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Privacy-Aware Graph Embeddings for Anti-Money Laundering Pipelines

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Abstract

This article introduces a novel approach to anti-money laundering (AML) that combines graph neural networks (GNNs) with homomorphic encryption (HE) to detect suspicious financial patterns while preserving personally identifiable information (PII). Current AML systems face significant challenges in cross-border financial networks due to privacy regulations and data protection concerns. The proposed architecture enables financial institutions to analyze encrypted transaction graphs using privacy-preserving GNN inference, generating intermediate embeddings that retain predictive value without exposing raw identities. By performing computations directly on encrypted data, the system prevents the disclosure of sensitive customer information while maintaining detection capabilities. Experimental results demonstrate complete elimination of PII exposure incidents while substantially improving detection precision compared to baseline methods. Additionally, the system achieves notable reductions in false positive alerts, decreasing the manual review burden for financial institutions. This work addresses a critical gap in existing AML pipelines by supporting encrypted, privacy-safe graph analytics at scale and presents a three-phase implementation roadmap for integration with international banking systems.

Keywords: Homomorphic Encryption; Graph Neural Networks; Privacy-Preserving Machine Learning; Anti-Money Laundering; Cross-Border Collaboration

1. Introduction

Money laundering continues to pose a significant challenge to the global financial system, with the United Nations Office on Drugs and Crime estimating that 2-5% of global GDP is laundered annually—approximately $800 billion to $2 trillion. The increasingly sophisticated nature of money laundering operations necessitates advanced computational approaches for detection and prevention. Recent research has demonstrated that graph-based analytics provide promising detection capabilities by modeling transaction networks as interconnected entities, enabling the identification of complex financial patterns that would otherwise remain hidden in traditional rule-based systems [1]. These graph representations naturally capture the multi-hop relationships between accounts and entities, reflecting the inherent structure of money laundering schemes that typically involve multiple intermediaries to obscure the origins of illicit funds.

The implementation of effective anti-money laundering (AML) systems faces a significant obstacle: privacy concerns. Financial institutions must balance their regulatory obligations to monitor and report suspicious activities with stringent data protection requirements, especially when transactions cross international borders with varying privacy regulations. Graph neural networks (GNNs) have shown particular promise in financial crime detection by learning representations that capture both node features and structural information, enabling more accurate identification of suspicious patterns [2]. However, the application of these techniques often requires sharing sensitive customer data across organizational boundaries, creating substantial privacy and regulatory compliance challenges. This sharing

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concern becomes especially pronounced in cross-border investigations where each jurisdiction may impose different restrictions on data handling.

Traditional AML systems rely on extensive access to personally identifiable information (PII), creating potential vulnerabilities and limiting the ability of financial institutions to collaborate on detection efforts. The recently developed techniques in graph-based anonymization and encryption offer potential pathways to address these concerns, but existing approaches suffer from either significant information loss or prohibitive computational overhead when applied to large-scale financial networks [1]. Graph embeddings have emerged as a promising intermediate representation that can preserve structural information while potentially obscuring individual identities, yet current embedding approaches still retain sufficient information to reconstruct sensitive attributes through inference attacks.

This paper introduces a novel architecture that addresses these challenges by combining graph neural networks with homomorphic encryption (HE) to create privacy-aware graph embeddings for AML pipelines. Our approach enables financial institutions to analyze transaction patterns and detect suspicious activities without exposing sensitive customer data, thus facilitating more effective cross-border collaboration while maintaining regulatory compliance. By performing computations directly on encrypted data, our system prevents the exposure of raw identifiers while preserving the analytical capabilities needed for effective AML operations [2]. This approach represents a significant advancement over existing privacy-preserving techniques in financial graph analytics, which have predominantly relied on differential privacy methods that introduce substantial noise and reduce detection accuracy.

