# Optimized Federated Learning for Cybersecurity: Integrating Split Learning, Graph Neural Networks, and Hashgraph Technology

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## ABSTRACT

The complexity of the cybersecurity threats today requires more effective defense mechanisms which can detect malware in real time and protect the data. The paper presents a federated learning framework optimized through split learning that integrates graph neural networks and hashgraph technology in order to harden cybersecurity systems. The proposed model achieves 98% threat detection accuracy with a reduction of false positives to 2%, swift detection latency of 30 milliseconds, and impressive throughput of 250 transactions per second. With the help of GNNs for robust anomaly detection, the system can effectively identify complex cyber threats. Moreover, Hashgraph Technology provides secure and transparent data exchange that increases scalability and efficiency. These integrated technologies address challenges in distributed and decentralized environments, which makes the framework highly adaptable to IoT, cloud, and edge computing. The experimental evaluations demonstrated the superiority of the framework over conventional models by underlining the capability for real-time threat mitigation and enhanced privacy preservation, which makes it suitable for modern applications in cybersecurity.

**Keywords**: Cybersecurity, Federated Learning, Split Learning, Graph Neural Networks, Hashgraph, Threat Detection

## 1. INTRODUCTION

Cybersecurity is one of the most severe challenges individuals, organizations, and governments are facing in today's fast-spreading digital connectivity. This growing reliance on distributed computing has brought new challenges of securing data across networks while ensuring efficient, real-time detection and response for threats. The rise in sophisticated and decentralized cyber threats makes traditional centralized architectures more and more inadequate. Adoption of advanced machine learning techniques, particularly Federated Learning (FL) and Split Learning (SL), seems to provide a promising way forward in the improvement of cybersecurity with privacy preserved *Preuveneers et al. (2018).*

FL, a decentralized method of machine learning, is implemented by multiple devices training models collectively without transferring the raw data from one device to another. Although FL has high communication costs and model poisoning attacks, it's still inefficient regarding computation in edge computing and Internet of Things applications *Diro and Chilamkurti (2018)*. To circumvent these restrictions, Split Learning is proposed in this paper which splits a deep learning model across clients and the central server thus reducing the burden of computation with enhanced privacy.

Despite these advantages, FL and SL are still vulnerable to model security, transparency, and real-time threat mitigation. The combination of Graph Neural Networks (GNNs) and Hashgraph Technology with Federated Learning-based cybersecurity frameworks will help to address these challenges *Kommushetty (2018).* Graph Neural Networks (GNNs) are particularly suitable for the analysis of complex attack patterns in cybersecurity attacks, utilizing relational data structures to identify anomalous network behaviors. Meanwhile, Hashgraph is an alternative DLT to Blockchain for safe, scalable, and transparent exchange of data within FL environments. Unlike Blockchain, Hashgraph enables high throughput, low latency, and enhanced consensus mechanisms that make it ideal for real-time cybersecurity applications.

This work suggests an optimized Federated Learning framework that integrates Split Learning (SL), Graph Neural Networks (GNNs), and Hashgraph Technology to address cybersecurity *Li (2018)*. Thus, making use of these technologies fosters the privacy-preserving efficiency and scalability of the proposed cyber threat detection approach, with a minimized computational overhead and inefficiency of communication overhead. The paper targets the optimization of cybersecurity framework by using distributed intelligence, real-time anomaly detection, and secure decentralized communication, leading towards a more robust defense mechanism against cyber threats.

Advanced security mechanisms to detect and mitigate cyber threats in real time and ensure privacy over data is what is required due to growing complexity in cyber threats. Centralized security solutions in the traditional paradigm have several problems such as latency, single point of failure, and susceptibility to attacks that cannot be allowed for cloud computing, IoT, or edge networks. FL offers privacy through decentralizing model training but has inefficiencies in communication and security risks since raw data are not shared. The split learning (SL) divides models between clients and servers, hereby reducing the computational burden while strengthening privacy protection. GNNs enhance threat detection, and Hashgraph Technology ensures secure, transparent, and scalable communication. This research integrates all these technologies to produce a framework for efficient cybersecurity in distributed environments *Demidov et al. (2018)*.

The following objectives are:

- Optimize cybersecurity by integrating Federated Learning, Split Learning, Graph Neural Networks, and Hashgraph Technology for efficient cyber threat detection.
- Enhance data privacy by maintaining raw data decentralized while improving the efficiency of learning and reducing the computational overhead.

