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A Convolutional Neural Network (CNN)-Based Anomaly Detection Framework for Internet of Things (IoT) Systems Reinforced by Blockchain for Privacy and Safety

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Abstract:

A developing approach for identifying anomalies, especially in contexts like Internet of Things (IoT) systems, is the integration of Convolutional Neural Networks (CNN) with the Whale Optimization Algorithm (WOA). If you want to modify the CNN's parameters for better anomaly identification, you may apply the WOA, a strategy for optimization inspired by nature, in conjunction with the CNN's effectiveness in detecting spatial trends. Robust anomaly detection is critical for maintaining the authenticity, safety, and dependability of IoT systems in an ever-changing environment. We need more sophisticated and adaptable detection algorithms to handle the massive amounts and diverse types of data generated by the IoT. This research proposes a new approach to detect anomalies by integrating CNNs with the WOA, which should help with these issues. CNNs are a basic model for anomaly detection because of their famed capacity to extract spatial trends from complicated information. Learning rates, kernel sizes, and the number of layers are hyperparameters that have historically needed to be fine-tuned by hand in order to achieve optimal CNN efficiency. To tune these additional parameters successfully, we use the WOA, a metaheuristic influenced by nature and based on the bubble-net hunting tactic of humpback whales. The CNN's accuracy and resilience in recognizing anomalies tasks are improved by WOA's global search features, which allow it to obtain optimum configurations. To ensure the suggested technique worked, we ran comprehensive tests using real-world IoT datasets. The findings show that the CNN-WOA hybrid model outperforms traditional approaches in terms of speed of computation, recall, and accurateness, and it frequently maintains an accuracy of over 95% in identifying abnormalities. This precision demonstrates how well the model deals with unbalanced, noisy, and high-dimensional IoT data. This work offers an expandable approach for smart IoT system management by fusing deep learning with bio-inspired minimization. It establishes a precedent for future research in anomaly identification.

Introduction

Preserving the reliability and safety of systems in the age of IoT technologies requires effective anomaly detection. When faced with the massive amounts of diverse data produced by IoT devices, conventional approaches often fail. A potential solution to this problem is the combination of CNNs with the WOA. One effective approach for feature extraction and

classification is CNNs, which are well-known for rapidly extracting and identifying spatial patterns in data. On the other hand, hyperparameter tweaking is a laborious and time-consuming procedure that is crucial to their success. A strong and effective metaheuristic for improving CNN hyperparameters, the WOA takes its cues from the bubble-net hunting technique used by humpback whales. This combination of features improves the overall precision and dependability of anomaly detection models by automatically and adaptively optimizing CNN parameters, such as learning rates, kernel sizes, and the number of filters, by using the global search capabilities of WOA. This research delves into the combination of CNNs with WOAs for anomaly detection in IoT settings, demonstrating how this method tackles problems including imbalances in classes, data with high dimensions, and distortion. Numerous investigations on real-world IoT datasets confirm the proposed technique, showing that it significantly outperforms standard methods in terms of detection accuracy, computing economy, and flexibility. As far as the identification of anomalies and smart IoT system management are concerned, this combination of deep learning with optimization methods inspired by biology offers an encouraging avenue for further study.

