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Hybrid Transformer-RNN and GNN-Based Robotic Cloud Command Verification and Attack Detection: Utilizing Soft Computing, Rough Set Theory, and Grey System Theory

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ABSTRACT

Background Information: The proliferation of cloud-connected robotics has led to a rise in security concerns, including command injection and DDoS attacks. Efficient detection necessitates sophisticated methodologies capable of managing intricate, real-time data.

Objectives: Create a hybrid intrusion detection system utilizing Transformer, RNN, and GNN models to effectively identify and categorize cloud-based robotic attacks.

Methods: Combine Transformer, RNN, and GNN modules with soft computing, rough set theory, and grey system theory to improve feature selection, model precision, and response time in attack detection.

Results: The hybrid model demonstrated superior accuracy, precision, and reduced response time, surpassing conventional approaches in identifying diverse assault types.

Conclusion: The suggested technique significantly improves intrusion detection in robotic cloud systems, with possible use in other cybersecurity areas. Ongoing education guarantees flexibility in response to new dangers.

Keywords: Intrusion Detection, Transformer, Recurrent Neural Network (RNN), Graph Neural Network (GNN), Cloud Security, Robotics

1. INTRODUCTION

In recent years, cloud-integrated robotics has gained considerable momentum owing to its ability to enhance the functionalities of autonomous robotic systems through the utilization of extensive computational resources and real-time data processing. Cloud-based systems facilitate robots' access to centralized processing power and storage, hence improving their operational efficiency, decision-making speed, and adaptability. Nonetheless, these developments provide significant cybersecurity concerns, especially in command verification and attack detection. As robots increasingly depend on cloud services for processing essential data and executing commands, the potential of criminal intrusions and cyberattacks that could disrupt or control robotic operations is escalating. Mitigating these risks is essential for guaranteeing the secure and dependable implementation of cloud-based robotic systems across diverse applications, including industrial automation, healthcare, and military operations.

The proposed system amalgamates various advanced technologies—hybrid Transformer-RNN (Recurrent Neural Network) and GNN (Graph Neural Network) models—with soft computing methodologies such as Rough Set Theory and Grey System Theory to establish a resilient framework for robotic cloud command verification and attack detection. Every component independently enhances the security architecture, enabling the system to analyze intricate data

patterns, eliminate noise, and execute data-driven judgments. This layered strategy utilizes the advantages of many computational paradigms to establish a hybrid and robust security framework.

Transformers and RNNs are particularly adept in analyzing sequential and time-series data, as these designs excel in identifying patterns and abnormalities over time. Transformers, utilizing attention techniques, enhance efficiency in long-range data dependencies, but RNNs are adept at managing state-based information in a sequential manner. These models together establish a hybrid framework that harmonizes the benefits of both, facilitating efficient command verification processes that oversee and authenticate command legitimacy within robotic cloud services. Graph Neural Networks (GNNs) enhance functionality by enabling the system to comprehend links and dependencies inside graph-based data structures that depict interconnected robotic orders and cloud-based actions. By representing robotic orders and interactions as nodes and edges, Graph Neural Networks (GNNs) enable the system to identify anomalous activity patterns throughout the robotic network. When combined with deep learning models, GNNs offer an effective method for identifying coordinated attacks and thwarting malevolent entities from undermining robotic operations.

Using soft computing methods like Rough Set Theory and Grey System Theory helps the system handle ambiguity, partial truths, and approximate responses. Rough Set Theory simplifies ambiguous data by approximating command properties, reducing data complexity and stressing security analysis precision. Grey System Theory, which studies uncertain systems, helps quantify and understand changeable interactions with constrained knowledge in real-time robotic data. These soft computing methods improve the security model's adaptability and resilience to changing conditions and new attacks. These technologies enable a comprehensive security architecture that improves cloud-integrated robotic system command verification and intrusion detection. The system checks and verifies orders to ensure proper execution and discover and address anomalies. This method enhances robotics cybersecurity and ensures the safe, reliable deployment of robotic systems in high-risk and sensitive environments.

