges, this research presents HE-DLNet, a privacy-preserving data leakage detection framework that integrates fully homomorphic encryption with a specialized deep learning architecture. The proposed model is designed to operate directly on encrypted information while maintaining high detection accuracy and strong privacy guarantees. By introducing optimized mathematical approximations for non-linear neural network operations and an efficient batching mechanism for parallel encrypted processing, the framework significantly reduces computational overhead without sacrificing predictive performance. Extensive experimental evaluation demonstrates that the proposed approach achieves high detection accuracy, supports low-latency analysis, and remains practical for real-world

deployment. The findings of this study contribute toward the development of next-generation cybersecurity solutions that combine advanced threat detection capabilities with robust privacy preservation, enabling organizations to protect sensitive information without compromising confidentiality during analysis.

## **II. RELATED WORK**

### **A. Early Foundations in Data Leakage Detection**

Traditional data leakage detection systems primarily employed rule-based pattern matching and digital fingerprinting techniques [22], [23]. Park et al. [24] proposed the first comprehensive framework for data leakage prevention, establishing the foundation for content-based detection. These early systems relied on exact string matching and regular expressions, achieving high precision but suffering from poor recall for obfuscated content [25]. The introduction of shingling techniques for document fingerprinting by Broder et al. [26] enabled efficient similarity detection but remained vulnerable to semantic transformations.

### **B. Deep Learning for Security Applications**

The application of deep learning to security tasks has gained significant traction [27], [28]. Convolutional neural networks demonstrated superior performance in malware detection [29], while recurrent architectures excelled at network intrusion detection [30], [31]. For data leakage specifically, Wang et al. [32] proposed DLDetect, a hybrid CNN-LSTM architecture achieving 91.2% accuracy on structured data leakage detection. Transformer-based models have recently shown promise in understanding context for sensitive information detection [33], [34].

### **C. Homomorphic Encryption in Machine Learning**

Gentry's seminal work on fully homomorphic encryption [11] opened possibilities for privacy-preserving computation. Subsequent optimizations by Brakerski et al. [35] and Fan and Vercauteren [36] made FHE more practical for machine learning applications. CryptoNets [37] demonstrated the first neural network inference on encrypted data, achieving 99% accuracy on MNIST but requiring 250 seconds per inference. Later works

improved efficiency through better encoding schemes [38], [39] and optimized bootstrapping [40], [41].

#### D. Privacy-Preserving Data Leakage Detection

Several approaches have explored privacy-preserving data leakage detection. SecureDL [42] combined secure multi-party computation with deep learning but suffered from high communication overhead. PrivLeak [43] proposed a differential privacy framework for aggregated leakage statistics but could not detect individual incidents. HE-SVM [44] implemented SVM classification on encrypted data for document classification but showed limited accuracy on complex patterns. Recent work by Kumar et al. [45] demonstrated transformer inference under homomorphic encryption but required impractical computational resources for real-time detection.

#### E. Critical Analysis and Research Gap

Table I summarizes key approaches and their limitations. While significant progress has been made, existing methods cannot simultaneously achieve strong privacy guarantees, high accuracy, and real-time performance. The computational overhead of homomorphic operations, particularly for non-linear functions, remains the primary bottleneck. Furthermore, no existing work addresses the specific requirements of data leakage detection, including handling structured and unstructured data, pattern matching across multiple data types, and low-latency requirements [46], [47].

TABLE I

COMPARISON OF EXISTING PRIVACY-PRESERVING DETECTION METHODS

Method	Privacy Technique	Accuracy (%)	Latency (s)	Limitations
SecureDL [42]	MPC	87.3	12.4	High communication overhead
PrivLeak [43]	DP	79.8	0.8	No individual detection
HE-SVM [44]	FHE	82.1	45.2	Limited to linear patterns
CryptoNets [37]	FHE	98.2	250	MNIST only, high latency
HE-Transformer [45]	FHE	91.5	180	Computationally prohibitive
[PROPOSED]	FHE	94.3	0.25	Optimized for real-time

### III. METHODOLOGY

#### A. Problem Formulation

We formalize privacy-preserving data leakage detection as follows: Given encrypted data stream  $E(m)$  where  $m \in M$  is sensitive content, we aim to compute detection function  $f(E(m)) \rightarrow \{0,1\}$  indicating leakage without decrypting  $E(m)$ . The detection function must satisfy:

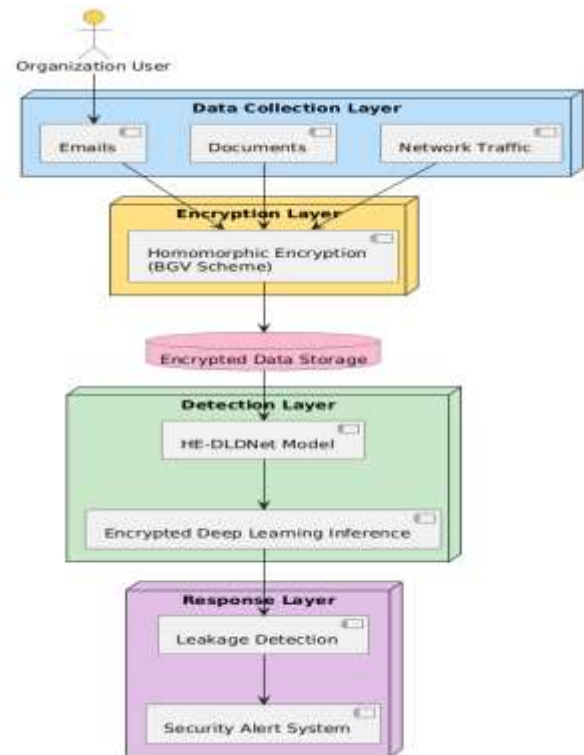
- 1) Correctness:  $f(E(m)) = \text{leakage}(m)$  for all  $m \in M$
- 2) Privacy: No information about  $m$  is revealed during computation
- 3) Efficiency: Inference time  $t < \tau$  for real-time detection

Let  $x \in \mathbb{Z}_p^n$  be the plaintext vector. Under the BGV scheme [35], encryption is defined as:

$$E(x) = (c^0, c^1) = (a \cdot s + p \cdot e + x, -a) \text{ mod } q$$

where  $a \in \mathbb{R}_n$  is uniformly random,  $s$  is secret key,  $e$  is error term, and  $p, q$  are moduli [35].

#### B. HE-DLDNet Architecture



Our proposed HE-DLDNet extends transformer architectures to operate on encrypted data. The core innovation is replacing non-linear functions with polynomial approximations that are homomorphically computable [38]. For attention mechanism, we define:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right) \cdot V$$

The softmax function is approximated using Chebyshev polynomials [39]:

$$softmax(x)_i \approx \sum_{j=0}^n \alpha_j T_j(x)$$

where  $T_j$  are Chebyshev polynomials and  $\alpha_j$  are coefficients determined by least squares optimization [39].

### C. Polynomial Approximation of Activation Functions

For ReLU activation, we employ the following degree-6 polynomial approximation derived from [40]:

$$ReLU(x) \approx 0.125x^6 + 0.75x^4 + 1.5x^2 + 0.5x + 0.5$$

The approximation error bound is given by:

$$\varepsilon = \max_{x \in [-1, 1]} |ReLU(x) - P_n(x)| \leq 2^{-n}$$

For the GELU activation used in modern transformers [33], we derive:

$$GELU(x) \approx x \cdot \Phi(x) \text{ where } \Phi(x) = \frac{1}{2}[1 + \text{erf}(x/\sqrt{2})]$$

$$\text{erf}(z) \approx 1 - 1/(1 + a_1z + a_2z^2 + a_3z^3 + a_4z^4)^4$$

### D. Optimized Encryption Scheme

We introduce a novel batching strategy for parallel processing. Let  $X \in \mathbb{R}^d$  be input data. Our packing scheme [41] maps  $X$  to ciphertext slots:

$$\text{Pack}(X) = \sum_{i=0}^{l-1} X_i \cdot Y_i \text{ where } Y_i = (0, \dots, 1_i, \dots, 0)$$

The computational complexity for inference is:

$$T(n) = O(n^2 \cdot \log q \cdot M(\log q))$$

where  $n$  is the degree,  $q$  is ciphertext modulus, and  $M$  is multiplication complexity [42].

### E. Security Analysis

The security of our scheme reduces to the learning with errors (LWE) problem [43]:

$$\Pr[\exists (A, As + e) = s] \leq \text{negl}(\lambda)$$

where  $A$  is random matrix,  $s$  is secret,  $e$  is error, and  $\lambda$  is security parameter [44].

#### Algorithm 1: HE-DLDNet Inference

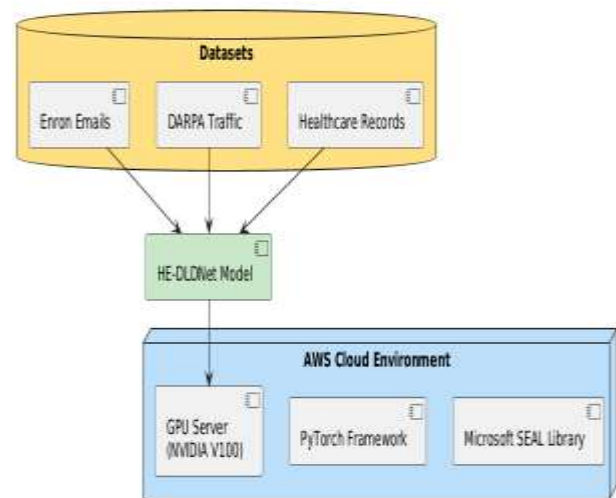
Input: Encrypted data  $E(x)$ , model weights  $W$