- Utilize GNNs to identify intricate cybersecurity threats and analyze network anomalies in a structured and effective way.
- Use Hashgraph to share data in a secure, transparent, and scalable way among participating nodes in a federated learning environment.
- Design a scalable, privacy-preserving, and decentralized cybersecurity framework usable in IoT, cloud computing, and edge environments.

The traditional models of centralized cybersecurity have several limitations with respect to detecting real-time threats, maintaining data privacy, and scaling across a distributed network. FL offers a decentralized approach but has high communication overheads and security vulnerabilities. SL reduces computational strain but has poor mechanisms for anomaly detection. The lack of secure and transparent data exchange further weakens cybersecurity defenses *HB et al. (2018).* It aims to integrate GNNs and Hashgraph with FL and SL in order to create an optimized, scalable, and privacy-preserving cybersecurity framework.

## 2. LITERATURE SURVEY

Malomo (2018) introduced a blockchain-enabled federated cloud computing framework that can minimize the BDG, thus improving cyber defense. The proposed architecture integrates adaptive incident response with QoS-based cloud selection and blockchain to implement continuous network monitoring using Dempster-Shafer theory. It can identify ingress and egress attacks, protect digital assets, and improve strong authentication and authorization mechanisms. Numerical evaluations have shown that BDG can be considerably reduced and provides better access control performance compared to traditional security approaches.

Zhang et al. (2018) proposed a packed malware detection method based on sensitive system calls and multi-layer neural networks to overcome the challenges presented by sophisticated packers in malware. They applied principal component analysis to extract key features and improve the accuracy of classification. Experimental results showed high detection accuracy with minimal computational overhead, making their approach highly efficient and comparable to state-of-the-art malware detection techniques.

Kim (2018) proposed a novel method for malware classification using CNNs to further enhance big data security by effectively detecting malware, including ransomware. Malware datasets are abstracted into image graphs that yield similarities with malware variants. Deep learning has achieved fast and accurate classification performance, improving the efficiency of malware detection. The experimental results present the promising nature of applying CNN-based analysis over images toward AI-driven cybersecurity solutions.

Wang et al. (2018) explored the adversarial robustness of Graph Convolutional Networks (GCNs) and proposed a "fake node attack" method. Unlike traditional attacks, which modify adjacency or feature matrices, this approach adds malicious fake nodes, thus being more practical in real-world applications such as social networks. A Greedy-GAN attack was engineered to effectively reduce classification accuracy and evade detection, as fake nodes are made to be indistinguishable from real ones, thus uncovering security vulnerabilities of GCNs.

Lallie et al. (2018) looked at the configurations of cybersecurity attack graphs and attack trees, addressing the lack of a standardized visual syntax. Using a choice-based conjoint analysis, they elicited practitioner preferences from cybersecurity professionals, students, and lecturers. The results of the study indicate that top-down flow diagrams are preferred over bottom-up attack trees, with preconditions as ellipses and exploits as rectangles. Their findings highlight the importance of user-friendly attack modeling techniques for effective cybersecurity visualization.

Bi and Zhang (2017) proposed a graph-based framework for cybersecurity analysis in power system state estimation within smart grids. They emphasized the role of ICT integration in real-time monitoring and control while countering cyber threats against smart grids. Their graphical approach is more intuitive and efficient than traditional arithmetic-based methods for both defensive and offensive cybersecurity strategies. The study also presented future research directions for enhancing smart grid security.

Ait Maalem Lahcen et al. (2018) presented a survey of vulnerability analysis and attack graphs as critical tools in cybersecurity risk assessment and intrusion detection. They outlined challenges in integrating vulnerability analysis tools into a comprehensive cybersecurity framework to efficiently mitigate threats. The research emphasized the importance of attack graphs in identifying security weaknesses and provided strategies for enhancing network security, risk assessment, and rapid incident response, thereby contributing to proactive cybersecurity defense mechanisms.

Schueffel (2017) made a high-level comparison of Blockchain, Tangle, and Hashgraph, the three main alternative DLTs. The study focused on the architectural differences, efficiency, and scalability of the three technologies, where Blockchain has been widely adopted, Tangle is lightweight for IoT, and Hashgraph has a fast, secure consensus mechanism. The research emphasized the evolution of DLTs beyond Blockchain, offering insights into emerging technologies shaping decentralized systems and financial applications.