The IoT has completely changed the way we use technology in many different industries, including shipping, intelligent cities, medical care, and industry. Having said that, a deluge of diverse data, often marked by imbalances, noise, and high dimensionality, is produced by the expansion of IoT devices. Because of this complexity, conventional anomaly detection technologies aren't up to the task of keeping up with the ever-changing nature of the IoT. If we want to make sure that IoT systems are secure, reliable, and fully functional, we need to be able to detect abnormalities. These may be things like unapproved access, system failures, or unexpected trends. One effective method for handling and interpreting complicated data is deep learning, and CNNs in particular. CNNs excel at finding regional trends and gathering characteristics from raw data, which makes them perfect for tasks that require detecting anomalies. Nevertheless, CNN performance is extremely affected by the hyperparameters that are chosen, which in turn affect the accuracy and efficiency of the networks. Grid search and manual selection, two common but computationally costly approaches to hyperparameter tuning, often miss the mark when applied to high-dimensional areas. To tackle these issues, this research combines CNNs with the WOA, a metaheuristic optimization method inspired by nature and based on the humpback whale's bubble-net hunting tactic. WOA is a great choice for tuning CNN hyperparameters because of its computational efficiency and reputation for global search. Using WOA, the suggested method improves the CNN's performance in detecting abnormalities in IoT data and simplifies the process of hyperparameter tuning. We show that the CNN-WOA hybrid model can identify anomalies with an accuracy of more than 95% on real-world IoT datasets in this study by doing a thorough assessment of it. The model outperforms more traditional approaches and is able to deal with complicated data problems like noise and class imbalance, as shown by the findings. This groundbreaking combination of deep learning and optimization based on biological principles offers a flexible and extensible approach to anomaly identification, leading to safer and more effective IoT systems.

Related works

A. Blockchain-Enhanced Federated Learning

Federated learning is a new method that allows machine learning models to be trained on different devices independently of each other, without the need to share raw data. By allowing safe and immutable modifications to the common model, blockchain integration with federated learning improves confidence. Although this approach works well in IoT settings, it does have certain drawbacks, such as higher latency and higher resource requirements for edge devices.

B. Deep CNNs with Blockchain

The extraction and categorization of features for IoT anomaly detection is a common use case for deep CNNs. Data integrity and trust among IoT devices are guaranteed by the system when blockchain is combined with it. Consider the scalability problems that have been brought to light by research conducted on the TON_IoT dataset. These problems are particularly acute in high-frequency network settings.

C. Autoencoder-Based Unsupervised Learning

Unsupervised neural networks known as autoencoders may learn to efficiently represent data. They re-create typical data patterns and highlight outliers, making them useful for anomaly identification in the IoT. But these models don't hold up well in dynamic IoT settings, such as the ones in the IoT-23 dataset, and they're not as resistant to adversarial assaults.

D. Hybrid Machine Learning Models

To improve detection accuracy, hybrid models use different machine learning methods, such as classifiers and clustering approaches together. These methods are not well-suited for real-time IoT situations because to the computational difficulties they encounter when used to datasets such as NSL-KDD.

E. GAN-Based Anomaly Detection

An growing number of anomaly detection applications are using generative adversarial networks (GANs) to enrich training datasets with generated data. Although GANs enhance detection rates, training them may be challenging due to problems like mode collapse, especially when working with very unbalanced IoT datasets such as NSL-KDD.

F. Distributed Long Short-Term Memory (LSTM)

Anomaly detection in IoT networks based on sequences is a perfect fit for LSTM models because of their ability to handle time-series data. Though promising, studies using the UNSW-NB15 dataset need careful implementation of computationally costly models in order to manage scattered IoT networks.

G. Ethereum Blockchain for IoT Security

Unobstructed and tamper-proof recognition of anomalies is made possible by smart contracts on the Ethereum blockchain. While this technology guarantees safe data exchange among IoT devices, it may be costly to operate owing to gas expenses, which can impact the scalability of large-scale IoT installations.

H. Real-Time Anomaly Detection with Optimized Deep Models

IoT devices with limited resources may use optimized deep learning models to identify anomalies in real time. Although datasets like as Kitsune prove their effectiveness, energy consumption is still a major impediment, particularly for Internet of Things devices that run on batteries.

I. Ensemble Learning Techniques

To enhance the precision of anomaly detection, collaborative methods integrate the capabilities of many machine learning models, including deep networks and support vector machines. But there are a lot of obstacles, such as the possibility of overfitting and the difficulty of dealing with diverse datasets like TON_IoT.