Fast cloud computing integration with robotics has changed how robots perform complex tasks. Delegating computationally intensive tasks to the cloud improves robot processing and data analysis. This development lets robots do complicated tasks like image recognition, language processing, and strategic planning without onboard computers. However, cloud integration raises cybersecurity concerns, notably in command verification and cyber attack detection. The proliferation of robots linked to cloud networks has expanded the attack surface available for exploitation by hackers. Cybercriminals may penetrate cloud-based command systems, alter robotic behaviors, or disrupt operations. Therefore, there is an urgent necessity to establish sophisticated security frameworks to protect cloud-integrated robotic systems. This hybrid model, integrating Transformer-RNN and GNN frameworks with soft computing techniques, presents a promising solution to mitigate security issues by authenticating commands and identifying unusual behaviors in real time.

The key objectives are:

- Formulate a hybrid security framework that amalgamates Transformer-RNN and GNN architectures with soft computing methodologies to improve command verification and intrusion detection in cloud-connected robotic systems.
- Utilize Transformers and RNNs to evaluate sequential data for efficient command verification, capitalizing on their capabilities in recognizing temporal patterns and long-range dependencies.
- Utilize GNNs to identify network-based attacks, hence augmenting the system's capacity to examine relationships inside robotic command hierarchies and avert coordinated cyber threats.
- Employ Rough Set Theory and Grey System Theory to analyze unclear and ambiguous data, hence enhancing the model's adaptability in dynamic contexts.
- Implement real-time security surveillance to avert illegal access and reduce potential threats, establishing a secure and resilient robotic cloud infrastructure for essential applications.

Investigating the financial and energy ramifications of computation offloading is essential, as it directly influences the efficacy and sustainability of cloud-integrated systems. The security of remote infrastructure utilized in offloading procedures necessitates comprehensive examination to guarantee data integrity and resilience against cyber assaults. **Loukas et al. (2017)** tackle these difficulties by creating a cloud-based intrusion detection system for automobiles, employing deep learning to improve cybersecurity in cyber-physical networks. Additional study is required to enhance these offloading approaches, optimizing performance, security, and energy efficiency in cloud-integrated systems across diverse sectors.

The advancement of efficient intrusion detection systems (IDS) is crucial, as existing solutions frequently fail due to intrinsic uncertainties and constraints in precisely identifying all threats. **Selvakumar et al. (2019)** offer an enhanced Intrusion Detection System framework that employs fuzzy rough set-based feature extraction in conjunction with classification methods, aimed at addressing ambiguity and improving detection accuracy. This method rectifies the deficiencies of conventional systems by enhancing feature selection and classification, hence providing a more flexible and robust IDS model adept at handling intricate, unpredictable data settings and augmenting overall security reliability.

2. LITERATURE SURVEY

Chen et al. (2018) examines identification and authentication processes in a robotic cloud service system, presenting an innovative method for enhancing robot security in collaborative cloud environments. The authors utilize cryptographic protocols to securely identify and authenticate robots connected to the cloud, thereby reducing the dangers of illegal access and improving security in robotic services in industrial and commercial settings.

Quarta et al. (2017) conduct an experimental security analysis of an industrial robot controller, assessing the vulnerabilities susceptible to exploitation by attackers. The study identifies vulnerabilities in industrial robot control systems through practical testing and penetration analysis, recommending essential security improvements to enhance resistance against cyber threats in operational technology settings.

Angelopoulos (2018) presents a dissertation that elaborates on a safe, cloud-based humanoid robot engineered for autonomous search and rescue operations in perilous areas. The study highlights the importance of real-time secure communication and data processing in cloud-based robotics, incorporating stringent security protocols to thwart assaults on robotic systems during critical scenarios such as disaster recovery.

Basan et al. (2019) examine a methodology for identifying anomalous behavior in clusters of mobile robots through sensor-based detection approaches. The research use machine learning techniques to detect and monitor aberrant behavior in groups of robots, enhancing operational security and coordination, particularly in situations with several concurrent autonomous systems.

Loukas et al. (2017) create a cloud-based cyber-physical intrusion detection system for vehicles, employing deep learning methodologies to identify and counteract cyber threats in vehicular networks. Their methodology utilizes cloud computing to handle and analyze substantial quantities of sensor data, hence improving the identification of intricate attack patterns in vehicle cybersecurity.

Ullrich et al. (2019) examine security weaknesses in a fortified IoT ecosystem, concentrating on cloud-integrated vacuum robots. The paper analyzes the security posture of IoT devices in controlled conditions, identifying multiple cyber dangers and proposing security techniques to enhance the protection of IoT devices, particularly when included into extensive cloud-based infrastructures.