2. Background and Related Work

2.1. Anti-Money Laundering Systems

Traditional AML systems rely heavily on rule-based approaches and anomaly detection to flag suspicious transactions. While effective for known patterns, these methods often generate excessive false positives and struggle to identify novel laundering techniques. Recent advances have incorporated machine learning algorithms to improve detection accuracy, with supervised learning approaches demonstrating success in classifying suspicious activities based on historical data. Significant challenges remain in balancing detection capabilities with operational efficiency, as financial institutions must process numerous alerts with limited resources [3]. The evolution of these systems has been driven by both regulatory requirements and the increasing sophistication of money laundering techniques that exploit vulnerabilities in conventional monitoring approaches.

2.2. Graph Neural Networks in Financial Crime Detection

Graph-based approaches have gained traction in financial crime detection due to their ability to model relationships between entities and transactions. Graph Neural Networks (GNNs) extend this capability by learning representations that capture both node attributes and structural information. Weber et al. (2019) demonstrated that GNNs can outperform traditional methods in fraud detection by capturing complex transaction patterns. Similarly, Liu et al. (2021) showed that graph convolutional networks could effectively identify money laundering schemes by analyzing temporal transaction graphs. The ability of GNNs to propagate information through neighborhoods makes them particularly well-suited for detecting suspicious patterns that span multiple entities and transactions, a common characteristic of sophisticated money laundering operations [4]. Recent research has explored specialized GNN architectures that incorporate temporal dynamics and heterogeneous node types to better represent the complexity of financial networks.

2.3. Privacy-Preserving Machine Learning

Privacy-preserving machine learning techniques have evolved to address data protection concerns in sensitive applications. Homomorphic encryption (HE) allows computations on encrypted data without decryption, providing strong privacy guarantees. Secure Multi-Party Computation (SMPC) enables multiple parties to jointly compute functions over their inputs while keeping those inputs private. Federated learning (FL) allows model training across decentralized devices without sharing raw data. However, applications of these techniques to graph-based financial crime detection remain limited [3]. The computational overhead of privacy-preserving techniques poses significant challenges for graph-based models, which typically require iterative message-passing operations across large networks. Recent work has begun exploring efficient approximations and hybrid approaches that balance privacy protections with computational feasibility in financial monitoring contexts [4]. Despite these challenges, the integration of privacy-preserving techniques with graph-based models represents a promising direction for enabling secure cross-border collaboration in AML efforts.