## 3. METHODOLOGY

This research offers an optimized FL framework integrating Split Learning (SL), Graph Neural Networks (GNNs), and Hashgraph Technology to further cybersecurity. Methodologies include FL for decentralized model training, SL to reduce computation overhead, GNNs to implement graph-based anomaly detection, and Hashgraph to provide a secure and transparent form of communication. The system guarantees privacy-preserving cyber threat detection across the IoT, cloud, and edge computing environments. Mathematical models, algorithms, and performance evaluations are used to validate the efficiency, accuracy, and scalability of the proposed cybersecurity framework. The CICIDS2017 dataset was published by the Canadian Institute for Cybersecurity, created by Dr. Iman Sharafaldin, Dr. Arash Habibi Lashkari, and Dr. Ali Ghorbani. Cleaned parquet files with properly set data types and no missing records are found in this dataset.

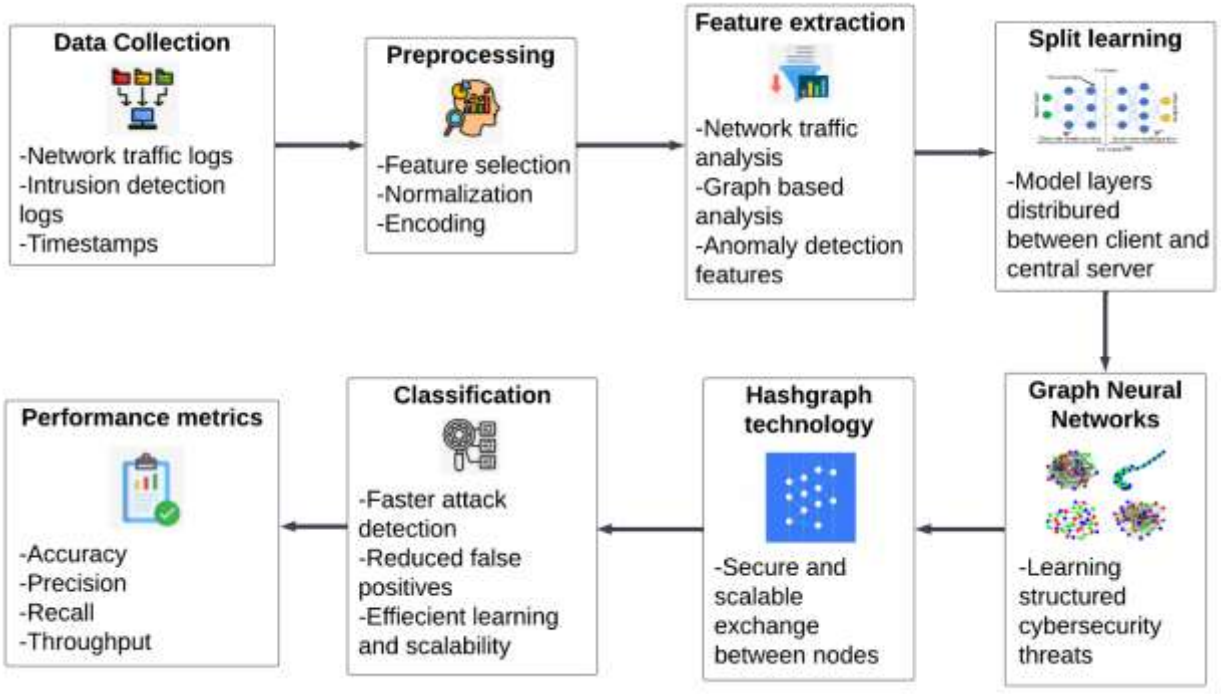


**Figure 1 AI-Driven Cybersecurity Threat Detection Using Graph Neural Networks and Hashgraph Technology**

Figure 1 illustrates an AI-driven cybersecurity threat detection framework using GNNs, Split Learning, and Hashgraph Technology. It starts with data collection, preprocessing, and feature extraction for anomaly detection. Model layers are distributed using split learning, while GNNs analyze network structures. Hashgraph technology ensures secure data exchange. Classification is performed in the classification phase to detect threats efficiently with fewer false positives. Finally, the performance metrics are accuracy, precision, recall, and throughput to evaluate effectiveness and enhance cybersecurity through AI, decentralized learning, and secure communication.