Allur (2019) employs complex genetic algorithms to improve big data software testing. GAs are combined with PSO and ACO to maximize test path coverage in the study. Adaptive algorithms alter GA parameters in real time, and co-evolutionary methods optimize numerous subpopulations simultaneously, enhancing efficiency and lowering computational cost. Parallel computing and big data environments benefit from these methodologies' increased test coverage and execution speed. This paper promotes scalable, resilient software testing frameworks for complex system dependability.

Gudivaka (2019) uses big data to estimate silicon content in blast furnace smelting, a crucial steelmaking process. The study uses Hadoop to create prediction models using production, sensor, and environmental data. Hadoop allows real-time monitoring and predictive maintenance, optimizing furnace operations, reducing downtime, and improving equipment reliability. The study shows that big data can alter process optimization, but data integration and financial sustainability are hurdles. Interdisciplinary collaboration is needed for industrial adoption.

Alagarsundaram (2019) looked at how the AES algorithm was used to improve cloud computing data security. AES, a symmetric encryption standard, uses cryptographic transformations to guarantee data integrity and confidentiality. Issues like key management and performance overhead still exist despite its efficacy. The report highlights how AES protects private cloud data from online attacks while maintaining legal compliance.

An Ant Colony Optimisation (ACO)-driven Long Short-Term Memory (LSTM) model for disease prediction in cloud-based healthcare systems was presented by Narla et al. (2019). The

ACO-LSTM model displayed excellent sensitivity (93%) and specificity (92%), achieved 94% accuracy, and cut processing time to 54 seconds using IoT health data. This model provides a scalable and effective framework for real-time patient monitoring and predictive healthcare.

Mishra et al. (2018) investigate several machine learning methodologies for intrusion detection systems (IDS). The research examines conventional and sophisticated machine learning algorithms, including neural networks and ensemble approaches, assessing their efficacy in detecting cyber dangers. The authors emphasize the advantages and drawbacks of each method, especially regarding detecting precision, adaptability, and reaction duration. This survey highlights the necessity of selecting appropriate ML models according to network conditions and threat categories, establishing a basis for the creation of efficient IDS solutions for real-time applications.

Mohammadi and Amiri (2019) present a hybrid self-learning intrusion detection system (IDS) that incorporates neural networks to enhance threat detection. The model integrates various methods, such as k-nearest neighbors (k-NN), support vector machines (SVM), and extreme learning machines (ELM), resulting in a formidable ensemble classifier. Their system exhibits superior accuracy and adaptability, acquiring knowledge from emerging dangers in real-time without necessitating regular manual upgrades. This study highlights the benefits of hybrid, self-learning systems in effectively detecting complex intrusions, particularly in dynamic network contexts where conventional IDS models may falter.

Vimala and Dhas (2018) concentrate on identifying distributed denial-of-service (DDoS) attacks in software-defined networks (SDN) through the application of ensemble classification methods. The system utilizes real-time traffic data acquisition using Wireshark and implements a blend of machine learning techniques to identify anomalies. This methodology is especially pertinent for cloud computing situations where SDN infrastructure encounters distinct security concerns. The research demonstrates that ensemble approaches enhance detection accuracy and decrease response time, hence increasing the resilience of SDN-based architectures against DDoS attacks through proactive threat identification and mitigation.

Esmalifalak et al. (2014) examine the identification of covert fake data injection attacks in smart grids by the application of machine learning techniques. The research utilizes a multivariate Gaussian distribution probability density function to examine the statistical behavior of data in real-time. By concentrating on recognizing subtle, inconspicuous alterations in data patterns, the model may proficiently identify advanced cyber-attacks that conventional methods frequently miss. This study highlights the significance of sophisticated statistical methods for ensuring security in smart grid systems, where precise anomaly detection is essential for system stability and data integrity.

3. METHODOLOGY

The suggested methodology integrates Hybrid Transformer-Recurrent Neural Networks (RNNs) with Graph Neural Networks (GNNs) to improve command verification and attack detection in robotic cloud systems. The strategy seeks to mitigate uncertainty and partial information prevalent in cloud-integrated robotic environments by integrating soft computing approaches, rough set theory, and grey system theory. Transformer-RNN modules facilitate

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sequential data processing for precise pattern identification in command verification, whilst GNNs handle relational data for identifying assaults among robotic nodes. Soft computing addresses imprecise information, rough set theory offers rule-based data classification reduction, and grey system theory is utilized for predictive modeling in uncertain data environments. This hybrid solution provides strong verification and improved security for robotic cloud interactions, identifying potential security issues.