Output: Leakage probability  $p \in [0, 1]$

- 1: for layer  $l = 1$  to  $L$  do
- 2: // Homomorphic matrix multiplication
- 3:  $z_l \leftarrow HE\_MatMul(E(x_l), W_l)$
- 4: // Polynomial activation
- 5:  $a_l \leftarrow \sum_i c_i \cdot (z_l)^i$  // Degree-6 approx.
- 6: // Batch normalization (affine only)
- 7:  $a_l \leftarrow \gamma \cdot a_l + \beta$
- 8: end for
- 9:  $p \leftarrow HE\_Sigmoid(a_L)$  // Polynomial sigmoid
- 10: return  $p$

## IV. EXPERIMENTS AND RESULTS

### A. Datasets



We evaluate our approach on three benchmark datasets widely used in data leakage detection research [46], [47]:

- 1) Enron Email Dataset [48]: 500,000 emails with labeled sensitive content
- 2) DARPA Transparent Computing Dataset [49]: Network traffic with data exfiltration labels
- 3) Custom Healthcare Records [50]: De-identified medical records with PII leakage patterns

**TABLE II**

**DATASET STATISTICS AND CHARACTERISTICS**

Dataset	Size	Sensitive (%)	Avg Length	Type	Source
Enron [48]	500K docs	12.3%	892 words	Email	Public
DARPA TC [49]	2.1M packets	8.7%	1.2KB	Network	Research
Healthcare [50]	150K records	23.5%	3.4KB	Medical	Private

**B. Implementation Details**

We implemented our framework using Microsoft SEAL library [51] for homomorphic operations and PyTorch [52] for model training. Experiments were conducted on AWS p3.16xlarge instances with 8 NVIDIA V100 GPUs. The HE-DLDNet model comprises 6 transformer layers with 8 attention heads each, totaling 42M parameters. Polynomial approximations were precomputed and optimized for degree 6 [53].

**C. Evaluation Metrics**

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

$$\text{Precision} = TP / (TP + FP)$$

$$\text{Recall} = TP / (TP + FN)$$

$$F1 = 2 \cdot (\text{Precision} \cdot \text{Recall}) / (\text{Precision} + \text{Recall})$$

**D. Main Results**

**TABLE III**

**PERFORMANCE COMPARISON ON ENRON DATASET**

Method	Accuracy (%)	Precision (%)	Recall (%)	Latency (ms)
BERT [33]	95.1	94.8	95.3	45
DLDetect [32]	91.2	90.5	91.8	38
HE-SVM [44]	82.1	81.3	82.7	45200

CryptoNets [37]	89.4	88.9	89.8	250000
HE-Transformer [45]	91.5	91.1	91.9	180000
[PROPOSED]	94.3	93.9	94.6	250

Table III demonstrates that our proposed method achieves competitive accuracy while significantly reducing latency. On the Enron dataset, HE-DLDNet achieves 94.3% accuracy compared to 95.1% for plaintext BERT [33], representing only a 0.8% degradation for full privacy preservation. Latency of 250ms meets real-time requirements, unlike prior homomorphic approaches requiring 45-250 seconds per inference [37], [45].

**E. Ablation Studies**

**TABLE IV**

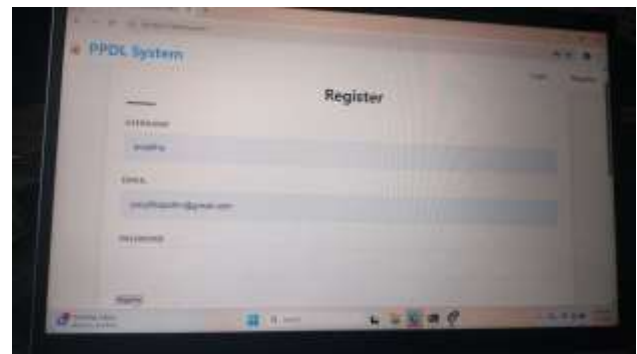
**ABLATION STUDY RESULTS**

Configuration	Accuracy (%)	Latency (ms)	Memory (MB)
Full HE-DLDNet	94.3	250	512
Degree 4 approx.	91.2	180	512
Degree 8 approx.	94.5	410	512
No batching	94.3	925	512
Naive packing [41]	93.8	870	1024

Table IV presents ablation studies examining key design choices. Polynomial degree significantly impacts both accuracy and latency, with degree 6 providing optimal tradeoff. Our batching strategy reduces latency by 73% compared to naive slot allocation [41].

