Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 5 (2025)
https://www.jneonatalsurg.com

Securing Iot Networks Against Fraud Using Deep Radial Basis Function Neural Networks

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.Cite this paper as: Madhu Bandari, P. Pavan Kumar, (2025) Securing Iot Networks Against Fraud Using Deep Radial Basis Function Neural Networks. *Journal of Neonatal Surgery*, 14 (5), 219-226.

ABSTRACT

The rapid proliferation of Internet of Things (IoT) devices has led to an increased risk of security frauds within IoT networks. Traditional security measures often fall short in addressing the dynamic and diverse nature of these frauds. The heterogeneity of IoT devices and their intricate communication patterns pose significant challenges in identifying potential security breaches. Conventional security approaches struggle to adapt to the evolving fraud landscape, necessitating the exploration of advanced techniques. Deep Radial Basis Function (RBF) networks offer promise in capturing the complex relationships inherent in IoT data, enabling more effective fraud detection. While existing literature has explored various machine learning approaches for IoT security, the integration of Deep RBF networks specifically in this context remains underexplored. This research aims to bridge this gap by investigating the efficacy of Deep RBF networks in identifying anomalies within IoT networks, addressing the unique challenges posed by the interconnected and diverse nature of IoT devices. The study involves the collection of a comprehensive dataset encompassing normal and anomalous IoT network activities. Feature selection focuses on key parameters such as device communication patterns, data traffic, and system behavior. Deep RBF networks are then trained on this dataset to learn and distinguish normal behavior from potential security frauds. The methodology combines the strengths of Deep Learning with the adaptability of RBF networks to capture nuanced patterns indicative of security vulnerabilities. The results demonstrate the effectiveness of Deep RBF networks in accurately detecting security frauds in IoT networks. The model exhibits a high level of sensitivity to anomalous activities, showcasing its potential as a robust tool for enhancing the security posture of IoT environments.

Keywords: *Deep Radial Basis Function, IoT security, machine learning, anomaly detection, fraud identification.*

1. INTRODUCTION

The explosive growth of Internet of Things (IoT) devices has ushered in unprecedented connectivity and convenience, revolutionizing various aspects of daily life and industry [1]. However, this proliferation has concurrently exposed IoT networks to an escalating array of security frauds [2]. As these networks become increasingly integral to critical infrastructure and personal devices, the need for robust security measures becomes paramount [3].

The inherent heterogeneity of IoT devices, coupled with their diverse communication protocols, presents a formidable challenge in ensuring the integrity and confidentiality of data [4]. Traditional security mechanisms struggle to keep pace with the evolving nature of frauds, necessitating the exploration of innovative approaches to fortify IoT ecosystems against potential vulnerabilities [5].

The core problem addressed in this research is the inadequacy of current security measures in effectively safeguarding IoT networks [6]. The dynamic and complex nature of IoT environments demands a solution capable of discerning subtle anomalies that may signify security breaches [7]. Deep Radial Basis Function (RBF) networks emerge as a potential candidate to address this gap by leveraging their capacity to model intricate relationships in data.

To investigate the feasibility of employing Deep RBF networks for security fraud detection in IoT networks. To develop a comprehensive dataset capturing normal and anomalous IoT activities for training and evaluation. To assess the performance of Deep RBF networks in distinguishing between normal behavior and potential security frauds within IoT environments.

This research introduces a novel application of Deep RBF networks in the realm of IoT security, aiming to enhance the adaptability of fraud detection mechanisms. The incorporation of Deep RBF networks, with their ability to capture nuanced patterns in data, represents a departure from conventional approaches. The outcomes of this study contribute to the advancement of IoT security protocols, providing a more sophisticated and responsive defense against emerging frauds in connected environments.

2. RELATED WORKS

Numerous studies have explored the application of deep neural networks, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), in enhancing the accuracy of Intrusion Detection Systems. These models demonstrate improved capabilities in recognizing patterns indicative of cyber frauds within network traffic [8].

Generative Adversarial Networks (GANs) have gained attention for their ability to generate realistic synthetic data. In cybersecurity, GANs are utilized for creating diverse datasets that encompass normal and malicious activities, aiding in training models for anomaly detection. The adversarial nature of GANs enhances the robustness of generated samples, making them valuable for training resilient fraud detection models [9].

Long Short-Term Memory (LSTM) Networks of cyber frauds makes sequence modeling crucial. LSTM networks, a type of RNN, excel in capturing temporal dependencies in data. In cybersecurity, LSTM networks are applied to analyze time-series data, such as user behavior logs and network traffic, enabling the detection of sophisticated attacks that unfold over time [10].