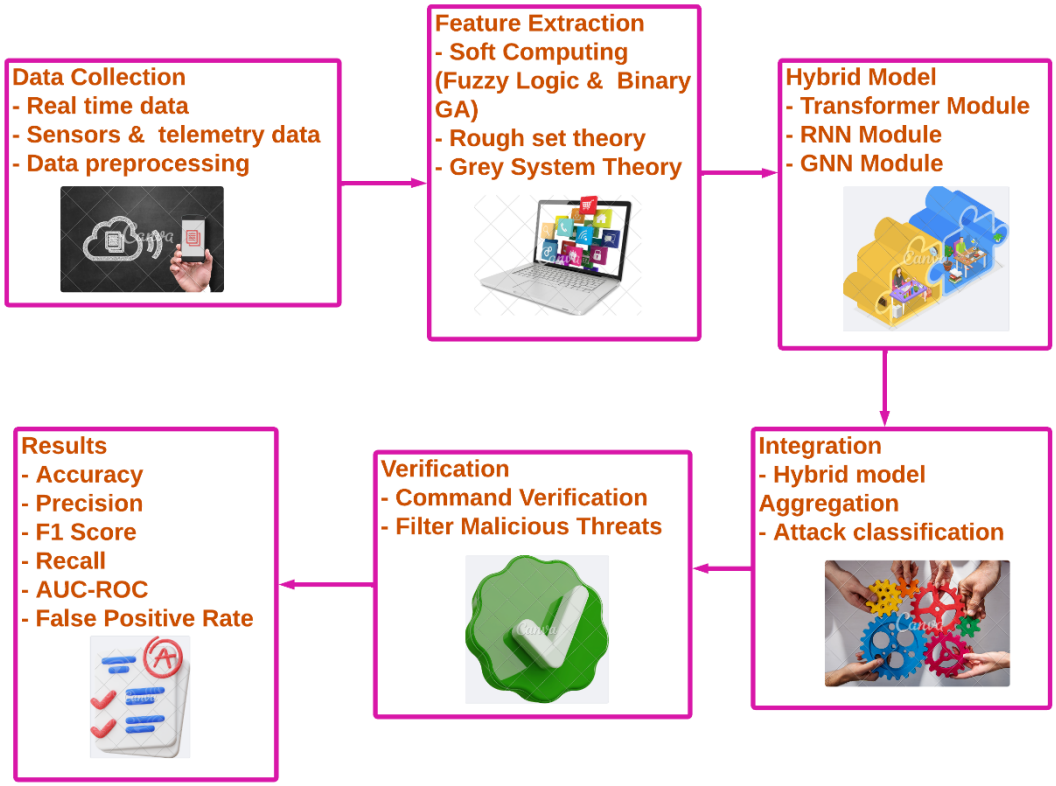

Figure 1 Architecture Diagram of Hybrid Transformer-RNN and GNN-Based Intrusion Detection System

Figure 1 depicts the architectural flow of a hybrid intrusion detection model that integrates Transformer, RNN, and GNN modules for robotic cloud command verification and attack detection. The procedure commences with Data Collection, utilizing real-time sensors and telemetry information. Feature Extraction utilizes soft computing methodologies, rough set theory, and grey system theory to enhance critical features. The Hybrid Model (Transformer, RNN, and GNN) analyzes these features, while Integration consolidates the model's insights for precise attack classification. Verification guarantees command fidelity by eliminating malicious threats, while Results measure model performance, emphasizing accuracy, precision, F1 score, and recall.

3.1 Transformer-RNN for Command Verification

The Transformer-RNN module integrates the attention mechanisms of Transformers with the sequential learning capabilities of RNNs to validate robotic commands. Transformers manage simultaneous data processing, emphasizing essential command attributes, whereas RNNs save command sequences to forecast the subsequent probable instruction. This hybrid methodology

facilitates precise identification of legitimate requests while screening out oddities that may suggest illegitimate access. The Transformer layers encode positional information, which the RNN layers utilize to establish sequential dependencies that improve verification accuracy. By integrating the advantages of both architectures, the model attains a responsive and dependable verification procedure, crucial for real-time robotic command validation.

$$h_t = \text{RNN}(\text{Attention}(Q, K, V), h_{t-1}) \tag{1}$$

Here, h_t represents the hidden state at time t, computed by the RNN using attention-weighted input, where Q, K, and V are the query, key, and value vectors in the Transformer layer. The attention mechanism emphasizes critical features for sequential analysis in the RNN.