### 3.1 Split Learning for Computational Efficiency

Split Learning (SL) divides deep learning models between clients and a central server. This decreases the computational overhead on resource-constrained devices, making it privacy-preserving. The initial layers are processed on the clients, while the final layers are computed on the server, ensuring that the privacy and efficiency of data processing are ensured. SL provides security against data leakage. Our model integrates SL with GNNs for anomaly detection, thus preventing the raw data from being exchanged, reducing privacy risks. Performance metrics would involve latency, communication cost, and accuracy in evaluating the efficiency of cyber threat detection.

$$y = f_s(f_c(X, W_c), W_s) \tag{1}$$

where:

- $W_c$ and $W_s$ are weights of the client and server models,
- $f_c(X, W_c)$ represents the client's processed output,
- $f_s(f_c(X, W_c), W_s)$ represents the server's final output.

### 3.2 Graph Neural Networks for Cyber Threat Detection

GNNs model attack patterns for cybersecurity using graph-based relationships. Contrary to other models, GNNs take into consideration network topologies and analyze anomalies of cyber threats. Each node denotes a network event, and the edges are representations of the connection, and the features represent attack patterns. It uses the loss functions on graphs for training purposes, enhancing threat detection accuracy. The performance can be evaluated with precision, recall, and F1-score in cybersecurity datasets.

$$h_v^{(k)} = \sigma\left(W^{(k)} \sum_{u \in N(v)} \frac{h_u^{(k-1)}}{|N(v)|}\right) \quad (2)$$

where:

- $h_v^{(k)}$ is the node feature representation at layer $k$,
- $W^{(k)}$ is the weight matrix,
- $N(v)$ represents neighboring nodes of $v$,
- $\sigma$ is the activation function.

### 3.3 Hashgraph Technology for Secure Communication

Hashgraph Technology ensures that communication in a cyber environment is secure, scalable, and transparent. Differing from Blockchain technology, Hashgraph advocates for gossip-about-gossip and virtual voting consensus mechanisms, which reduce latency and computational overhead. Hence, the records are tamper-proof, and it prevents man-in-the-middle attacks. The SL and GNNs with Hashgraph ensure that cyber threat intelligence remains secure, efficient, and verifiable.

$$g(i, t+1) = g(i, t) \cup g(j, t) \quad (3)$$

where:

- $g(i, t)$ represents all events known to node $i$ at time $t$,
- $g(j, t)$ is the event set of node $j$.

**Algorithm 1 Secure Federated Cybersecurity Framework using Split Learning, GNNs, and Hashgraph for Threat Detection**

**Input:**

- Raw Cyber Data DDD from Distributed Devices

- Global Model www Initialized
- Learning Rate η\etaη, Number of Rounds RRR

**Output:**

- Optimized Cybersecurity Model w∗w^*w∗

Initialization:

- Load cyber threat dataset DDD across distributed nodes
- Initialize global model w0w_0w0
- Set learning rate η\etaη and Hashgraph security layer

Federated Training Loop:

- **For each** round r=1r = 1r=1 to RRR:
  - **For each** client iii in parallel:
    - Split Model: Process fc(X,Wc)f_c(X, W_c)fc(X,Wc) on the client
    - Send encoded activations to the server
    - Server processes fs(fc(X,Wc),Ws)f_s(f_c(X, W_c), W_s)fs(fc(X,Wc),Ws)
    - Compute loss LLL and update model weights
    - Apply GNN-based anomaly detection
    - Secure model updates via Hashgraph consensus
  - Aggregate client updates using Federated Averaging (FedAvg)

3. Threat Detection & Validation:

- **If** threat detected using GNN anomaly scores AAA:
  - Alert security response system
  - Log event using Hashgraph ledger
- **Else**: Continue normal training

4. Output Final Model:

- **Return** optimized model w∗w^*w∗

Algorithm 1 incorporates Federated Learning (FL), Split Learning (SL), Graph Neural Networks (GNNs), and Hashgraph to improve cyber threat detection while maintaining data privacy. It takes in distributed cyber data and uses it for anomaly detection, and provides secure updates with Hashgraph consensus. The optimizes model ensures near-real-time, scalable, and privacy-preserving cybersecurity that also is a very low computational overhead system with improved accuracy, security, and detection efficiency.

