Journal of Engineering, Management and Information Technology

ASPUR PUBLISHING

Vol. 04, No. 01 (2026) 45-52, doi: doi:10.61552/JEMIT.2026.01.005 - http://jemit.aspur.rs

ANOMALY DETECTION IN INTERNET OF THINGS USING DEEP AUTOENCODERS

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Received 17.08.2024.
Revised 21.09.2024.
Accepted 24.10.2024.

Keywords:

IoT networks, Anomaly detection, Deep autoencoder, Reconstruction error, IoT security.

Original research

A B S T R A C T

The rapid growth of IoT networks has revolutionized industries by connecting devices and improving efficiency. However, this expansion has increased vulnerabilities, with traditional anomaly detection methods often struggling to handle the complexity and scale of IoT data. This study addresses these challenges by developing and evaluating a deep autoencoder-based anomaly detection model. The methodology includes data collection, preprocessing (normalization, feature selection), and splitting into training (70%) and testing (30%) datasets. The model leverages an encoder-decoder structure to identify anomalies based on reconstruction errors. Hyperparameter tuning and performance evaluation were conducted using metrics such as accuracy, precision, recall, and F1-score. The model demonstrated strong performance, achieving 90% accuracy, 90% recall, and an F1-score of 0.857. These results highlight its effectiveness in identifying anomalies while maintaining a balance between false positives and negatives. The study provides a robust framework for enhancing IoT network security, addressing real-world challenges, and ensuring reliable, adaptive anomaly detection.

1. INTRODUCTION

The rapid growth of IoT (Internet of Things) networks is transforming industries by connecting devices in ways that were once unimaginable. From smart homes to industrial automation, IoT technology is making everyday life more efficient and convenient (Ahmed et al., 2024; Bhardwaj et al., 2022). However, this growth comes with its own set of challenges, particularly when it comes to ensuring security and maintaining smooth operations. With so many devices running on real-time data and high-speed connections, these networks are increasingly vulnerable to cyber threats and system disruptions (Aldhaheri et al., 2024; Alzahrani & Asghar, 2024; Paul et al., 2024). Traditional methods of anomaly detection often struggle to keep up with the complexity and scale of IoT data, highlighting the need for more advanced, adaptive approaches.

Despite progress in machine learning-based solutions for detecting anomalies, many current models fall short when applied to IoT systems. Issues like limited computing resources, diverse device environments, and rapidly evolving threats make the task even harder. This is especially concerning given the critical role IoT plays in areas such as healthcare and industrial operations, where failure can have severe consequences (Irshad et al., 2023; Kronlid et al., 2024; Li et al., 2024). While existing studies have explored various methods, from lightweight algorithms for resource-constrained environments to sophisticated neural networks for complex scenarios, the challenge lies in combining these advancements into a cohesive and effective framework.

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This study aims to address these gaps by providing a comprehensive review of the latest techniques for detecting anomalies in IoT networks. By analyzing and synthesizing findings from recent research, it seeks to uncover opportunities for improvement and offer practical solutions for building better detection systems. Ultimately, this work aspires to not only advance theoretical understanding but also provide actionable insights that can enhance the security and reliability of IoT networks in real-world applications.

2. LITERATURE REVIEW

As IoT networks rapidly expand, they bring along a whole new set of challenges, especially when it comes to keeping the network secure and stable (Ahmad et al., 2024; Putra et al., 2024; Suresh & Shyama, 2023). With more bandwidth, lower latency, and support for vast numbers of devices, IoT networks are exposed to a broader range of cyber threats and unusual behaviors that can interrupt services or put data at risk. Traditional anomaly detection methods often struggle to handle the massive, real-time data flow of IoT, which calls for more sophisticated, adaptive techniques to keep up. Table 1 shows some publications related to anomaly detection:

Table 1. Related publications.