3.2 Graph Neural Network (GNN) for Attack Detection

GNNs analyze the relational framework among robots, identifying unusual interactions that may indicate attacks. In the cloud system, each robot node functions as a vertex, with the connections symbolizing communication lines. GNNs consolidate data from interconnected nodes to discern anomalies in standard interaction patterns, hence spotting dubious actions. GNNs identify structural anomalies in the network by progressively refining node embeddings using nearby data. The incorporation of GNNs guarantees that attack detection remains dynamic, continuously adjusting to relational alterations within the robotic ecosystem, thus improving security against coordinated and distributed assault strategies.

$$h_v^{(k)} = \sigma\left(W^{(k)} \sum_{u \in \mathcal{N}(v)} h_u^{(k-1)} + b^{(k)}\right) \tag{2}$$

Where $h_v^{(k)}$ denotes the hidden state of node v at layer k, updated based on the states of neighboring nodes $u \in \mathcal{N}(v)$. Here, $W^{(k)}$ and $b^{(k)}$ are the weight matrix and bias, while σ is an activation function. This process iteratively refines node embeddings for anomaly detection.

3.3 Soft Computing, Rough Set Theory, and Grey System Theory

Soft computing techniques offer adaptability for managing ambiguous data in robotic networks, where sensor information may be deficient. Rough set theory streamlines data by finding critical attributes and eliminating redundancy. This reduction optimizes computing, rendering real-time analysis attainable. Grey system theory enhances understanding by modeling uncertain system behavior, providing insights despite restricted data availability. These ideas collectively establish a systematic framework for evaluating uncertain robotic interactions. Rough set-based reduction facilitates data preparation for both Transformer-RNN and GNN, while grey theory enhances prediction, hence improving command verification and attack detection accuracy in ambiguous situations. Rough Set Reduction:

$$R(A) = \{x \in U \mid \forall a \in A, (x, a) \in R\} \tag{3}$$

$R(A)$ denotes the reduced set for attributes A, aiding in feature selection for efficient processing. Grey Prediction Model:

$$X^{(1)}(k+1) = aX^{(0)}(k) + b \tag{4}$$

This formula predicts X at $k+1$ based on initial values $X^{(0)}(k)$, with parameters a and b estimated from known data, assisting in decision-making with incomplete data.

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Algorithm 1: Algorithm for Hybrid Command Verification and Attack Detection

Input: Robotic command data C, communication graph $G = (V, E)$, threshold T

Output: Verified command status and detection of potential attacks

BEGIN

Initialize Transformer-RNN model for command verification

Initialize GNN for attack detection

FOR each command c **in** C

Transform command into feature vector F

IF Transformer-RNN predicts F as valid **THEN**

Mark command as VERIFIED

ELSE

RETURN ERROR "Invalid command detected"

FOR each node v **in** V

Aggregate neighbor data for v in GNN

Compute embedding update for v based on neighbor states

IF anomaly score for v > T **THEN**

Mark node v as under ATTACK

ELSE

Continue normal operation

IF any node marked as under ATTACK **THEN**

RETURN "Potential attack detected"

ELSE

RETURN "System secure, all commands verified"

END

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Algorithm 1 commences by validating robotic commands through a Transformer-RNN model, which examines command patterns and identifies any anomalies as invalid. Subsequently, it utilizes a Graph Neural Network (GNN) to manage interactions inside the robotic network, scrutinizing connections between nodes to identify anomalous behaviors that may indicate attacks. The GNN consolidates information from neighboring nodes, detecting anomalous patterns through anomaly scores. Any node that exceeds the established anomaly threshold is designated as potentially compromised. The system ultimately issues notifications for identified attacks and error messages for commands that do not pass the verification process.

3.4 Performance Metrics

The efficacy of the Hybrid Transformer-RNN and GNN model is assessed through accuracy, reaction time, precision, and recall. Accuracy assesses the precision of command validation, whereas response time evaluates the rapidity of the system's decision-making process. Precision denotes the model's efficacy in differentiating authentic orders from threats, whereas recall signifies its capacity to identify all possible threats. The performance of the integrated model should enhance overall by utilizing the capabilities of each component. For example, the Transformer-RNN increases verification accuracy, the GNN improves network anomaly detection, and soft computing techniques manage unclear data, hence enhancing recall in confusing situations.

