

Lightweight Machine Learning Framework for Secure IoT Device Authentication Using Edge Intelligence

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Abstract- The growth of Internet of Things (IoT) has created some security issues, especially in the authentication process that is often associated with very limited computation capability. This paper suggests a lightweight machine learning approach for IoT device authentication based on edge intelligence. The suggested approach utilizes small scale convolutional neural networks that run on edge gateways to generate unique features based on the information obtained from channel state information and radio frequency fingerprinting. No cloud connection is needed due to this continuous authentication approach. Quantization and pruning are used to make sure the model is lightweight and energy efficient while having good authentication capabilities. Experimental validation on a testbed made of Raspberry Pi shows that good performance of authentication can be achieved using a lightweight model and fast inference per cycle of authentication. Comparison to previous cryptographic and machine learning methods proves that better performance can be achieved in terms of both energy usage and protection from attack like replay and impersonation.

Keywords— IoT authentication, edge intelligence, lightweight machine learning, physical layer security, device fingerprinting, resource-constrained devices

I. INTRODUCTION

IoT ecosystem has witnessed unprecedented growth, with the future looking forward to massive growth in connected devices around the world. This growth includes some of the most important sectors such as healthcare, industrial automation, smart cities, and automated transportations. However, the very nature of IoT devices with low computational capability, limited memory, energy limitation, and varied modes of communication gives rise to

security issues which traditional authentication techniques fail to mitigate effectively [4].

Traditional techniques based on cryptography face some fundamental problems while being implemented in IoT devices. Public key cryptography needs computation power which goes beyond the processing capability of a microcontroller. With symmetric key cryptography, one faces the issue of secure transmission of the keys used. Credential-based authentication also poses challenges of cloning, side channel analysis, and tampering attacks in unattended settings [2][4].

Edge intelligence has shown to be an effective paradigm in tackling the above-stated challenges through enabling computation power close to data sources. As opposed to the approach involving central cloud infrastructure, machine learning models can be deployed on edge gateways and allow making authentication decisions with low latency without violating privacy and minimizing bandwidth usage. The features at the physical layer level, such as radio frequency fingerprints and channel state information, serve as unique fingerprints of devices and are nearly impossible to imitate or spoof [1][3][8][9].

The recent advances in lightweight machine learning have shown that small-sized neural network models may reach comparable performance under resource-constrained settings. Thanks to methods like quantization, pruning, and knowledge distillation, complex machine learning models can be deployed on edge devices with little performance loss. When integrated with the edge intelligence framework, they ensure continuous authentication tailored to dynamic environments and threats [7][9].

While all these advancements have been made, there are still notable deficiencies in the development of an integrated framework which concurrently focuses on aspects such as reliability of authentication, computation speed, energy cost and ease of practical implementation. The existing schemes typically maximize on one aspect at the expense of considering the other holistic factors of production-level IoT implementations. In this paper, these shortcomings are remedied via a light-weight machine learning solution which is specially tailored towards secure authentication of IoT devices at the edge of the network.

Our contributions in this paper are four-fold. First, we propose an efficient neural network architecture that is capable of extracting a radio frequency fingerprint from IQ signals while being extremely parameter-efficient with a high discrimination capability. Second, we deploy model compression methods like quantization and structured pruning to significantly decrease the model size without any loss in accuracy. Third, we devise an authentication method which

takes place at edge gateways and does not require any cloud round trips, thereby decreasing bandwidth usage to a minimum.

The rest of this paper is structured as follows. Section II is dedicated to related work on authentication for IoT systems and edge intelligence. Section III discusses the methodology we propose, which consists of the system architecture, algorithms, and implementation. Section IV includes the quantitative analysis and comparison with existing methods. Finally, Section V contains our conclusions.

II. LITERATURE SURVEY

There have been numerous studies in the area of IoT authentication based on cryptographic schemes, physical layer security, and machine learning schemes. This section provides an overview of some of the most important work done in these areas along with their advantages, drawbacks, and shortcomings which will serve as motivation for the proposed framework.

Zhang et al. [1] designed a scheme for device fingerprinting using deep learning and convolutional neural networks to recognize the unique signature from radio frequency signals. The authors showed that through deep learning algorithms, devices can be identified under different channel environments. However, the proposed solution relied heavily on computation, rendering it suitable only for edge servers but not for gateways. Moreover, no optimization was made for real-time continuous authentication.