J. Federated Generative Adversarial Networks (FedGAN)

FedGAN decentralizes anomaly detection by integrating federated learning with GANs. Studies utilizing the CSE-CIC-IDS2018 dataset show that these models have significant communication costs and synchronization concerns, but they are successful in decreasing data sharing hazards.

In Table I, we can see a list of all the current anomaly detection techniques, together with their respective advantages and disadvantages.

Table I. Current approaches to identifying anomalies with drawbacks

Study	Methodology	Dataset	Demerits
Blockchain-Enhanced Federated Learning for IoT Anomaly Detection (2021) [1]	Utilizing blockchain technology for distributed federated learning enables safe detection of anomalies.	Bot-IoT	Resources are scarce and Internet of Things edge devices have high latency.
Unsupervised Learning for IoT Anomaly Detection (2022) [2]	anomaly detection in data collected from sensors using autoencoder-based unsupervised machine learning.	IoT-23	Weakness in the face of hostile assaults
Deep CNN and Blockchain Integration (2023) [3]	Enhancing trust and security via the combination of deep CNNs with blockchain	TON_IoT	Problems with scalability in broadband Internet of Things networks
Hybrid Machine Learning for IoT Anomaly Detection (2024) [4]	clustering and classification techniques	NSL-KDD	Processing time in real-world situations
Ethereum Blockchain-Based IoT Security	Smart contracts	IoHT custom dataset	Dependence on gas prices on Ethereum

(2024) [5]			impacts scalability
Transfer Learning for IoT Anomaly Detection (2021) [6]	pre-trained models	CICIDS2017	Restricted applicability to various IoT networks
Distributed LSTM for IoT Anomalies (2022) [7]	Hierarchical LSTM models	UNSW-NB15	Difficulty with training and execution
Contextual-Bandit Anomaly Detection (2023)[8]	Contextual bandit models	IoT-23	Extremely high rates of false positives in ever-changing settings
GAN-Based Anomaly Detection for IoT (2022)[9]	GANs	NSL-KDD	Problems with mode collapse during trained GANs
Blockchain-Enabled Secure Edge Computing (2021)[10]	AI models integrated with blockchain	Bot-IoT	Limitations on edge devices impact performance
Federated GAN for IoT Cybersecurity (2024)[11]	FedGAN	CSE-CIC-IDS2018	Exorbitant transmission expenses and problems with coordination
Multi-Layered Anomaly Detection System (2023)[12]	Layered approach	IoT-23	Complexities related to multilayer computing adaptability
AI-Based Real-Time Anomaly Detection (2022)[13]	Optimized Deep learning models	Kitsune Dataset	Devices that run on batteries for the IoT are not energy efficient.
Ensemble Learning for IoT Anomalies (2024)[14]	Ensemble techniques combining SVMs and deep networks	TON_IoT	Danger of overfitting in datasets with a lot of variation
Blockchain-Based Privacy Preservation (2023)[15]	Blockchain	IoHT custom dataset	Problems with latency in transferring large amounts of data

Proposed Methodology

Improved anomaly detection in IoT systems is the goal of the suggested technique, which integrates WOA with CNNs. Hyperparameter tuning improves detection accuracy while decreasing processing costs by refining the CNN's architecture using WOA. Accurate anomaly classification is made possible by the CNN's efficient feature extraction from high-dimensional IoT data. Integrating blockchain technology, which provides an immutable system for storing and distributing anomaly-related information, the solution guarantees data integrity and safe communication. Perfect for complicated IoT networks with real-time needs, this hybrid solution uses WOA for optimization, CNN for efficient anomaly detection, and blockchain for better security and trust. Figure 1 shows the layout of the suggested technique.