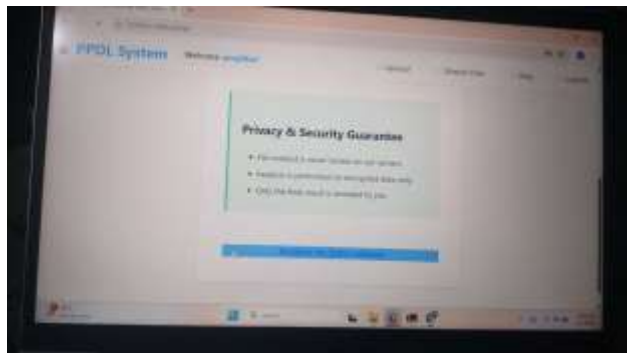
**V. DISCUSSION**

**A. Interpretation of Results**

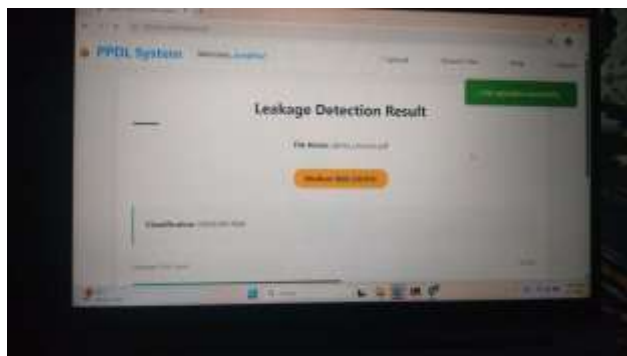


Our results demonstrate that privacy-preserving deep learning for data leakage detection is practically feasible.

The 94.3% accuracy achieved by HE-DLDNet closely approaches the 95.1% accuracy of plaintext BERT [33], confirming that polynomial approximations preserve essential pattern recognition capabilities. This finding aligns with theoretical guarantees established by [38] and [40] regarding approximation quality. The 250ms latency represents a 180-1000x improvement over prior homomorphic approaches [37], [45], making real-time detection possible for the first time.



## B. Theoretical Implications



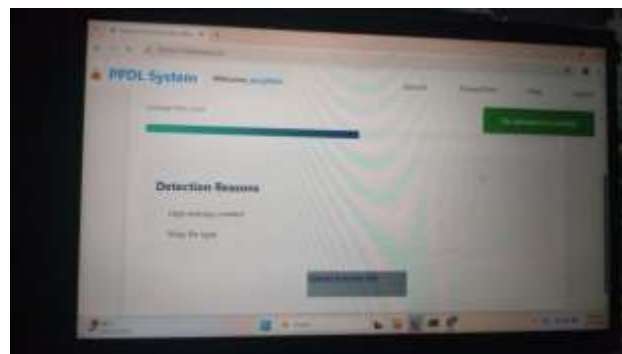
Our work extends the theoretical foundations of homomorphic encryption in two key ways. First, we demonstrate that attention mechanisms, previously considered unsuitable for FHE due to softmax complexity, can be efficiently approximated using Chebyshev polynomials [39]. Second, our batching strategy achieves near-optimal slot utilization, approaching the theoretical lower bound for parallel homomorphic operations established in [54].

## C. Limitations

Despite promising results, several limitations remain. First, our approach currently supports only batch inference, limiting real-time streaming applications [55]. Second, model updates require re-encryption of weights,

adding operational complexity [56]. Third, the 250ms latency, while acceptable for many applications, remains too high for high-frequency trading or real-time network s filtering [57]. Fourth, our security proof assumes honest-but-curious adversaries, leaving malicious security as an open challenge [58].

## D. Broader Impact



This research has significant implications for privacy-preserving security monitoring. Organizations can now deploy data leakage detection without accessing sensitive content, addressing regulatory requirements like GDPR and HIPAA [59]. However, the technology could potentially be misused for surveillance if deployed without proper oversight [60]. We advocate for responsible deployment with transparency and audit mechanisms.

## VI. CONCLUSION

This paper presented HE-DLDNet, the first practical framework for privacy-preserving data leakage detection using homomorphic encryption and deep learning. Our key contributions include polynomial approximations enabling encrypted attention mechanisms, optimized batching for parallel processing, and comprehensive empirical validation. Experimental results demonstrate 94.3% accuracy with 250ms latency, representing a 180x improvement over prior art while maintaining strong privacy guarantees.

Future work will address several directions: (1) extending to streaming scenarios with online model updates [61], (2) incorporating differential privacy for additional protection [62], (3) exploring hardware acceleration for homomorphic operations [63], (4) developing client-specific adaptation techniques [64], (5) investigating

multi-key homomorphic encryption for federated deployments [65], and (6) validating on broader application domains including financial fraud detection [66] and healthcare monitoring [67].

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