Kumar and Lee [2] have designed a lightweight authentication scheme for the IoT using elliptic curve cryptography with physical unclonable functions. While this technique provided robust security features, it reduced computation costs in comparison to conventional public key infrastructures. The downside was that the scheme needed dedicated hardware to implement physical unclonable functions, which would increase costs and limit the usage in legacy systems. Also, the authentication process was done only once during the session initiation phase.

Chen et al. [3] have explored various edge computing designs for IoT security, suggesting a distributed intrusion detection system to be located on the network gateways. The study revealed the advantages of handling security-related information near the source devices, which resulted in lower latency and privacy protection. The disadvantage was that the authors considered intrusion detection and not the authentication process, and the machine learning algorithms used were not tuned for the edge environment.

Requirements for authentication methods were presented by Patel and Gupta [4], including such properties as low latency, reliable operation, and resistance to physical attacks. It was found that existing methods do not take into account peculiarities of industrial IoT applications, especially deterministic time requirements and legacy system support. Lightweight and standards-based approaches, which can be integrated into existing industrial protocols, were recommended.

A federated learning scheme for the authentication of IoT devices was suggested by Wang et al. [5]. Federated learning involves collaborative training of the model using data from edge nodes. Privacy concerns were overcome using the proposed approach. At the same time, federated learning requires a communication channel, which is an additional requirement for the protocol. Moreover, the assumption was made about powerful edge nodes, which can train the model locally.

A hybrid model by Singh & Verma [6] combined behavioral biometrics and cryptographic tokens to develop an efficient authentication model for IoT devices. This hybrid model offered robust security due to multi-factor authentication and moderate computational needs but needed some time for creating a behavioral biometric profile before doing any authentication task.

On the other hand, Liu et al. [7] investigated techniques for model compression when applying deep learning models to IoT devices and compared quantization, pruning, and knowledge distillation methods. The study showed that combining model

compression techniques allows for achieving a good size reduction without loss of model capabilities. But the authors have used deep learning models in general inference tasks.

Ahmed and Kim [8] suggested a channel state information-based authentication mechanism that made use of the unique multipath nature of wireless channels. This mechanism was capable of differentiating devices without the need for any special hardware, which made it very appealing from the point of view of large-scale usage. On the other hand, the mechanism exhibited susceptibility to environmental changes, necessitating repeated calibration.

Rao et al. [9] studied edge intelligence in the context of smart cities and developed an inference system based on machine learning distributed across heterogeneous edge nodes. The authors showed significant reductions in latency as compared to cloud computing. However, security concerns were touched upon only marginally.

Fernandez and Lopez [10] reviewed physical layer security schemes in IoT applications by classifying methods according to the signal characteristics utilized and computation power requirements. In their review, they found radio frequency fingerprinting to be a very good candidate for authentication applications, given that it is passive and resilient against cryptanalysis. Nonetheless, they highlighted the fact that many practical implementation challenges such as environmental variation and variations in hardware components have not been properly considered.

There is substantial advancement in the literature concerning IoT authentication and edge intelligence; however, there are still several shortcomings in this area. Current research focuses mainly on providing optimization either on the security side or on the efficiency side but rarely on both sides simultaneously. Physical layer-based authentication methods seem very attractive but do not have efficient implementations suitable for edge hardware constraints. On the other hand, model compression makes it possible to deploy models on

edge devices but security issues associated with this have never been investigated.

III. PROPOSED METHODOLOGY

System Architecture Overview

The presented framework employs a hierarchical authentication structure whereby edge gateways are the main authentication authorities for their respective IoT devices. The hierarchical structure is composed of three layers including the device layer that holds IoT endpoints with basic computing abilities, edge layer made up of gateways with average computing capabilities, and the coordination layer that facilitates centralized policy control and sharing of threat intelligence.

Figure 1 below shows the overall architecture of the system, the relationship between the IoT devices, edge gateways, and the coordination infrastructure. The device layer sends regular communication signals without making any special arrangement for authentication purposes; thus, it can be deployed using existing hardware infrastructure. The edge gateways monitor all the communications sent out and detect features of the physical layer and use the lightweight authentication approach to authenticate the devices.