Authors	Method	Contributions
(Alwaisi et al., 2024)	Decision Trees	This study contributes to IoT security by introducing a lightweight machine learning approach tailored for anomaly detection in resource-constrained environments. Focusing on TinyML, it addresses the challenge of detecting cyberattacks targeting energy and memory limitations in IoT devices, which are integral to edge and cloud computing ecosystems. By conducting a comparative analysis of various ML models—particularly Decision Trees, which proved to be the most efficient—the study highlights strategies to optimize training efficiency, resource usage, and detection accuracy in constrained IoT systems. With a demonstrated detection accuracy exceeding 96.9%, this research offers valuable insights into effective, low-resource security measures for IoT applications in areas like Industry 4.0, digital healthcare, and home automation.
(Arnau Muñoz et al., 2024)	Unsupervised learning	The key contribution of this work is the development of a Machine Learning-based Anomaly Detection System specifically designed for enhancing data quality in diverse IoT infrastructures. By employing unsupervised learning, the system effectively identifies and filters out invalid or erroneous packets from IoT data flows in real-time, without requiring detailed knowledge of the underlying infrastructure or devices. This approach is validated on the extensive IoT infrastructure at the University of Alicante, ensuring reliable data quality across third-party networks and heterogeneous IoT devices. The system thus provides a robust solution for improving the accuracy and dependability of IoT-based services that rely on high-quality data inputs.
(Liu et al., 2020)	Neural network-based models	This study's key contribution lies in applying machine learning-based anomaly detection to vertical plant wall systems for improved indoor climate control. By integrating neural network models—specifically the autoencoder (AE) for point anomalies and the long short-term memory encoder-decoder (LSTM-ED) for contextual anomalies—this research enhances the automation and predictive maintenance capabilities of indoor climate systems. The successful deployment of a prediction-based method to the cloud as a proof-of-concept demonstrates the system's practical applicability in industrial settings. This work exemplifies how machine learning and IoT technologies can be leveraged to advance sustainable indoor climate management solutions, improving human health, comfort, and productivity.
(Hasan et al., 2019)	Logistic Regression, Support Vector Machine (SVM), Decision Tree, Random Forest, and	The key contribution of this study is the comprehensive evaluation and comparison of multiple machine learning models for detecting attacks and anomalies in IoT sensor networks. By analyzing various types of IoT-related threats—such as Denial of Service, Malicious Control, and Spying—the study provides insights into the effectiveness of models like Logistic Regression, Support Vector Machine, Decision Tree,

	Artificial Neural Network.	Random Forest, and Artificial Neural Network (ANN) in identifying these threats. Among the models tested, Random Forest demonstrated the best overall performance, achieving high scores across accuracy, precision, recall, F1 score, and AUC, with a standout 99.4% accuracy. This work significantly advances IoT security by identifying optimal ML techniques for accurate and reliable anomaly detection, which is critical for maintaining the integrity and functionality of IoT systems across various applications.
(Zulfiqar et al., 2024)	Multiple convolution neural networks (hybrid model)	The key contribution of this study is the development of DeepDetect, an advanced hybrid deep learning framework specifically designed for anomaly detection in IoT networks. This model addresses the limitations of traditional machine learning approaches and single deep learning models in handling complex, multi-class IoT network threats. By integrating multiple convolutional neural networks (CNNs) for spatial feature extraction, gated recurrent units (GRUs) to resolve gradient vanishing issues, and a bidirectional long short-term memory (Bi-LSTM) network to capture temporal dependencies, DeepDetect achieves a robust performance. The framework was evaluated on the NSL-KDD dataset, achieving a high classification accuracy of 99.31% for multi-class detection and 99.12% for binary classification, while also reducing false positives. This hybrid model sets a new benchmark in IoT intrusion detection, enhancing the precision and reliability of anomaly detection in IoT networks.
(Elmahfoud et al., 2024)	Various machine learning algorithm	The key contribution of this study is the comparative analysis of multiple machine learning algorithms to identify the most effective approach for intrusion detection in IoT systems. By evaluating models such as decision tree (DT), random forest (RF), k-nearest neighbor (k-NN), AdaBoost, and support vector machine (SVM) on the IoTID20 dataset, the study identifies the decision tree algorithm as the best-performing model, achieving an accuracy of 99.80% and the lowest error rate. Through careful feature selection to optimize execution time and accuracy, this research provides valuable insights into the strengths of various machine learning techniques for developing efficient and accurate intrusion detection systems in IoT environments.