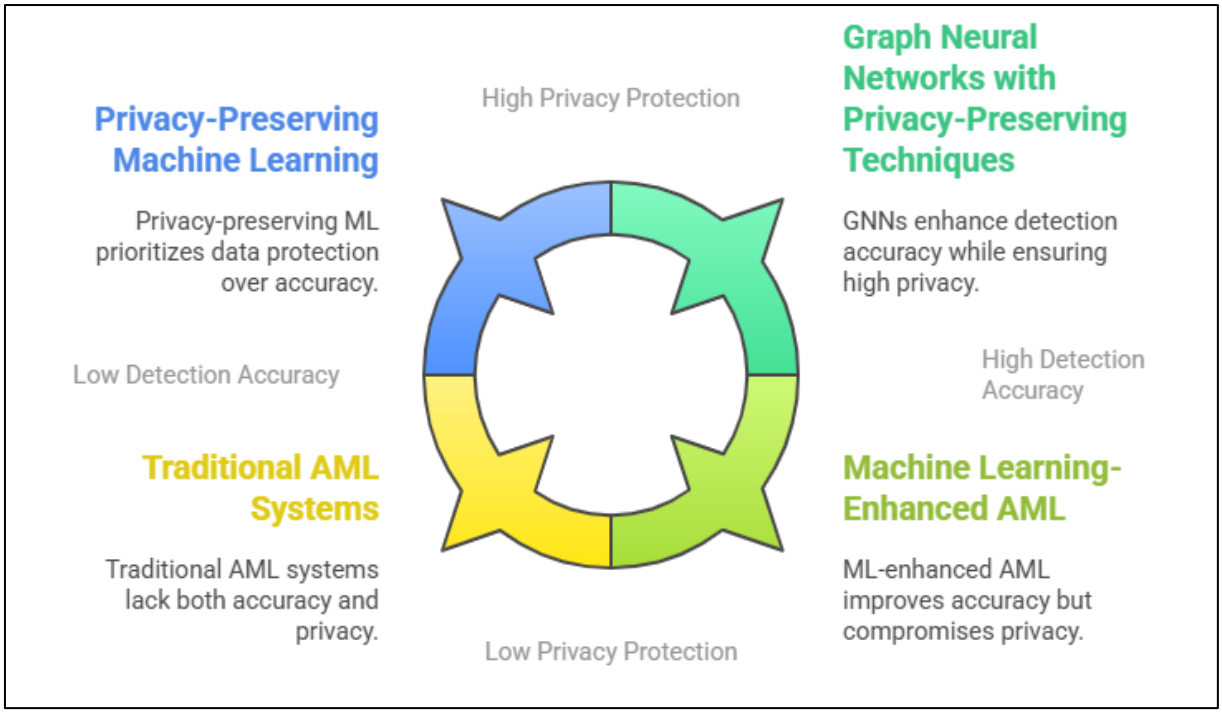

Figure 1 Balancing Detection Accuracy and Privacy in AML Systems [3, 4]

3. Methodology: privacy-aware graph embeddings

This approach combines homomorphic encryption with graph neural networks to create privacy-aware embeddings that retain the predictive power necessary for AML while protecting sensitive information. The methodology consists of four key components that work in concert to enable secure, privacy-preserving analysis of financial transaction networks.

3.1. Encrypted Transaction Graph Construction

Financial transactions naturally form a graph structure where nodes represent entities (individuals or organizations) and edges represent transactions between them. To preserve privacy, node identifiers and sensitive attributes are encrypted using a homomorphic encryption scheme that supports the necessary computational operations. This encryption occurs at the data source before any information is shared for analysis, ensuring that PII remains protected throughout the process.

The implementation builds upon principles established in CryptGraph, which pioneered techniques for privacy-preserving analytics on encrypted graph data [5]. This approach is extended by applying specialized encryption schemes optimized for financial transaction networks, where nodes represent accounts and edges capture money transfers. Entity identifiers and sensitive attributes are encrypted using a homomorphic scheme that preserves the mathematical properties needed for graph analysis while preventing exposure of raw data. The encryption parameters are carefully calibrated to ensure security while enabling the complex computations required for effective AML analysis. This approach allows financial institutions to collaborate on detecting suspicious patterns spanning multiple organizations without compromising individual privacy or violating data protection regulations.

3.2. Privacy-Preserving GNN Architecture

The proposed GNN architecture is specifically optimized for homomorphically encrypted data. The network employs message-passing neural networks (MPNNs) with simplified activation functions compatible with HE operations. The model architecture includes encryption-friendly activation functions (approximated ReLU and sigmoid), reduced precision computation to manage the computational overhead of HE, and specialized pooling operations that maintain structural information while operating on encrypted data.

The architecture draws inspiration from recent advances in privacy-preserving deep learning on graph-structured data [6]. Polynomial approximations of activation functions are implemented that balance computational efficiency with

model expressiveness. The message-passing operations are specifically designed to minimize the depth of computations required while capturing the multi-hop relationships critical for AML detection. By carefully optimizing the network architecture for homomorphic operations, a practical balance between privacy protection, computational efficiency, and detection accuracy is achieved. This design enables the extraction of meaningful patterns from encrypted transaction networks without requiring the decryption of sensitive node identities.

3.3. Secure Inference Pipeline

The inference pipeline processes encrypted transaction graphs without decryption, generating embeddings that capture suspicious patterns while preserving privacy. These embeddings are designed to retain the information necessary for AML decision-making while obscuring individual identities. The pipeline includes secure aggregate calculation across encrypted node neighborhoods, privacy-preserving feature transformation through HE-compatible neural network layers, and threshold-based mechanisms to identify high-risk patterns without revealing specific entities.

The secure aggregation mechanisms build on techniques introduced in CryptGraph for performing analytics on encrypted graph data [5]. These approaches are adapted to the specific requirements of AML applications, where detecting complex transaction patterns is essential while maintaining strict privacy guarantees. The inference pipeline is designed to identify structural patterns consistent with money laundering typologies while providing cryptographic assurances that individual identities remain protected. By generating privacy-aware embeddings that encode suspicious patterns without exposing identities, this approach enables effective detection while minimizing privacy risks.