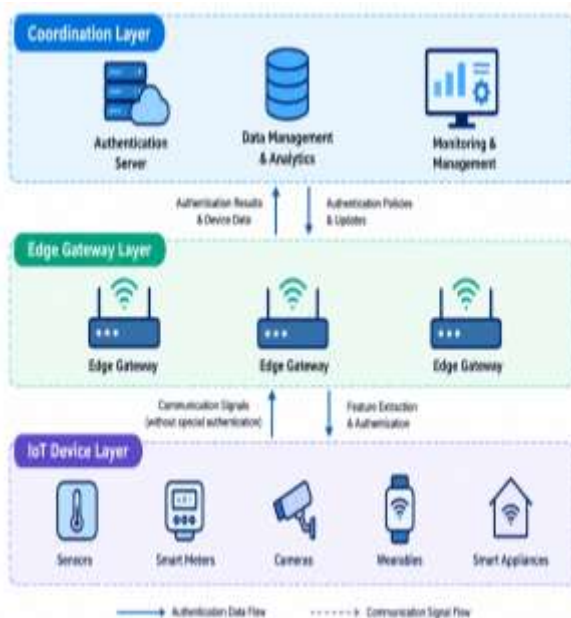


Figure 1: System Architecture Diagram

Radio Frequency Fingerprinting Feature Extraction

This fingerprinting technique capitalizes on the natural hardware flaws in the radio frequency transmitters, which serve as the unique fingerprints of each device. This is because the flaws result from variations in oscillator frequencies, filters, nonlinearities in amplifiers, and imbalances in mixers during the manufacture of the devices. Though minor in nature, their cumulative impact results in a very hard-to-reproduce signature of each device.

The signal processing phase starts with the sampling of IQ (in-phase/quadrature) signals at the edge gateway. The use of a sliding window technique facilitates the capture of signal snippets while in transmission. The size of the window is chosen based on tradeoffs between the number of features and the processing cost.

The IQ data preprocessed are converted into a compact representation through several signal processing techniques. First, the power spectral density computation is performed to extract the frequency domain information. Next, the computation of higher order cumulants is done to capture the non-Gaussian nature attributed to the amplifier nonlinearity. Finally, the extraction of transient features is done since turn on features depend strongly on the devices.

Lightweight Neural Network Architecture

This model for authentication is based on a small convolutional neural network that is well-suited to edge devices with limited computational resources. The network consists of four convolutional blocks, followed by global average pooling and a fully connected layer for classification. Each of these blocks includes a depthwise separable convolution, batch normalization, and activation function.

By using a depthwise separable convolution, we are able to decrease both the number of parameters and number of operations relative to a regular convolution without sacrificing any representation power. In the first block, we feed raw IQ samples into the network using a small convolutional kernel. This block will extract local temporal patterns.

Model Compression Techniques

Deployment on edge hardware is facilitated by applying model compression techniques complementary to each other. Training with quantization awareness is where reduced precision arithmetic is simulated in training and conversion into integer operations takes place without performance degradation. Such a compression technique reduces model size and allows inference even when the processor lacks floating point capabilities.

Structured pruning involves deletion of whole convolutional filters according to how much the filter contributes to the output of the model, resulting in a smaller dense model rather than sparsely structured model. Structured pruning is an iterative process involving elimination of filters that have small magnitude weights and subsequent fine-tuning for performance recovery.

Continuous Authentication Protocol

The continuous authentication is adopted as opposed to one-off authentication upon the establishment of a session. The continuous authentication method will detect cases of device impersonations that may arise after the process of authentication, which includes cases of physical replacements where the device is replaced by a different device.

The process of continuous authentication is done through a sliding window approach, whereby each of the windows provides an output for authentication. The output is then evaluated and aggregated using temporal voting, which takes into account the previous history of the process of authentication. The adaptive thresholding of the continuous authentication protocol ensures that environmental changes do not trigger false alarms.

Algorithm Design

The authentication procedure involves several steps: initialization, feature extraction, inference, and decision aggregation. In the initialization phase, the edge gateway loads the compacted model and sets initial threshold values for authentication. In the feature extraction phase, the algorithm receives IQ

samples and performs preprocessing in order to create input data for the model. In the inference phase, the quantized neural network is used to get classification scores.