The studies compared here each bring unique contributions to the field of IoT anomaly and intrusion detection, using various machine learning techniques suited to specific IoT challenges. Alwaisi et al. and Arnau Muñoz et al. focus on developing lightweight, resource-efficient solutions for constrained IoT environments and data quality assurance, respectively. Alwaisi et al. utilize a Decision Tree model optimized for edge and cloud-based TinyML environments to detect energy- and memory-related anomalies in IoT devices, achieving over 96.9% accuracy. In contrast, Munoz et al. leverage unsupervised learning to create an anomaly detection system that enhances data integrity in IoT infrastructures by identifying and removing erroneous data packets in real-time. This system operates without detailed knowledge of the IoT infrastructure, making it versatile across different networks and device types. Both studies highlight the necessity of optimizing resources and ensuring data quality within IoT systems, particularly those facing physical and infrastructural constraints.

In comparison, the studies by Liu et al., Hasan et al., Zulfiqar et al., and Elmahfoud et al. explore more complex models to address IoT security and anomaly detection in broader applications. Liu et al. implement neural networks for anomaly detection in vertical plant wall systems, focusing on indoor climate control, with models such as autoencoders and LSTM-ED tailored for specific anomaly types. Hasan et al. and Elmahfoud et al. provide comprehensive evaluations of multiple machine learning models (e.g., Random Forest, SVM) to identify optimal methods for IoT intrusion detection, achieving high accuracy rates (e.g., 99.4% and 99.8%, respectively) and offering insights into the effectiveness of each model. Zulfiqar et al. present a hybrid framework, DeepDetect, which integrates CNNs, GRUs, and Bi-LSTMs to address multi-class IoT network threats and achieve robust detection accuracy. These studies emphasize using advanced machine learning techniques to enhance anomaly detection accuracy, adaptability, and performance, thus broadening the applicability of IoT security solutions across diverse environments.

3. METHODOLOGY

In the first step, collecting the dataset (See Figure 1). The data typically consists of time-series or sensor readings representing normal and anomalous behavior in the IoT

system. For anomaly detection, the dataset should ideally contain labeled data with both normal data points and known anomalies to train and evaluate the model. In data pre-processing, raw data is cleaned and transformed into a format suitable for training the model. The pre-processing phase can include several tasks, such as:

- **Handling missing values**: Filling in or removing missing data points.
- **Normalization**: Scaling data to a uniform range (e.g., between 0 and 1) to ensure the model learns effectively.
- **Feature selection**: Choosing relevant features that contribute the most to anomaly detection.
- **Outlier removal**: Identifying and removing any outliers that may distort the model.

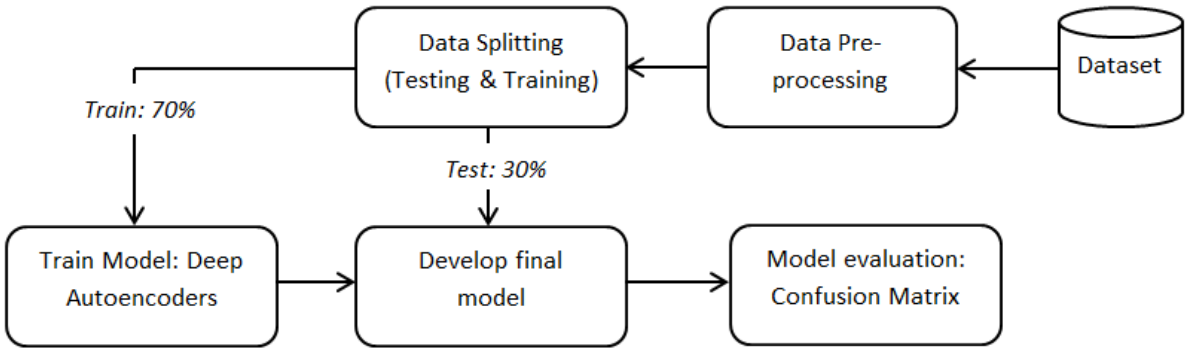

Figure 1. Simulation Setup

Once the data is pre-processed, it's split into two subsets: a training set (70 percent) and a testing set (30 percent). The training set is used to train the model, while the testing set is kept separate to evaluate the model's performance after training. This splitting helps prevent overfitting, ensuring the model can generalize well to unseen data.