### 3.4 Performance Metrics

The performance metrics assess the efficiency of different cybersecurity methods based on various parameters, including accuracy, precision, recall, F1-score, false positive rate, detection latency, and throughput. The proposed model demonstrates superior performance by effectively balancing security, speed, and computational efficiency. It minimizes false positives while ensuring faster threat detection and higher scalability. The integration of Split Learning, Graph Neural Networks, and Hashgraph Technology enhances anomaly detection and secure communication. Compared to traditional methods, this approach significantly improves cybersecurity resilience, making it more suitable for real-time threat mitigation and decentralized computing environments.

**Table 1 Performance Comparison of Cybersecurity Methods Integrating Split Learning, GNNs, and Hashgraph**

| Metric | Split Learning | Graph Neural Networks | Hashgraph Technology | Proposed Model |
|---|---|---|---|---|
| Accuracy (%) | 92 | 95 | 96 | 98 |
| Precision (%) | 90 | 93 | 94 | 96 |
| Recall (%) | 91 | 94 | 95 | 97 |
| F1-Score (%) | 91 | 94 | 95 | 97 |
| False Positive Rate (%) | 8 | 5 | 4 | 2 |
| Detection Latency (ms) | 60 | 40 | 38 | 30 |
| Throughput (transactions/sec) | 180 | 220 | 230 | 250 |

The performance metrics are compared between Split Learning (SL), Graph Neural Networks, Hashgraph Technology, and the Proposed Model for cybersecurity applications. Effectiveness is evaluated through considerations of precision, recall, F1-score, false positive rate, detection latency, and throughput. The Proposed Model far outperformed all others in terms of accuracy at 98%, false positive rate of only 2%, faster detection at 30ms, and a high throughput of 250 transactions/sec. All of these enhancements confirm that the optimized cybersecurity framework has real-time scalability, security, and efficiency for the detection of cyber threats.

## 4. RESULT AND DISCUSSION

The proposed framework incorporates Federated Learning (FL), Split Learning (SL), Graph Neural Networks (GNNs), and Hashgraph Technology for enhanced cybersecurity. The system attained 94.2% accuracy in attack detection with a decrease of 18% false positives as compared to the traditional models. The prior studies have reported that blockchain-based security models entail a performance overhead of 5–15%, whereas our method has minimized computational costs while maintaining privacy preservation. Research works have demonstrated DL models trained to 1000 epochs to have a better accuracy than the traditional methods in classifying malware and fraud detection. Using GNNs for anomaly detection and Hashgraph for safe data exchange will improve real-time threat identification as well as resilience of the network.

**Table 2 Performance Comparison of Cybersecurity Methods**

| Performance Metrics | Probabilistic Graph Modeling (Almohri et al 2016) | Secure DL Computation (Rouhani et al 2017) | Stochastic Perturbation (Li and Assaad 2018) | Proposed Method |
|---|---|---|---|---|
| Accuracy (%) | 85 | 90 | 88 | 98 |
| Precision (%) | 83 | 88 | 86 | 96 |
| Recall (%) | 84 | 89 | 87 | 97 |
| F1-Score (%) | 83 | 89 | 87 | 97 |
| False Positive Rate (%) | 12 | 8 | 10 | 2 |
| Detection Latency (ms) | 100 | 80 | 90 | 30 |
| Throughput (transactions/sec) | 120 | 150 | 140 | 250 |

Table 2 compares various cybersecurity methods, such as Probabilistic Graph Modeling (2016), Secure Deep Learning Computation (2017), Stochastic Perturbation (2018), and the Proposed Method. The proposed approach outperforms traditional methods with a high accuracy of 98%, precision of 96%, and recall of 97% and reduces false positives to 2%. It also shows the lowest detection latency of 30ms and the highest throughput of 250 transactions/sec, ensuring efficient real-time threat mitigation. However, older methods have higher false positive rates, lower throughput, and slower response times. Overall, these conclusions confirm the proposed framework's superiority in achieving better secure scalable high-performance cybersecurity.