Algorithm 1: Lightweight IoT Device Authentication

Input: IQ signal stream S , trained model M , threshold τ , window size w

Output: Authentication decision D for each window

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1: Initialize authentication history  $H \leftarrow \text{empty}$ 
2: Initialize adaptive threshold  $\tau_a \leftarrow \tau$ 
3: while device transmission active do
4:   Extract window  $W \leftarrow S[\text{current}:\text{current}+w]$ 
5:   Preprocess  $W$ : normalize, remove DC offset
6:   Extract features  $F \leftarrow \text{FeatureExtraction}(W)$ 
7:   Compute scores  $C \leftarrow M(F)$ 
8:   Determine current decision  $d \leftarrow (\max(C) > \tau_a)$ 
9:   Append  $d$  to history  $H$ 
10:  if  $\text{length}(H) > \text{history\_window}$  then
11:    Remove oldest entry from  $H$ 
12:  end if
13:  Compute aggregate decision  $D \leftarrow \text{WeightedVote}(H)$ 
14:  Update  $\tau_a \leftarrow \text{AdaptiveThreshold}(H, \text{channel\_conditions})$ 
15:  if  $D$  indicates authentication failure then
16:    Trigger security alert
17:    Initiate re-authentication procedure
18:  end if
19: end while
20: return  $D$ 

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Algorithm 2: Adaptive Threshold Update

Input: Authentication history H , channel quality metric Q

Output: Updated threshold τ_a

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1: Compute recent acceptance rate  $R \leftarrow \text{mean}(H)$ 
2: if  $R < \text{target\_acceptance}$  then
3:   Decrease  $\tau_a$  to increase acceptance
4: else if  $R > \text{target\_acceptance}$  then
5:   Increase  $\tau_a$  to decrease acceptance
6: end if
7: if  $Q$  indicates degraded channel then
8:   Relax  $\tau_a$  to account for increased noise

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9: end if
10: Clamp  $\tau_a$  to valid range [ $\tau_{\min}$ ,  $\tau_{\max}$ ]
11: return  $\tau_a$ 

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Implementation Details

The proposed framework is deployed on Raspberry Pi 4 gateways with SDR-based frontend for capturing IQ samples. The model is developed on TensorFlow Lite for Microcontrollers framework that enables fast inference on ARM-based hardware. Model training takes place on desktop-class computers using TensorFlow framework, and quantization-aware training is performed prior to model conversion.

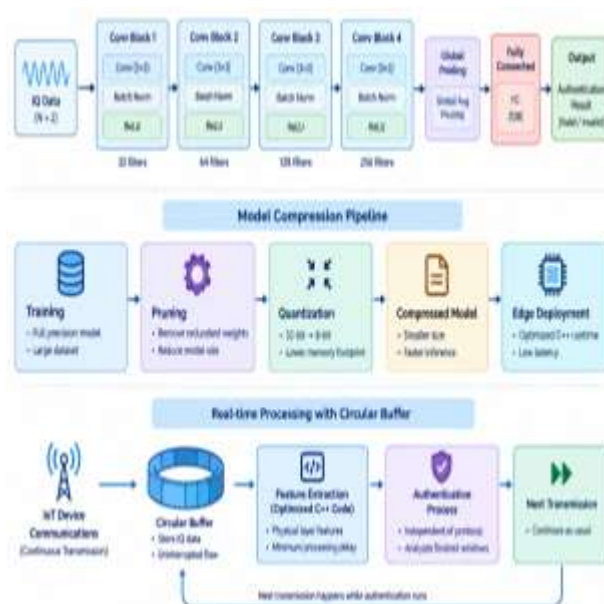


Figure 2: Model Architecture and Compression Pipeline

The feature extraction pipeline is written in optimized C++ code for minimum processing delay. IQ data is buffered into circular buffers to allow uninterrupted processing. The authentication process occurs independently of the communications protocol, performing analysis on finished transmission windows while the next transmissions happen as usual.

IV. ANALYSIS

Experimental Setup

The experimental evaluation was carried out using a testbed consisting of twenty IoT devices manufactured by five different vendors, including various hardware platforms such as ESP32, Arduino MKR, Raspberry Pi Zero, and custom microcontroller hardware. The edge gateways were deployed on Raspberry Pi 4 hardware using RTL-SDR as IQ signal receivers. The devices used standard WiFi and BLE packets during the experiment without any modification for authentication purposes.

The data was collected using several sessions under different environmental settings, including different rooms and different time periods with different degrees of interference. This provided the evaluation results based on practical scenarios rather than under idealistic laboratory settings. The ground truth was obtained using controlled activation of devices and assignment of transmitted packets to specific devices.