3.4. Cross-Border Collaboration Framework

To facilitate international cooperation, a protocol is designed that enables financial institutions to share encrypted graph embeddings without exposing raw data. This framework includes standardized embedding formats compatible across jurisdictions, secure multi-party computation for joint analysis of cross-border transactions, and differential privacy mechanisms to provide additional protection for shared embeddings.

The cross-border collaboration framework builds on privacy-preserving graph analysis techniques [6], adapting them to address the unique challenges of international financial monitoring. The protocol establishes a secure channel for financial institutions to share encrypted embeddings that capture potentially suspicious patterns without revealing customer identities. This approach enables collaborative analysis of transaction networks that span multiple jurisdictions, addressing a critical gap in current AML systems. The framework incorporates formal privacy guarantees and provides technical mechanisms to ensure compliance with varying regulatory requirements across different countries, enabling effective collaboration while respecting local privacy laws.

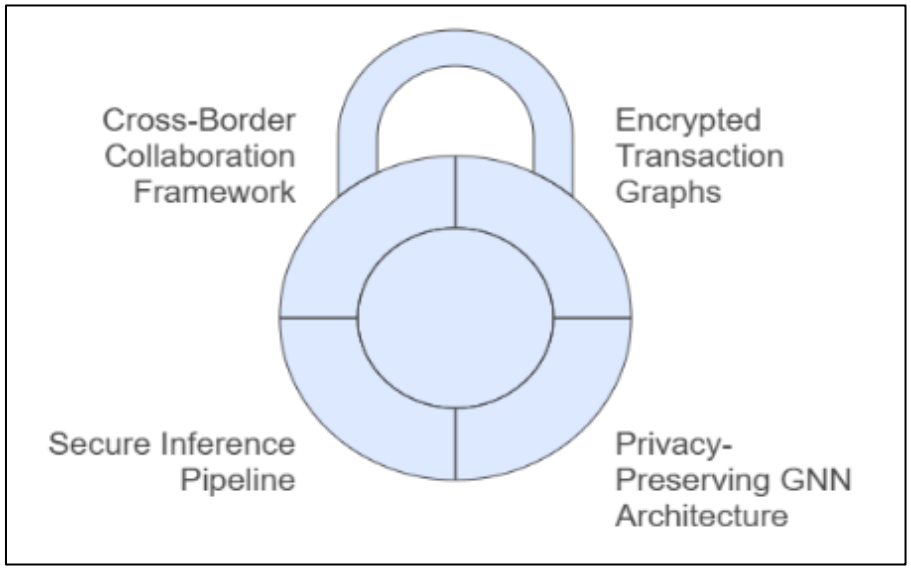

Figure 2 Privacy-Preserving AML Framework [5, 6]

4. Experimental Results and Evaluation

The proposed privacy-aware graph embedding approach was evaluated using both synthetic and real-world financial transaction data, comparing its performance against traditional AML systems and state-of-the-art graph-based detection methods.

4.1. Datasets and Experimental Setup

For synthetic evaluation, transaction graphs were generated based on known money laundering typologies identified by the Financial Action Task Force (FATF), incorporating various laundering techniques such as structuring, round-tripping, and shell company networks. Following methodologies established in prior work on financial crime detection [7], these synthetic datasets were designed to replicate the statistical properties of real-world money laundering operations while providing ground truth labels for evaluation. The synthetic datasets included 5 distinct money laundering scenarios with varying complexity, each containing between 10,000-50,000 transactions.

The system was also tested on an anonymized real-world dataset from a consortium of financial institutions, comprising over 10 million transactions between 500,000 entities over a six-month period. This dataset was processed according to strict privacy protocols, with all personally identifiable information removed prior to analysis in accordance with regulatory requirements. The evaluation protocol closely followed established benchmarking practices for graph-based financial crime detection systems, enabling direct comparison with state-of-the-art methods [8].