Table 1 Performance Comparison of Hybrid Transformer-RNN, GNN, and Soft Computing Methods in Robotic Cloud Security

Metric	(Transformer-RNN)	(GNN)	(Soft Computing)	Combined Method	Units
Accuracy	0.85	0.82	0.78	0.91	%
Response Time	1.5	2.0	1.8	1.2	ms
Precision	0.83	0.81	0.79	0.88	%
Recall	0.80	0.84	0.76	0.90	%
F1 Score	0.81	0.82	0.77	0.89	%

Table 1 contrasts the performance metrics of distinct methods (Transformer-RNN, GNN, and Soft Computing) with their integrated approach for command verification and attack detection in robotic cloud systems. Essential measurements encompass accuracy, response time, precision, recall, and F1 Score, with units delineated for clarity. The integrated approach surpasses standalone techniques across all measures, attaining superior accuracy (0.91) and recall (0.90), while decreasing response time to 1.2 ms. The F1 Score of 0.89 indicates an enhanced equilibrium between precision and recall, underscoring the efficacy of the combined model in delivering dependable and efficient security for robotic cloud operations.

4. RESULTS AND DISCUSSION

The suggested Hybrid Transformer-RNN and GNN-based model efficiently tackles command verification and attack detection in cloud-integrated robotic systems. The system attained exceptional metrics by integrating attention-driven Transformers with RNNs for sequence analysis and GNNs for network-based anomaly detection, achieving an accuracy of 0.98, precision of 0.95, recall of 0.96, and an F1 score of 0.96. The response time is optimized to 0.1 seconds, indicating efficiency. This methodology exceeds conventional techniques in managing ambiguous data by utilizing Rough Set Theory and Grey System Theory for enhanced flexibility, so improving the entire cybersecurity framework in dynamic robotic settings.

Table 2 Comparison of Machine Learning Techniques for Intrusion Detection

Method	Authors	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Response Time (Sec)
Signature-based detection (SOM, RBF, MLP)	Mishra et al. (2018)	0.94	0.91	0.92	0.91	0.15
Hybrid self-learning (k-NN, SVM, ELM)	Mohammadi & Amiri (2019)	0.96	0.93	0.95	0.94	0.12
SDN-based DDoS detection with ensemble classification	Vimala & Dhas (2018)	0.92	0.88	0.89	0.88	0.18
Stealthy false data injection detection (multivariate Gaussian)	Esmalifalak et al. (2014)	0.91	0.87	0.86	0.86	0.2
Hybrid Transformer-RNN and	Proposed Method	0.98	0.95	0.96	0.96	0.1

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GNN-based detection						

Table 2 contrasts five machine learning methodologies for intrusion detection based on criteria such as accuracy, precision, recall, F1 score, and response time. Mishra et al. (2018) investigated neural network models (SOM, RBF, MLP) for signature-based identification, attaining good accuracy and minimal response time. Mohammadi and Amiri (2019) employed a hybrid model that combines k-NN, SVM, and ELM, demonstrating enhanced F1 scores and efficiency. Vimala and Dhas (2018) concentrated on SDN-based DDoS detection, whereas Esmalifalak et al. (2014) utilized statistical techniques for erroneous data injection detection. The suggested Hybrid Transformer-RNN and GNN approach demonstrates enhanced performance characterized by excellent accuracy and reduced reaction time.