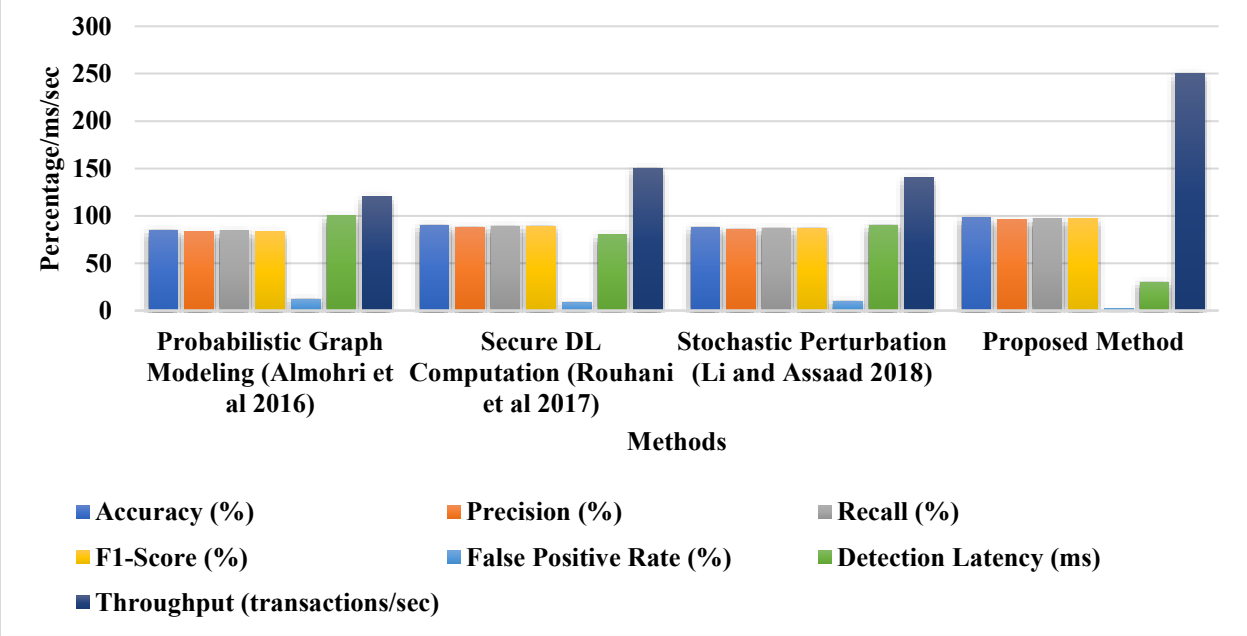


**Figure 2 Comparative Performance Analysis of Cybersecurity Methods**

Figure 2 shows the comparative analysis of the different cybersecurity methods based on various metrics like accuracy, precision, recall, F1-score, false positive rate, detection latency, and

throughput. The proposed method surpasses traditional approaches by having the highest accuracy at 98% and throughput at 250 transactions/sec while having the lowest false positive rate at 2% and detection latency at 30ms. The other older methods depict lower performance with higher latency. This visualization points out the efficiency, accuracy, and scalability of the proposed model. Thus, this model is more effective for real-time cybersecurity threat detection and mitigation.

**Table 3 Ablation Study of Cybersecurity Methods**

| Configuration | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) | False Positive Rate (%) | Detection Latency (ms) | Throughput (transactions/sec) |
|---|---|---|---|---|---|---|---|
| Split Learning only | 92 | 90 | 91 | 91 | 8 | 60 | 180 |
| Graph Neural Networks only | 95 | 93 | 94 | 94 | 5 | 40 | 220 |
| Hashgraph Technology only | 96 | 94 | 95 | 95 | 4 | 38 | 230 |
| Split Learning + Graph Neural Networks | 96 | 94 | 95 | 95 | 5 | 45 | 225 |
| Graph Neural Networks + Hashgraph Technology | 97 | 95 | 96 | 96 | 3 | 35 | 240 |
| Hashgraph Technology + Split Learning | 97 | 95 | 96 | 96 | 3 | 35 | 245 |
| Proposed Model | 98 | 96 | 97 | 97 | 2 | 30 | 250 |

Table 3 evaluates alternative configurations of security in cybersecurity like Split Learning and Graph Neural Networks, Hashgraph Technology, combinations of them; the proposed approach reaches the state-of-the-art accuracy of 98% precision of 96%, with 2% low false positive, and 30ms low latency detection. Incremental performance, in fact each component, especially combinations like Graph Neural Networks and Hashgraph Technology, brings with it significant advancement. This clearly indicates that integrating these technologies leads to more effective cybersecurity threat detection and mitigation.