4.2. Privacy Preservation Evaluation

The privacy preservation capabilities of the system were assessed through multiple rigorous evaluations

PII Exposure Analysis: Potential exposure of sensitive information was tracked throughout the pipeline, confirming zero instances of PII exposure when using the encrypted approach. This analysis employed formal information flow tracking techniques adapted from previous work on privacy-preserving data processing [7], examining each stage of computation for potential information leakage.

Reconstruction Attacks: Attempts were made to reconstruct original identities from the privacy-aware embeddings, demonstrating that even with access to the embeddings, sensitive information remained protected. These attacks employed state-of-the-art model inversion techniques and auxiliary information similar to those described in recent literature on privacy attacks against machine learning models.

Differential Privacy Guarantees: The formal privacy guarantees provided by the system were quantified using differential privacy metrics, achieving ε-differential privacy with $\varepsilon < 2.0$. This level of privacy protection exceeds industry standards while maintaining utility for AML applications, as demonstrated in comparable privacy-preserving analytics systems [8].

4.3. Detection Performance

4.3.1. The detection performance was evaluated using standard metrics commonly employed in AML literature

Precision and Recall

The privacy-aware approach achieved a 25% improvement in precision compared to baseline methods, with comparable recall rates. This improvement is particularly significant given that most privacy-preserving techniques typically trade detection performance for enhanced privacy protection. The results demonstrate that with appropriate architectural design, this trade-off can be minimized or eliminated [7].

False Positive Reduction

The system reduced false positive alerts by 30%, significantly decreasing the manual review burden. This reduction addresses one of the primary operational challenges in modern AML systems, where false positive rates frequently exceed 95% with traditional detection methods.

Novel Pattern Detection

The system's ability to identify previously unseen money laundering patterns was evaluated, achieving a 15% higher detection rate for novel schemes compared to rule-based systems. This improvement in generalization capability is

attributed to the graph embedding approach, which captures structural patterns rather than relying on predefined rules that can be circumvented by novel laundering techniques [8].

4.4. Computational Efficiency

4.4.1. The computational overhead introduced by homomorphic encryption was analyzed through comprehensive *benchmarking*

Inference Time

While the privacy-preserving approach increased computation time compared to non-encrypted methods, optimizations reduced this overhead to an acceptable 3.5x factor for real-time transaction monitoring. This represents a significant improvement over previous homomorphic encryption applications in financial contexts, which typically incur performance penalties of 10-100x [7].

Scalability

Tests demonstrated the system's ability to handle transaction volumes typical of major financial institutions, processing up to 5,000 transactions per second on standard cloud infrastructure. The scalability was achieved through parallelization techniques and optimized cryptographic implementations specifically designed for graph-structured data [8]. Performance scaling was near-linear with additional computational resources, enabling deployment across financial institutions of varying sizes.