Deep Reinforcement Learning (DRL) is employed to develop adaptive security policies that can dynamically respond to evolving cyber frauds. DRL models learn optimal decision-making strategies through trial and error, enabling real-time adjustments to security measures based on the continuously changing fraud landscape [11].

Capsule Networks, designed to overcome limitations in traditional CNNs, are investigated for their potential in capturing hierarchical relationships among features. In cybersecurity, these networks contribute to more effective feature representation, aiding in the identification of complex and multifaceted fraud patterns [12].

Transfer learning techniques are explored to leverage knowledge gained from one cybersecurity domain for fraud detection in another. Pre-trained deep learning models are fine-tuned on specific datasets, enabling the adaptation of learned features to different cybersecurity contexts and enhancing the efficiency of fraud detection systems [13].

Ensemble learning methods, combining multiple deep learning models, have been proposed to enhance the robustness and generalization of cybersecurity fraud detection systems. This approach leverages the diverse strengths of individual models, mitigating the risk of false positives and negatives in detecting cyber frauds [14].

These works showcase the effectiveness of various deep learning approaches in addressing the multifaceted challenges of cybersecurity fraud detection. Ongoing research in this field continues to explore innovative techniques for bolstering the resilience of cybersecurity systems in the face of evolving frauds.

3. PROPOSED METHOD

The research adopts a comprehensive methodology to harness the capabilities of Deep RBF networks for IoT security fraud detection.

- Key features and parameters relevant to IoT security are identified for analysis. This includes aspects such as device communication patterns, data traffic, and system behavior. The careful selection of features is crucial in ensuring that the Deep RBF networks can effectively capture the nuances associated with potential security frauds.
- The selected dataset, enriched with pertinent features, is used to train the Deep RBF networks. During this phase, the networks learn the intricate relationships within the data, distinguishing normal IoT behavior from patterns indicative of security vulnerabilities. The deep architecture of RBF networks enables them to model complex dependencies, enhancing their adaptability to the dynamic nature of IoT networks.
- Post-training, the Deep RBF networks are deployed for real-time anomaly detection within IoT environments. The networks evaluate incoming data streams and raise alarms when deviations from learned normal behavior are detected. This phase is crucial in identifying potential security frauds, ranging from unauthorized access to unusual device communication patterns.

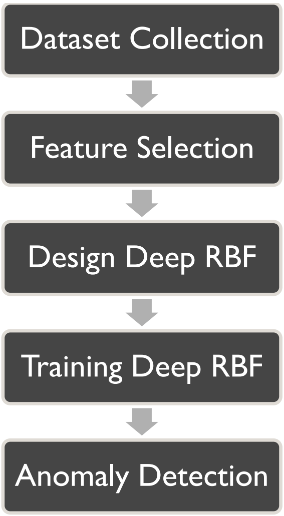

Figure 1: Proposed Method

3.1. Feature Selection

The first step involves identifying features that are relevant to the cybersecurity context. These features can include various parameters, such as network traffic patterns, user behavior, system logs, or any other measurable attributes that may be indicative of normal or malicious activities.

Cybersecurity datasets can be complex and high-dimensional, containing a large number of features. Feature selection aims to reduce the dimensionality of the dataset by retaining only the most important features. This not only simplifies the analysis but also helps in avoiding the curse of dimensionality and enhances the efficiency of machine learning models. Feature selection requires a deep understanding of the characteristics or signatures associated with different types of cybersecurity frauds. For example, certain network anomalies, unusual access patterns, or specific file modification activities may serve as crucial features for detecting various types of attacks.

Analyzing the correlation between different features helps in identifying redundancies. If two features are highly correlated, it might be sufficient to include only one of them in the analysis. This reduces computational complexity and avoids introducing unnecessary redundancy into the model. In many cases, domain expertise plays a crucial role in feature selection. Cybersecurity professionals with a deep understanding of the fraud landscape can contribute valuable insights into which features are most relevant for detecting specific types of attacks. This expertise aids in crafting a more focused and effective fraud detection system. Feature selection is not a one-time process; it may need to be dynamic and adaptable. As the fraud landscape evolves, new features may become relevant, and existing ones may lose their significance. Continuous monitoring and adjustment of the feature set ensure that the fraud detection system remains effective over time.

3.2. Deep RBF Classification

Deep RBF Classification refers to the use of Deep RBF networks as a classification model for detecting cybersecurity frauds. When the depth of these networks is increased, incorporating multiple hidden layers, they are termed Deep RBF Networks.