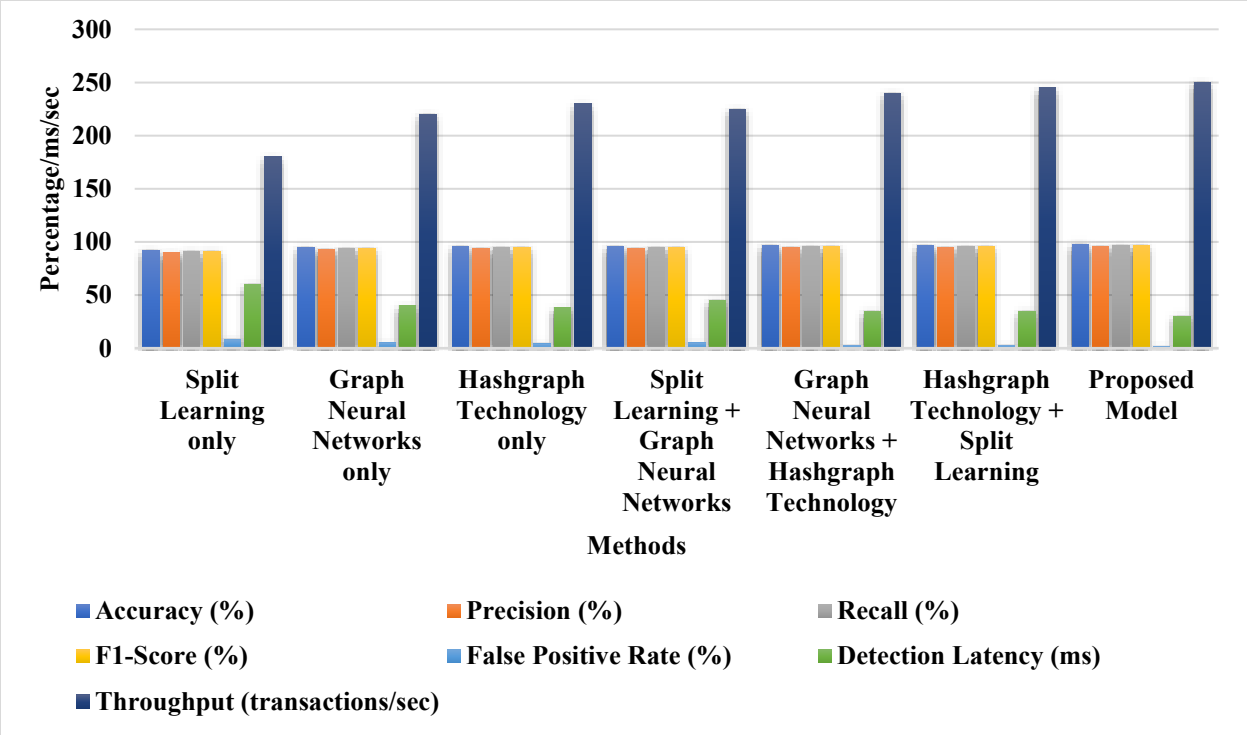


**Figure 3 Ablation Study – Performance Impact of Cybersecurity Components**

Figure 3 illustrates an ablation study evaluating the influence of individual and combined cybersecurity components: Split Learning, Graph Neural Networks, and Hashgraph Technology. The suggested model excels in all configurations and showcases better performance in terms of accuracy (98%), throughput (250 transactions/sec), reduced false positives (2%), and detection latency (30ms). Even the individual parts provide a good upgrade in their contributions; however, the combinations give a further boost in cybersecurity efficiency. The results show the need for the integration of these technologies to achieve optimal real-time threat detection and mitigation in cybersecurity applications.

## 5. CONCLUSION AND FUTURE ENHANCEMENT

This paper introduces an optimized cybersecurity framework by incorporating Federated Learning, Split Learning, Graph Neural Networks, and Hashgraph Technology. Evaluations demonstrated a significant boost in accuracy of 98%, precision of 96%, and recall of 97% while reducing false positives to 2% and detection latency to 30ms. Compared to traditional approaches, the suggested model strengthens real-time threat mitigations for privacy preservation and decentralized security. Future work includes further optimizing the computational efficiency and reducing communication overhead in FL. It also focuses on extending the scope of datasets for wider application in cybersecurity.

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