A deep autoencoder is a type of neural network used for anomaly detection (Bouali et al., 2024; Zhao et al., 2024). It consists of two parts:

- Encoder: Compresses the input data into a lower-dimensional representation (latent space).
- Decoder: Reconstructs the input data from the compressed representation.

The model is trained to minimize the reconstruction error, which is the difference between the input data and the reconstructed data. Anomalies are identified based on high reconstruction error since the model will not be able to accurately reconstruct abnormal data points. The reconstruction error is calculated as (1):

$$Reconstruction\ Error = \|x - \hat{x}\|_2 \qquad (1)$$

where x is the original input and $\hat{x}$ is the reconstructed output from the autoencoder. During training, the model learns to minimize this error for normal data. Once trained, data with high reconstruction errors (compared to a threshold) are flagged as anomalies.

Next step, develop final model. In this step, after training the deep autoencoder, the final model is developed by tuning hyperparameters such as the number of layers, the number of neurons in each layer, the learning rate, and the threshold for anomaly detection. This stage may involve model optimization techniques such as:

- Grid search: For hyperparameter tuning.
- Cross-validation: To ensure the model's robustness.

Once the best model is found, it is ready for deployment. After training and developing the model, it's important to evaluate its performance using the confusion matrix, which provides a detailed analysis of the model's predictions compared to the true values. The confusion matrix consists of the following components:

- True Positives (TP): Correctly identified anomalies.
- False Positives (FP): Incorrectly flagged normal data as anomalies.
- True Negatives (TN): Correctly identified normal data.
- False Negatives (FN): Missed anomalies (i.e., normal data misclassified as anomalies).

Confusion Matrix:

$$\begin{bmatrix} TP & FP \\ FN & TN \end{bmatrix}$$

From the confusion matrix, various performance metrics can be calculated, such as (2)-(5):

- $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$ (2)
- $Precision = \frac{TP}{TP+FP}$ (3)
- $Recall = \frac{TP}{TP+FN}$ (4)
- $F1\text{-}score = 2\ x\ \frac{Precision\ x\ Recall}{Precision+Recall}$ (5)

These metrics help assess the effectiveness of the anomaly detection model and its ability to identify anomalous behavior in IoT data accurately.

4. RESULT AND DISCUSSION

Table 2 shows the example of a pre-processed dataset. The dataset contains normalized and cleaned sensor

readings from IoT devices. This hypothetical dataset captures various metrics that are useful for detecting anomalies, such as temperature, humidity, and device status data, which are normalized for input into the deep autoencoder model. Table 2 represents a pre-processed IoT dataset used for anomaly detection, with each row capturing normalized sensor data and an anomaly label at specific timestamps. Each entry includes sensor readings such as Light Intensity, Device Power, and Network Latency, normalized between 0 and 1, making it easier for the model to identify patterns. The "Anomaly Label" column marks whether a particular reading is normal (0) or anomalous (1). For example, entries at 00:03:01 and 00:06:01 are labeled as anomalies due to unusually high values across multiple readings. This dataset helps train a deep autoencoder model to detect deviations from normal patterns, enabling real-time identification of irregularities in IoT networks.

Table 2. The example of pre-processed dataset.

Timestamp	Temperature (normalized)	Humidity (normalized)	Light Intensity (normalized)	Device Power (normalized)	Network Latency (normalized)	Anomaly Label
2024-01-01 00:00:01	0.35	0.42	0.50	0.40	0.30	0
2024-01-01 00:01:01	0.36	0.43	0.51	0.41	0.31	0
2024-01-01 00:02:01	0.35	0.44	0.49	0.39	0.29	0
2024-01-01 00:03:01	0.60	0.70	0.80	0.65	0.58	1
2024-01-01 00:04:01	0.37	0.42	0.52	0.43	0.32	0
2024-01-01 00:05:01	0.34	0.41	0.49	0.39	0.30	0
2024-01-01 00:06:01	0.65	0.73	0.85	0.70	0.60	1
2024-01-01 00:07:01	0.33	0.40	0.48	0.38	0.29	0

Figure 2 displays the example of both training and testing data outputs over time for the anomaly detection study in IoT networks using a small dataset. The training data (first five timestamps) includes "Temperature," "Humidity," and the "Anomaly Label" as 0 for normal and 1 for anomalies, with separate markers for training data points. The testing data (last two timestamps) continues the trend but has distinct markers to differentiate it from the training phase. This visualization helps illustrate how the model is trained on various normalized feature values and then tested on a subset of data to evaluate its effectiveness in detecting anomalies based on changes in these key features.