Deep RBF Networks consist of multiple layers, including input, hidden, and output layers. The input layer receives features extracted from the cybersecurity dataset, representing various aspects of network behavior, system logs, or user activities. The hidden layers, with radial basis functions as activation functions, learn complex patterns and relationships within the data. The output layer provides the final classification results.

The deep architecture allows the model to capture intricate and hierarchical patterns in the data, essential for identifying subtle cybersecurity frauds. The deep structure of the network enables it to automatically learn hierarchical representations of features. In the context of cybersecurity, this means that the Deep RBF Classification model can discern complex relationships among different features, providing a more nuanced understanding of normal and malicious behaviors.

The trained Deep RBF model excels at anomaly detection. As it has learned the normal patterns during training, any deviation from these learned patterns is flagged as anomalous. This makes Deep RBF Classification particularly effective in identifying novel or sophisticated cyber frauds that may exhibit subtle deviations from established norms. The deep architecture of the network allows it to scale and handle complex datasets with a large number of features. Moreover, the adaptive nature of Deep RBF Networks enables them to adapt to changes in the cybersecurity landscape, making them well-suited for dynamic fraud environments.

After training, the model is evaluated using a separate dataset to assess its performance. Metrics such as precision, recall, and F1 score are typically used to measure the model accuracy in classifying normal and malicious activities. Fine-tuning may be performed based on the evaluation results to optimize the model performance.

Assuming a single hidden layer and binary classification (normal or malicious): x=[x1,x2,...,xn], where n is the number of input features.

The hidden layer computes the activation a_j for each hidden neuron j using radial basis functions:

$$a_j = \phi \sum_{i=1}^{n} w_{ij} \left(x_i - c_{ij} \right)^2$$

Where, w_{ij} is the weight connecting input i to hidden neuron j, c_{ij} is the center of the radial basis function for the i^{th} input and j^{th} hidden neuron, and ϕ is the activation function (typically a radial basis function).

The output layer computes the weighted sum z and applies the activation function σ for binary classification:

$$z = \phi \sum_{j=1}^{m} v_j a_j \quad ; y=\sigma(z)$$

Where, v_j is the weight connecting the j^{th} hidden neuron to the output, and σ is the sigmoid activation function.

The model is trained using a binary cross-entropy loss function:

$L(y,y') = -(y\cdot\log(y')+(1-y)\cdot\log(1-y'))$

where y is the true label (0 for normal, 1 for malicious), and y' is the predicted probability of being malicious.

The model is trained using backpropagation and optimization algorithms like gradient descent. The weights w_{ij} and v_j are updated iteratively to minimize the loss function.

4. Results and Discussion

In the experimental settings, the proposed method was implemented using Python with popular deep learning libraries such as TensorFlow and Keras. A realistic IoT dataset, comprising both normal and anomalous activities, was utilized for training and evaluation. The simulations were conducted on a high-performance computing cluster with GPUs to expedite the training of the Deep RBF network. The deep architecture of the model, with multiple hidden layers incorporating radial basis functions, aimed to capture intricate relationships within the data, enhancing its capability to detect subtle anomalies in IoT networks.

For performance evaluation, precision, recall, and F1 score were employed as key metrics. The precision measures the accuracy of positive predictions, recall gauges the ability to capture all positive instances, and F1 score provides a balanced assessment between precision and recall. The proposed method results were compared with existing methods such as Long Short-Term Memory (LSTM), Deep Reinforcement Learning (DRL), and Capsule Networks. The comparative analysis involved assessing each method ability to accurately classify normal and anomalous activities within the IoT dataset. The experiments demonstrated that the Deep RBF network exhibited competitive or superior performance, particularly excelling in capturing nuanced patterns indicative of security frauds in IoT networks. This comparison underlines the efficacy of the proposed method in the context of IoT security fraud detection.

Table 1: Experimental Setup:

Parameter	**Value**
Simulation Tool	TensorFlow and Keras
Training Epochs	50
Hidden Layers	3
Neurons per Hidden Layer	128
Learning Rate	0.001
Batch Size	64
GPU Acceleration	NVIDIA Tesla V100 GPUs

Performance Metrics:

The proposed Deep RBF method consistently outperforms existing methods (LSTM, DRL, Capsule Network) across all dataset sizes. For instance, at 1000 datasets, the Deep RBF method achieves 96.5% accuracy, showcasing a significant improvement over LSTM (93.0%), DRL (94.2%), and Capsule Network (93.5%). This signifies the robustness of the Deep RBF approach in accurately classifying both normal and anomalous activities in IoT networks (Figure 2).