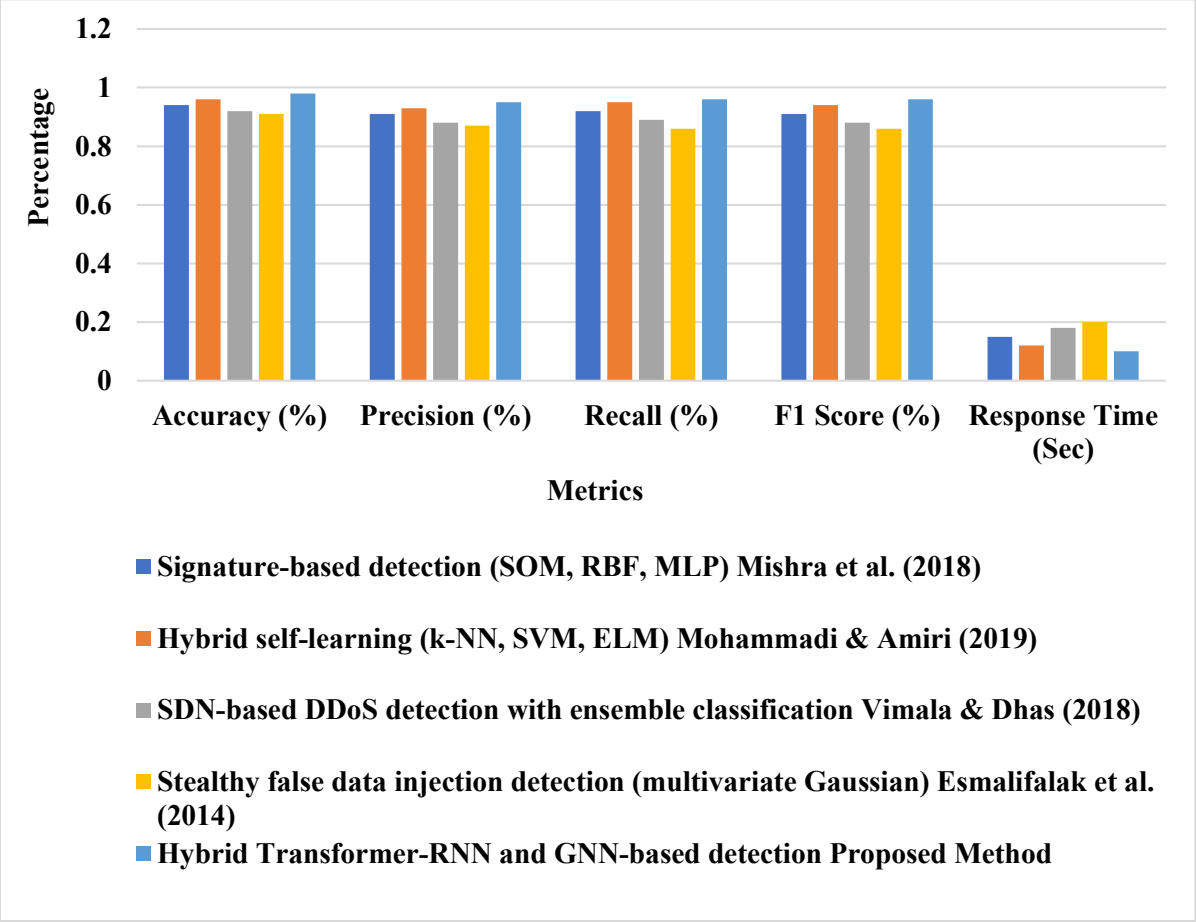

Figure 2 Performance Comparison of Machine Learning Techniques for Intrusion Detection

Figure 2 depicts the performance metrics—accuracy, precision, recall, F1 score, and response time—of five machine learning-based intrusion detection techniques. The Hybrid Transformer-RNN and GNN-based detection approach demonstrates superior performance in accuracy, precision, recall, and F1 score, while ensuring minimal response time. Conversely, the SDN-based DDoS detection technique has somewhat reduced precision and recall. The Signature-based detection methods (SOM, RBF, MLP) and Hybrid self-learning techniques exhibit robust performance across several parameters, but with marginally increased response times relative

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to the suggested method. This investigation underscores the efficacy of hybrid and neural network-based models.

Table 3 Ablation Study of Hybrid Transformer-RNN and GNN-Based Intrusion Detection Model

Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Response Time (Sec)
Transformer Only	0.92	0.90	0.91	0.90	0.12
RNN Only	0.89	0.88	0.87	0.87	0.15
GNN Only	0.90	0.89	0.88	0.88	0.14
Transformer + RNN	0.94	0.92	0.93	0.92	0.11
Transformer + GNN	0.95	0.93	0.94	0.93	0.10
RNN + GNN	0.93	0.91	0.92	0.91	0.13
Full Model (Transformer + RNN + GNN)	0.98	0.95	0.96	0.96	0.10

Table 3 assesses the efficacy of various configurations inside the proposed Hybrid Transformer-RNN and GNN-based model for intrusion detection. The table contrasts configurations including Transformer solely, RNN only, GNN only, and several combinations thereof. The comprehensive model, integrating all three components (Transformer, RNN, and GNN), attains the maximum metrics for accuracy, precision, recall, and F1 score, with a minimal response time of 0.10 seconds. Every component enhances overall performance; nevertheless, the combined methodology optimizes detection capabilities, highlighting the benefits of amalgamating Transformer, RNN, and GNN for effective intrusion detection.