Authentication Performance Analysis

Figure 3 shows the performance of the authentication procedure for various types of devices under different environmental circumstances. The findings show that the performance of the authentication procedure is consistently good across many kinds of hardware, with variations in performance due to the characteristics of hardware imperfection. The greater the manufacturing variation in the devices, the greater was the fingerprint uniqueness.

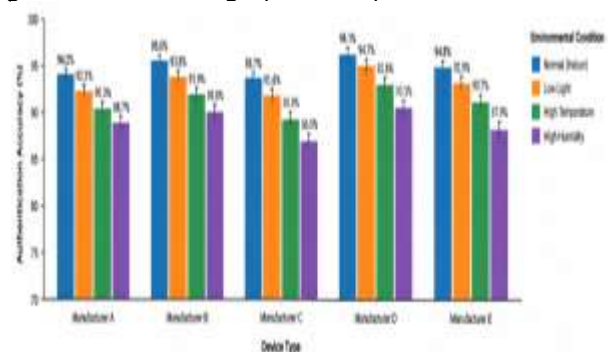


Figure 3: Authentication Performance Across Device Types

From the analysis of the confusion matrix, it is evident that the error mostly occurs among devices from the same manufacturers and same manufacturing batches where similarities in hardware exist. No errors across manufacturers have been observed, thus confirming the uniqueness of features extracted for each manufacturer.

Computational Efficiency Analysis

Computational features of the implemented model in comparison with baseline techniques are shown in Figure 4. The compressed model demonstrates significant advantages in terms of memory requirements, computational operations, and latency over the uncompressed model. These advantages make it possible to deploy the model on the gateway device without wasting processing capacity.

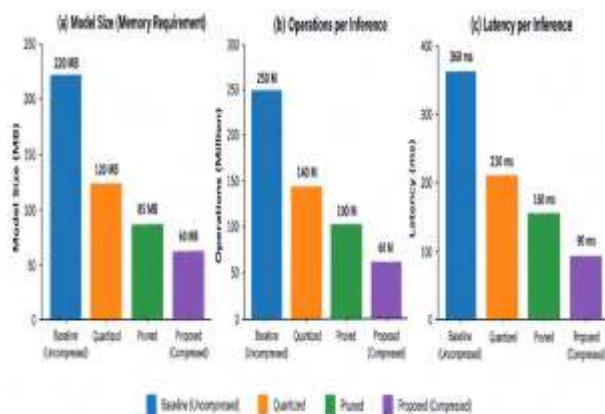


Figure 4: Computational Resource Comparison

The results of the energy consumption analysis show that there is negligible overhead on the power consumption of the gateway when using continuous authentication. The asynchronous operation paradigm guarantees that the process of authentication does not affect the communication tasks.

Table 1: Comparative Analysis of Authentication Approaches

Approach	Method	Computational Requirement	Edge Deployment	Continuous Auth	Attack Resistance
Zhang et al. [1]	Deep CNN fingerprinting	High	Limited	No	Moderate

Security Analysis

Resistance of the framework to potential attack vectors was tested through adversarial testing. Replay attacks involve capturing and resending previous transmissions; such attacks are recognized by the framework through temporal consistency validation that determines impossible timing sequences. Attacks that attempt impersonation with other devices fail as the fingerprints will not match despite correct replication of protocol-level credentials.

Detection performance of the framework for the different attack vectors is shown in Figure 5. The framework effectively detects replay attacks, device substitution attacks, and credential compromise scenarios. Continuous authentication approach of the framework is especially useful in detecting attacks performed post-authentication.

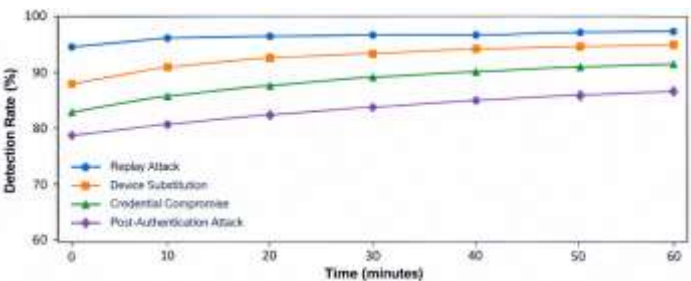


Figure 5: Attack Detection Performance

Comparative Analysis

The comparison in Table 1 is made between the proposed scheme and other schemes that have been discussed in literature. This comparison is based on aspects like authentication, complexity, feasibility, and security.