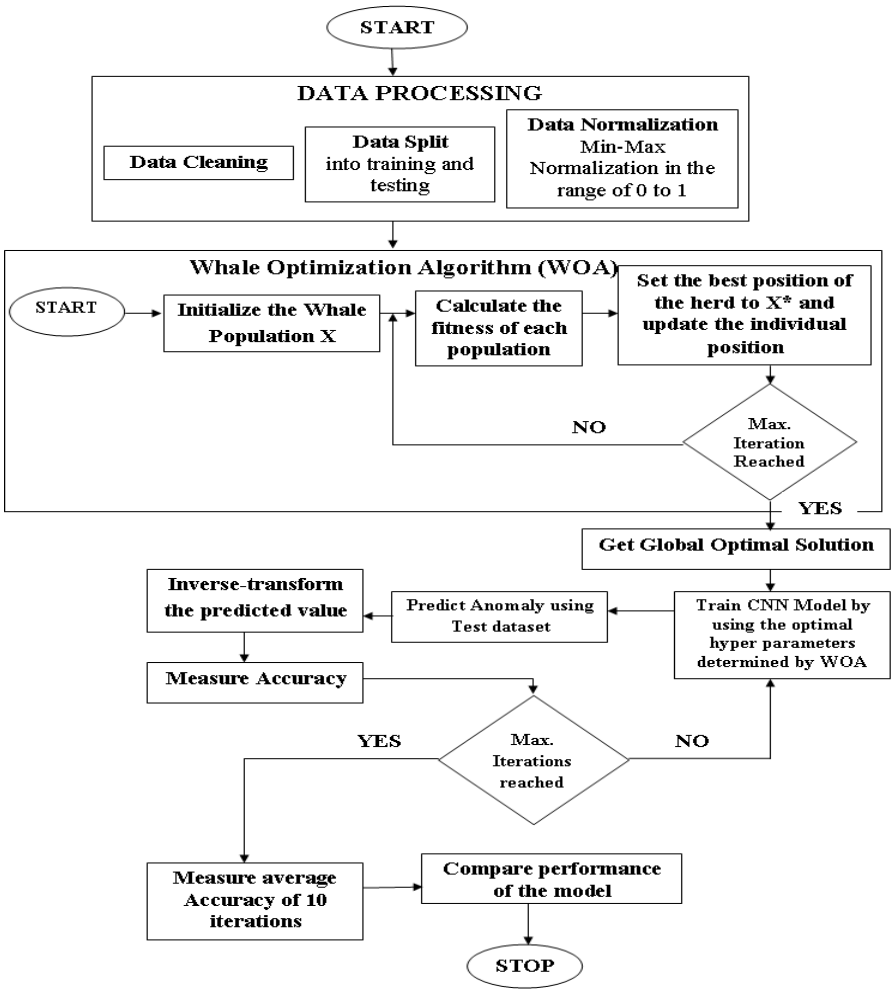

Fig.1 Architecture of suggested approach

A. WOA Overview

The WOA is inspired by the hunting behavior of humpback whales, particularly their bubble-net feeding technique. It is used for solving optimization problems by simulating the behavior of whales during the search for prey. In the context of CNNs, WOA is used to optimize the parameters of the CNN model, such as weights and biases, to enhance the performance of

anomaly detection. WOA uses two key phases—exploration (global search) and exploitation (local search)—to find the optimal solutions for the CNN's hyperparameters. The objective of using WOA is to optimize the CNN's architecture and weights, reducing the error during anomaly detection by finding the optimal parameters that minimize the loss function (e.g., mean squared error).