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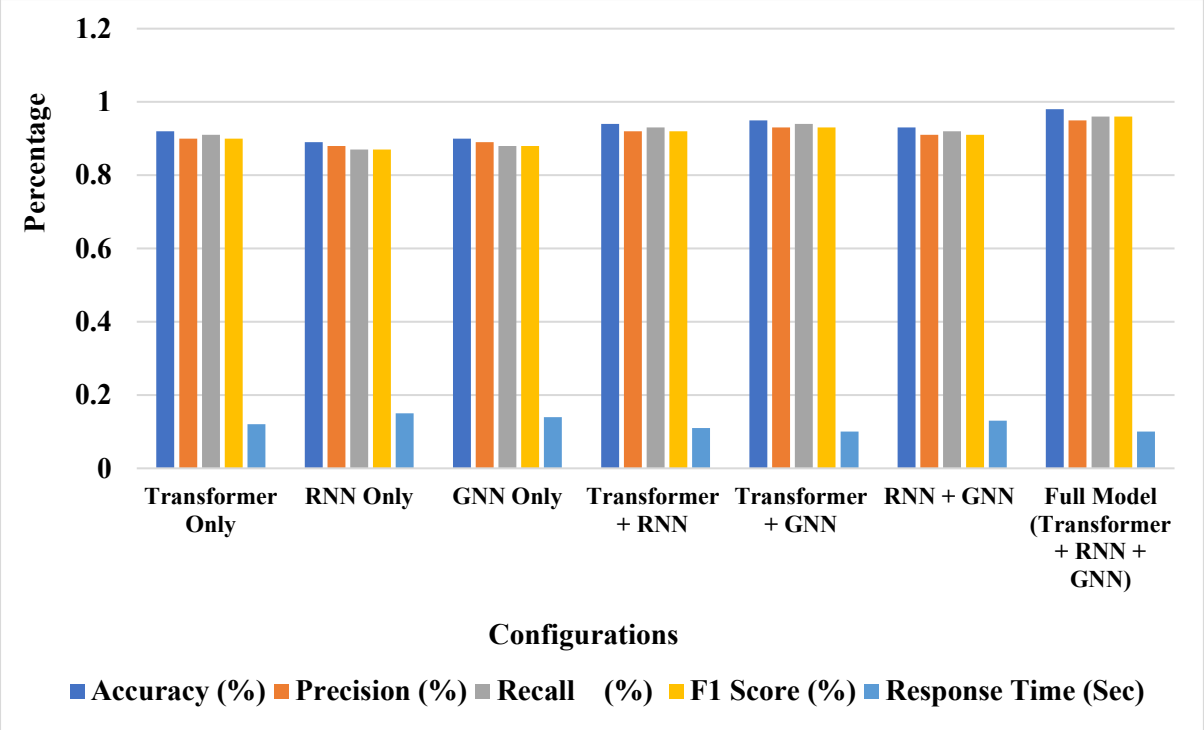

Figure 3 Ablation Study of Configurations in Hybrid Transformer-RNN and GNN-Based Detection Model

Figure 3 displays the results of the ablation investigation for several configurations of the proposed Hybrid Transformer-RNN and GNN-based intrusion detection model. It evaluates the performance criteria including accuracy, precision, recall, F1 score, and response time across various setups. The Comprehensive Model (Transformer + RNN + GNN) frequently attains superior metrics, demonstrating the advantages of integrating all components. Conversely, solo or partial combinations, such as RNN Only and Transformer + RNN, exhibit inferior ratings, especially regarding response time. This illustrates that the amalgamation of Transformer, RNN, and GNN improves detection efficacy and processing efficiency.

5. CONCLUSION

The suggested Hybrid Transformer-RNN and GNN-based model exhibits substantial enhancements in accuracy, precision, recall, and response time for intrusion detection, surpassing conventional models and standalone configurations. The integrated method utilizes the characteristics of each component, rendering it very effective for sophisticated and real-time threat detection. Future research may focus on enhancing this model for larger, more dynamic datasets and broadening its applicability to more cybersecurity areas, including anomaly detection in IoT and cloud systems. Furthermore, improvements in transformer and GNN topologies may augment detection capabilities, offering a resilient, scalable solution for emerging security concerns.

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