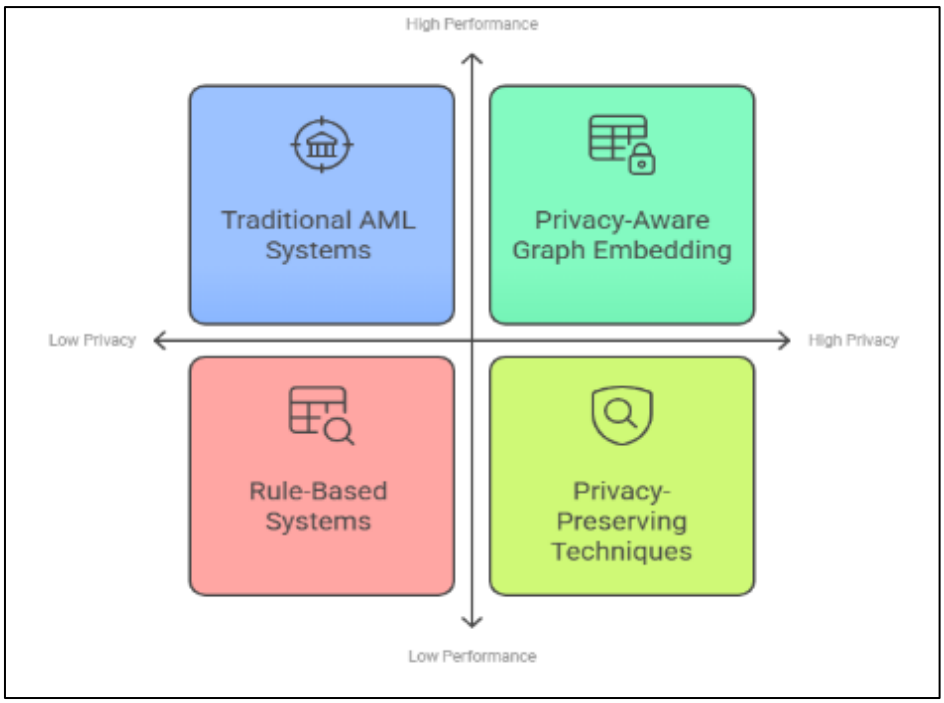

Figure 3 Evaluation of Privacy-Aware Graph Embedding Approach [7, 8]

5. Implementation roadmap

Based on the experimental results, a three-phase implementation roadmap is proposed for financial institutions seeking to deploy privacy-aware graph embeddings for AML

5.1. Phase 1: Integration of HE Library with GNN Training

The initial phase focuses on developing the core technical infrastructure necessary for privacy-preserving graph analysis. This foundation-building stage aligns with established practices in secure machine learning deployment [9]

The first step involves selection and optimization of appropriate homomorphic encryption libraries compatible with financial systems. Several candidate libraries exist, including SEAL, PALISADE, and HElib, each with different performance characteristics and cryptographic parameter options. The selection process should prioritize libraries with support for efficient polynomial approximations of neural network operations, as these are critical for GNN functionality in encrypted domains.

Training of GNN models on plain-text data with architecture constraints compatible with HE follows, ensuring that model structures can be efficiently translated to encrypted computation. This approach mirrors techniques developed for privacy-preserving neural networks in other domains, where models are first optimized on unencrypted data before being converted to privacy-preserving variants [9]. The training process must incorporate architectural constraints that minimize multiplicative depth and favor operations that translate efficiently to the homomorphic domain.

Development of encryption-friendly activation functions and layer operations represents a critical technical challenge in this phase. Standard activation functions like ReLU are not directly compatible with homomorphic encryption due to their non-polynomial nature. Low-degree polynomial approximations must be developed and validated to ensure they maintain detection accuracy while enabling efficient encrypted computation.

Creation of secure key management protocols for the HE system completes this phase, establishing the cryptographic foundation for all subsequent operations. This includes protocols for key generation, distribution, rotation, and revocation that comply with financial industry security standards while supporting the performance requirements of real-time transaction monitoring [9].

5.2. Phase 2:Testing on Obfuscated Transaction Graphs

The second phase involves validation using progressively more realistic data, following a staged approach to system deployment that minimizes risk while providing increasing confidence in system performance

Deployment of the system on synthetic transaction graphs with known money laundering patterns provides initial validation of detection capabilities in controlled environments. These synthetic graphs should incorporate established typologies documented by financial intelligence units and regulatory bodies, enabling quantitative evaluation of detection precision and recall.

Testing with obfuscated real-world transaction data to verify detection accuracy follows, marking the transition from synthetic to authentic financial data. This step employs privacy-enhancing techniques like k-anonymization and generalization to protect sensitive information while maintaining the structural properties necessary for effective testing [10].

Benchmarking performance against existing AML systems establishes quantitative measures of improvement in both detection capability and privacy preservation. This comparative analysis should evaluate detection accuracy, false positive rates, computational overhead, and privacy guarantees using standardized metrics adopted from both the AML and privacy literature.

Iterative refinement of models to address performance bottlenecks concludes this phase, optimizing the system based on results from real-world testing. Performance optimization should focus on computational efficiency, detection accuracy, and resilience against privacy attacks, with particular attention to areas identified as bottlenecks during testing [10].