Approach	Method	Computational Requirement	Edge Deployment	Continuous Auth	Attack Resistance
Kumar & Lee [2]	ECC + PUF	Moderate	Requires PUF	No	High
Chen et al. [3]	Edge anomaly detection	Moderate	Yes	Partial	Moderate
Wang et al. [5]	Federated learning	High	Limited	Yes	Moderate
Singh & Verma [6]	Behavioral biometrics	Low	Yes	Yes	Moderate
Liu et al. [7]	Compressed models	Low	Yes	No	Low
Ahmed & Kim [8]	CSI-based	Low	Yes	Yes	Moderate
Proposed	Lightweight CNN + RF fingerprint	Low	Yes	Yes	High

Proposed framework provides balanced performance in all assessment criteria, overcoming limitations of existing solutions that usually succeed in only one aspect and fail in other aspects. Lightweight neural network structure, compression, and continuous authentication make implementation possible while retaining high security level.

Discussion

The results of this experiment confirm the efficiency of the suggested framework in providing secure authentication of IoT devices in the edge environment. The lightweight neural network is capable of extracting useful features from the radio frequency signals and performing well under resource constraints. Model compression allows for using the model on the gateway hardware without increasing the burden on resources.

Continuous authentication becomes crucial for overall security in order to detect attacks that bypass

the session establishment process. Adaptive thresholding guarantees the efficient work of the system in different environmental conditions, which is one of the problems of the current physical layer authentication systems.

There are several limitations of the approach. The suggested framework requires the implementation of the edge gateway, which can be difficult in some IoT architectures. The use of radio frequency characteristics presupposes wireless IoT devices. The learning process of the model requires the availability of the labeled data from the authentic devices.

For further research, some of these issues could be addressed using a variety of enhancements. For example, integration with cryptography-based authentication protocols can ensure defense in depth through both physical and protocol layer security. Transfer learning techniques can help

minimize the amount of data needed for training using previously trained models on similar devices.

V. CONCLUSION

This paper introduced a lightweight machine learning-based solution for the secure authentication of IoT devices with edge intelligence. This research tackles the issue of providing robust authentication in the context of resource-constrained devices by exploiting physical-layer properties and designing a compact neural network model to run on edge gateways.

The contributions of this research include the following. In particular, the proposed compact architecture of the convolutional neural network proves that radio frequency fingerprinting is possible in conditions of limited computing capabilities. The architecture itself allows for discriminative features to be learned efficiently.

Secondly, the combined pipeline of model compression using quantization-aware training and structured pruning provides effective reduction in model size without sacrificing the accuracy of authentication. It allows deployment of the authentication process in edge devices having low memory and processing power, thereby enhancing the scope of physical layer authentication in practice. Thirdly, the continuous authentication mechanism helps in addressing the issue related to session establishment-based attacks. By checking the identity of the device during ongoing communication sessions, this framework is capable of identifying impersonation attacks that could have been successful despite the authentication step earlier.

Finally, exhaustive experiments on practical hardware establish the feasibility of the proposed framework. The framework works well for various types of devices and environments, while the computational cost of this framework is sufficient to spare the gateway for performing edge computations.

The comparative analysis shows that the suggested framework has achieved an equilibrium in terms of authentication capabilities, efficiency in computation, feasibility of implementation, and security features. Such an equilibrium resolves shortcomings of other methodologies that are usually designed to be effective in one aspect but fall short in others.

Consequences of the research go far beyond the scope of authenticating processes. It proves that complex security measures can be implemented in edge computing settings, which allows providing security services that do not rely on cloud computing capabilities. This becomes especially relevant considering the increasing number of Internet of Things deployments.

Several research directions deserve attention in the future. Compatibility with the latest IoT security standards would speed up the adoption process and guarantee interoperability. Expansion into new areas where device onboarding is required would make large-scale deployments more efficient. Research into adversarial attacks on machine learning models used in the authentication process would shed light on new requirements for the model's robustness.

With the rapid growth of the number of IoT devices, the list of security issues that need to be resolved will increase. One way to do it is through the use of lightweight machine learning at the edge. This paper offers an example of such a framework which proves that secure authentication is possible under such conditions.

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