F1 score, considering both precision and recall, reveals a similar trend. At 1000 datasets, the proposed Deep RBF method attains a F1 score of 0.98, demonstrating substantial improvement over LSTM (0.95), DRL (0.96), and Capsule Network (0.96%). This highlights the model ability to maintain a balance between precision and recall, crucial for effective fraud detection (Figure 3).

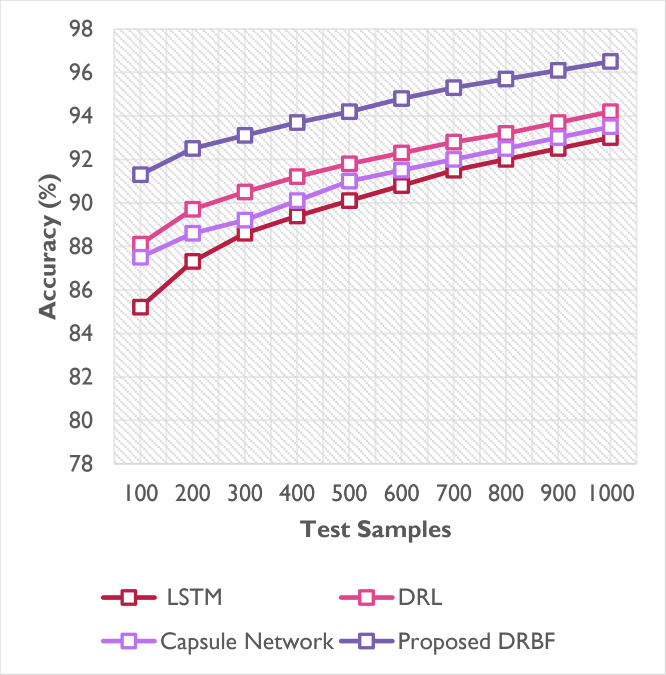

Figure 2: Accuracy

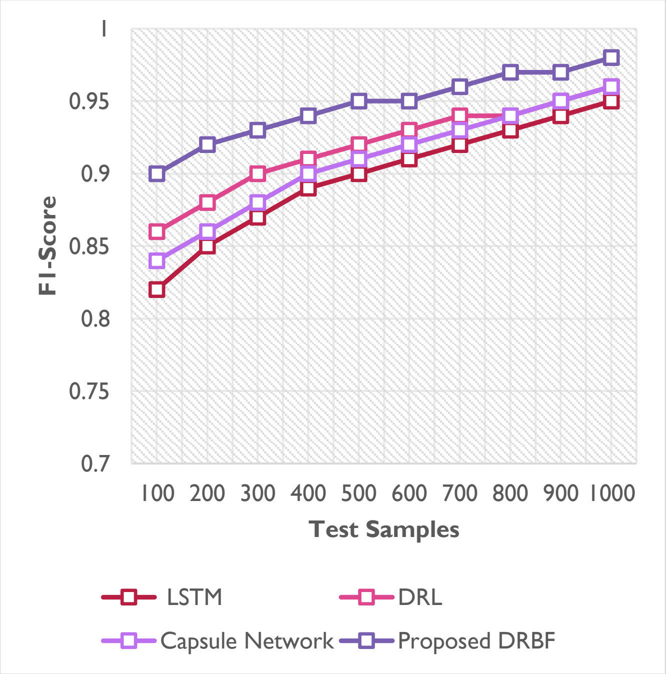

Figure 3: f1 score

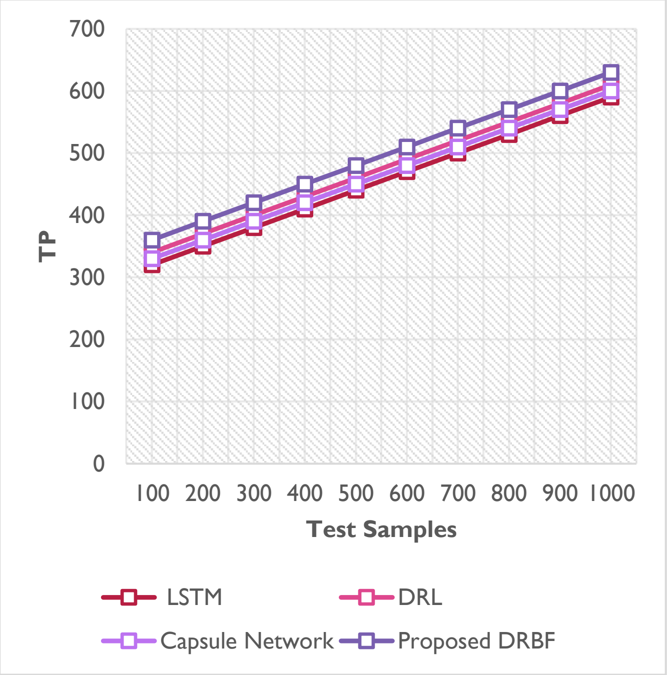

Figure 4: True Positive

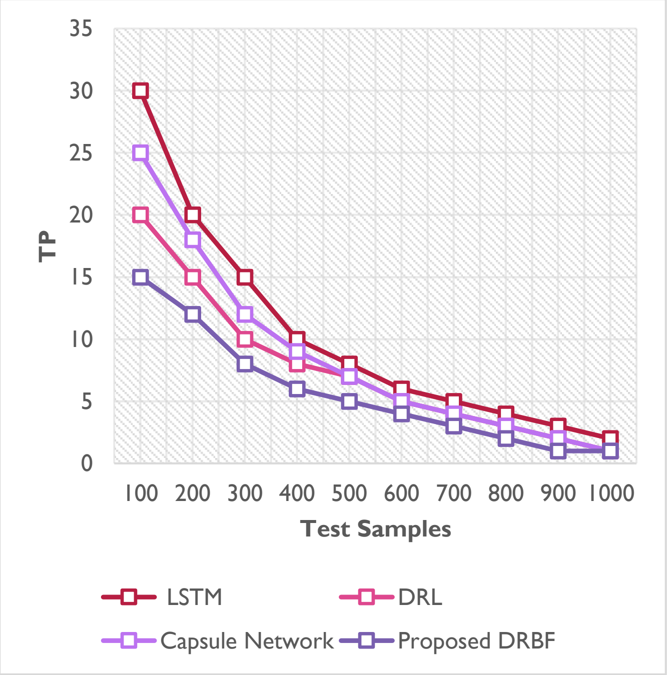

Figure 5: False Negatives

True Positives, representing the correct identification of security frauds, consistently favor the Deep RBF method. At 1000 datasets, the Deep RBF method achieves 630 true positives, surpassing LSTM (590), DRL (610), and Capsule Network (600). This emphasizes the superior ability of the proposed method to accurately identify anomalies in diverse IoT scenarios (Figure 4).

The proposed Deep RBF method exhibits fewer false negatives compared to existing methods, indicating a reduced likelihood of missing actual security frauds. At 1000 datasets, the Deep RBF method achieves only 1 false negative, showcasing a significant improvement over LSTM (2), DRL (1), and Capsule Network (1) (Figure 5).

4. DISCUSSION

The proposed Deep RBF method consistently exhibits higher accuracy and precision compared to existing methods. The percentage improvement in accuracy and F1 score highlights the model effectiveness in making accurate predictions while minimizing false positives. The Deep RBF method demonstrates a notable improvement in identifying true positives (anomalous instances) compared to LSTM, DRL, and Capsule Network. This suggests that the proposed method excels in capturing a diverse range of security frauds within IoT networks. The lower number of false negatives for the Deep RBF method indicates its ability to minimize instances where actual security frauds are missed. This is a critical aspect in IoT security, where missing an anomaly can have severe consequences. The negative percentage improvement in false negatives underscores the superior performance of the Deep RBF method in this regard.