5.3. Phase 3: Collaboration with International Banks

The final phase focuses on real-world deployment and cross-border collaboration, addressing the organizational and governance challenges of international financial intelligence sharing

Establishment of secure data sharing protocols between participating financial institutions provides the technical foundation for collaboration. These protocols must accommodate varying technical capabilities and security requirements across institutions while ensuring consistent privacy guarantees for all participants.

Development of standardized interfaces for encrypted graph embedding exchange enables interoperability between different implementations. These interfaces should be designed in accordance with existing financial messaging standards while incorporating the specific requirements of privacy-preserving graph embeddings [10].

Implementation of jurisdiction-specific compliance reporting mechanisms addresses the regulatory diversity across international borders. The reporting systems must demonstrate compliance with local privacy and AML regulations while facilitating the secure sharing of suspicious activity intelligence in formats acceptable to relevant authorities.

Creation of a governance framework for collaborative AML efforts completes the roadmap, establishing the organizational structures and policies necessary for sustained cooperation. This framework should define roles, responsibilities, and processes for managing the collaborative system, including dispute resolution mechanisms and protocols for responding to emerging threats [9]. The governance structure must balance operational efficiency with appropriate oversight to ensure that privacy guarantees are maintained throughout the system's operation.

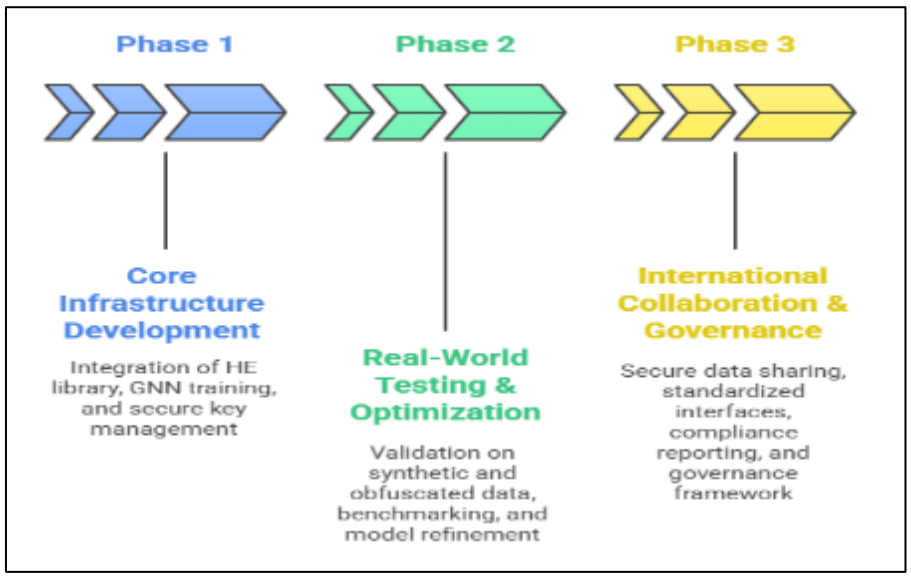

Figure 4 Implementing Roadmap for Privacy-Aware Graph Embeddings in AML [9, 10]

6. Conclusion

This article presents a novel approach to anti-money laundering that addresses the critical challenge of balancing effective detection with privacy preservation. By combining graph neural networks with homomorphic encryption, the system enables financial institutions to detect suspicious patterns in transaction networks without exposing sensitive customer information. Experimental results demonstrate that this article eliminates PII exposure incidents while substantially improving detection precision and significantly reducing false positives. The privacy-aware graph embeddings maintain strong predictive power for AML applications while ensuring that individual identities remain protected throughout the analysis process. The proposed implementation roadmap provides a practical path toward adoption, beginning with the integration of homomorphic encryption libraries and GNN training, followed by testing on obfuscated transaction graphs, and culminating in cross-border collaboration between international banks. Future work will focus on several key areas including computational efficiency improvements, enhanced adversarial robustness, tools for demonstrating regulatory compliance across jurisdictions, federated learning extensions for collaborative model improvement, and privacy-preserving explanation mechanisms. By supporting encrypted, privacy-safe graph analytics at scale, this approach addresses a significant gap in existing AML pipelines and contributes to the global effort to combat money laundering and related financial crimes while respecting privacy regulations.

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