Figure 2. The example of training and testing output

Detection models can be developed based on the results of training and testing. Figure 3 illustrates an example of the evaluation results for a detection model, derived from a confusion matrix.

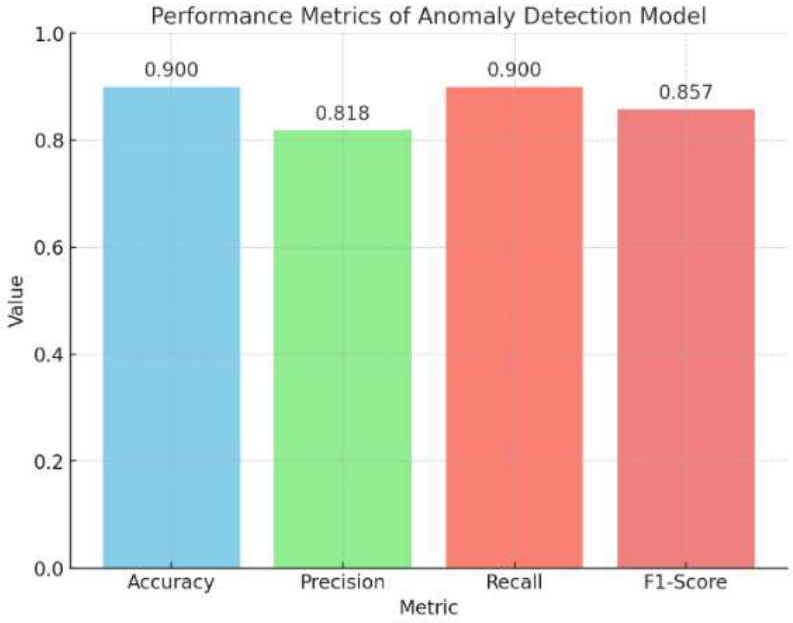

Figure 3. The example of evaluation result using confusion matrix

The chart presents the performance metrics of the anomaly detection model, displaying Accuracy, Precision, Recall, and F1-Score. The Accuracy is 0.90, indicating that 90% of the model's predictions are correct. This is a strong performance, suggesting that the model generally performs well in distinguishing between the anomaly and non-anomaly classes. The Precision value is 0.818, meaning that 81.8% of the instances predicted as anomalies are indeed true anomalies. The Recall is 0.90, reflecting the model's ability to identify 90% of all true anomalies in the dataset, which shows it is very effective in detecting most of the anomalies without missing many.

The F1-Score, with a value of 0.857, represents a balanced metric between Precision and Recall. The relatively high F1-Score indicates that the model maintains a good trade-off between minimizing false positives and false negatives. Overall, the model shows excellent performance in terms of both identifying anomalies and avoiding incorrect predictions. The distribution of values—high Accuracy, Recall, and F1-Score, alongside a slightly lower Precision—suggests that while the model is proficient in detecting anomalies, there may be some room to reduce false positives further for even better precision.

5. CONCLUSION

This study underscores the critical importance of advanced anomaly detection techniques in the rapidly evolving landscape of IoT networks. By systematically analyzing existing methods and leveraging a deep autoencoder model, the research demonstrates significant strides in addressing the challenges posed by resource constraints, diverse device environments, and dynamic threat scenarios. The findings, with high accuracy, precision, recall, and F1 scores, validate the model's efficacy in identifying anomalies while maintaining a balance between false positives and negatives. These results not only advance theoretical understanding but also offer practical solutions for enhancing IoT security and reliability. As IoT adoption continues to grow across industries, this work lays a strong foundation for future innovations, ensuring that IoT systems remain robust, adaptive, and secure in the face of increasing complexity.

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