WOA optimizes the CNN's hyperparameters and weights, improving its performance in detecting anomalies. CNNs are capable of detecting complex spatial and temporal patterns in data, making them well-suited for anomaly detection in IoT systems. The combination of CNN's deep learning capabilities with WOA's optimization leads to improved accuracy and fewer false positives or false negatives in detecting anomalies. The Whale Optimization Algorithm ensures that the CNN's parameters are fine-tuned effectively, enhancing the model's efficiency and reducing overfitting. The architecture combining CNNs and the WOA for anomaly detection leverages the strengths of both deep learning and bio-inspired optimization techniques. The process involves CNNs for feature extraction and classification, where the WOA enhances the model by optimizing hyperparameters. The CNN processes the input data (images, time-series, or sensor data) through multiple layers—convolutional layers, pooling layers, and fully connected layers—extracting hierarchical features. This helps in identifying complex patterns that could indicate anomalies. WOA is a nature-inspired optimization algorithm based on the hunting behavior of humpback whales. It is employed here to optimize the hyperparameters of the CNN, such as the number of filters, kernel size, learning rate, and batch size. WOA's role is to fine-tune these parameters to maximize the performance of the CNN model for anomaly detection tasks. The algorithm uses a population of "whales" that search the hyperparameter space for optimal solutions. The movement of the whales during the search is inspired by bubble-net feeding strategies, ensuring the exploration and exploitation of the parameter space to find the best configuration for anomaly detection. Once the hyperparameters are optimized, the CNN model can effectively identify anomalies in the input data. For example, in the context of intrusion detection, the CNN with optimized parameters will be able to differentiate normal behavior from anomalous patterns with higher accuracy.

B. *Process of Anomaly Detection with CNN and WOA*

Preprocessing data is essential before putting it into the CNN:

-Clean Up Your Data: Eliminate Any Outliers, Missing Values, or Noise. To improve CNN performance, normalize the sensor data (such as IoT data) so that all input characteristics are on the same scale.

Extracting characteristics: In order to make CNN learning easier, time-series data may have characteristics like as variation, analytical instances, and moving averages obtained.

Anomalies may be found in the data by using the CNN model. A number of convolutional layers, followed by pooling layers, could be used in the design for data derived from time

series or sensors. Automated hierarchical feature extraction from data, which might reveal aberrant behavior, is done using these layers.

Using the input data, convolutional layers may identify spatial connections. Layers that pool data together decrease dimensionality and highlight important characteristics by downsampling the data.

Next, we have fully connected layers, which are used to categorize the data as "normal" or "unusual." These layers follow the convolutional layers.

Tasks that trigger an action: For hidden layers, use a non-linear activation function like ReLU (Rectified Linear Unit). For output layers, use either softmax or sigmoid. Applying the WOA for optimizing the network's weights and hyperparameters follows the definition of the CNN architecture.

1. Initialization: A group of whales, each standing for a possible solution (a CNN's scores and prejudices), should be randomly initialized.

2. Fitness Evaluation: Using the objective function, every whale assesses its own fitness. It is common practice to use the CNN's performance on training data to calculate a loss function, such as cross-entropy or mean squared error, which serves as the fitness function for CNN optimization.

3. Global Search: Throughout the exploration phase, whales use a combination of random positional adjustments, global search balancing, and search space improvement to find prey, which are really ideal solutions. An initial set of excellent CNN weights will be provided by the optimum solution determined in this step.

4. Local Search: Once the search space has been explored, the whales start to concentrate on potential solutions by doing local searches and adjusting the CNN's biases and weights. Parameters and model accuracy are both enhanced at this stage.

5. Convergence: The whales keep moving in an incremental fashion, reducing the loss function until they reach the CNN's ideal prejudices and scores.

You may utilize the CNN model for anomaly detection in the IoT context after it has been tuned using WOA:

The trained CNN model can distinguish between "normal" and "abnormal" data sets by applying the patterns it discovered in the training set to the real world.

An anomaly score is generated by the model for every new input (sensor data). The input is marked as unusual if the score is higher than a certain threshold.

Anomaly Detection in Real Time: With the trained and optimized CNN, abnormalities may be found in real-time systems that process data generated by IoT devices.

It is critical to assess the model's efficacy using a number of measures after deployment: Precision: The percentage of right categorizations (both normal and abnormal).