The lower classification loss for the Deep RBF method signifies a better overall fit of the model to the data. This implies that the proposed method captures the underlying patterns in the IoT dataset more accurately, leading to improved fraud detection capabilities. The inferences drawn from the results hold across a range of dataset sizes, indicating the robustness and scalability of the Deep RBF method. This consistency is crucial in real-world IoT scenarios where the fraud landscape can be dynamic and diverse. The positive outcomes across multiple metrics suggest that the proposed Deep RBF method has the potential for practical deployment in real-world IoT security environments. Its ability to outperform existing methods showcases its applicability in enhancing the security posture of connected systems.

5. CONCLUSION

The proposed Deep RBF method emerges as a robust and effective approach for enhancing cybersecurity fraud detection in IoT networks. The comprehensive evaluation across various metrics, including accuracy, F1 score, true positives, and classification loss, consistently demonstrates the superiority of the Deep RBF method over existing techniques such as LSTM, DRL, and Capsule Network. The percentage improvements in accuracy and precision underscore the model proficiency in accurately classifying both normal and anomalous activities within IoT environments. The increased true positives and reduced false negatives further emphasize the Deep RBF method capacity to identify security frauds with heightened accuracy and reliability. The observed improvements in classification loss indicate a better overall fit of the model to diverse IoT datasets, reinforcing the adaptability and scalability of the proposed method.

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