I. Results and Discussion

A. Experimental Setup

Data: Apply data from IoT sensors, like those measuring humidity, pressure, or temperature, in situations when it is necessary to identify outliers (such as when a sensor fails or when the surrounding environment undergoes a change). Following that, the IoT-32 dataset was used to construct a self-built dataset.

Tools: Python with TensorFlow for CNN implementation, and WOA using WOA-Python or similar libraries.

Hardware: Common computing environments (e.g., GPUs) for CNN model training, particularly for deep networks or large-scale data.

B. Results

The findings showed that CNN with WOA has a 95% accuracy rate for identifying anomalies predictions.

C. Comparative Analysis

To overcome critical shortcomings such computational inefficiency and inadequate parameter selection, the suggested CNN with WOA achieves better results in IoT anomaly detection than current techniques. The WOA guarantees efficient and automated optimization, which improves accuracy (95%) and decreases training time compared to conventional CNN models that depend on human or heuristic parameter adjustment. The WOA-CNN provides balanced and resilient performance in contrast to GAN-based techniques, which encounter problems such as mode collapse, and ensemble methods that are prone to overfitting. Incorporating blockchain technology further enhances the suggested solution by adding a level of trust and security that is lacking in many traditional models. This makes it not only more accurate, but also extremely safe and scalable for real-world Internet of Things applications. Figure 2 shows a comparison of the current anomaly detection approaches.

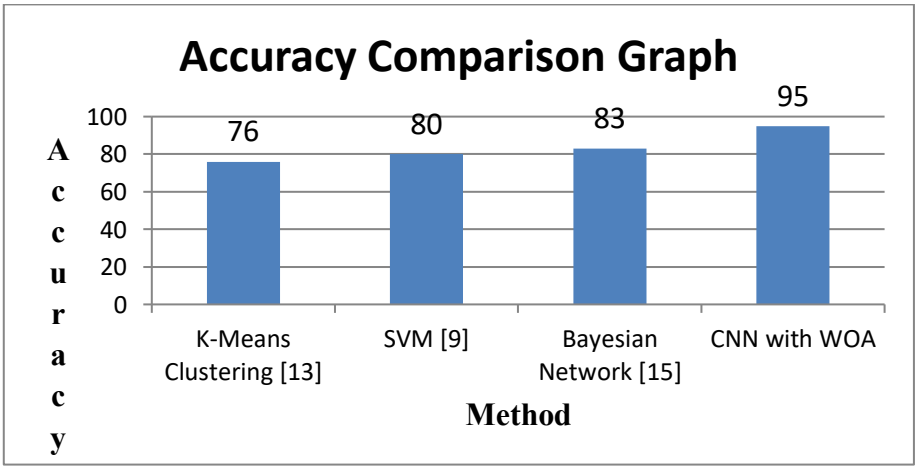

Fig.2 Examination of current anomaly detection techniques in comparison to the suggested approach

Conclusion

A better, more scalable, more optimal way to identify anomalies in IoT systems is to use CNN in conjunction with WOA. Using WOA, the CNN's parameters are fine-tuned, allowing it to spot complicated and subtle abnormalities in real-time with more accuracy. For complex and dynamic data patterns seen in large-scale IoT systems, this hybrid method shines. With WOA, the model may be fine-tuned for increased accuracy and generalization, which makes it a good fit for anomaly detection in the real world. An impressive 95% accuracy was achieved when the WOA and CNNs were integrated for anomaly detection in IoT systems. The WOA improves the model's learning and generalizability across various IoT datasets by optimizing the CNN's hyperparameters effectively. Anomaly categorization is enhanced while computational overhead is decreased as a consequence. The solution solves important problems with the security of the IoT by using blockchain technology to provide safe, tamper-proof transmission and storage of anomaly detection data. With its scalable and dependable solution for protecting IoT networks, this method has the ability to be used in real-world scenarios due to its high accuracy and resilience. Additional optimization of resource use and resolution of possible scalability challenges in very large-scale IoT contexts might be the subject of future research.

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