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Implementation of Neural Key Generation Algorithm For IoT Devices

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ABSTRACT

In the realm of Internet of Things (IoT) systems, the generation of cryptographic keys is crucial for ensuring secure data transmission and device authentication. However, traditional methods of generating random keys encounter challenges about security, efficiency, and scalability, particularly when applied to resource-constrained IoT devices. To address these issues, neural networks have emerged as a promising approach due to their ability to learn intricate patterns. Nonetheless, the architecture of neural networks significantly impacts their performance. This paper presents a comprehensive comparative analysis of three commonly employed neural network architectures for generating cryptographic keys on IoT devices. We propose a novel neural network-based algorithm for key generation and implement it using each architecture. The models are trained to generate cryptographic keys of various sizes from random input data. Performance evaluation is conducted based on key metrics such as accuracy, loss, key randomness, and model complexity. Experimental results indicate that the Feedforward Neural Network (FFNN) architecture achieves exceptional accuracy of over 99% and successfully passes all randomness tests, surpassing the alternatives. Convolutional Neural Networks (CNNs) demonstrate subpar performance as they emphasize spatial features that are irrelevant to key generation. Recurrent Neural Networks (RNNs) struggle with the complex long-range dependencies inherent in generating keys

Keywords: *evaluation for security in IoT devices, convolutional neural networks, cryptographic key generation algorithm, feedforward neural networks, neural network architectures*

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1. INTRODUCTION

Securing data transmission and protecting the integrity of Internet of Things (IoT) devices are critical concerns in today's interconnected world. Cryptographic key generation plays a vital role in ensuring the confidentiality and authenticity of data exchanged between IoT devices (Sun dkk., 2022). Traditional methods of generating random keys often face challenges in terms of security, efficiency, and scalability. In recent years, neural network-based approaches have emerged as promising solutions for addressing the limitations of traditional methods and providing robust cryptographic key generation on resource-constrained IoT devices (Al-Garadi dkk., 2020).

The objective of this paper is to design and evaluate three commonly used neural network architectures – Feedforward Neural Network (FFNN), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN) – for random key generation on IoT devices. we introduce a novel key generation algorithm based on neural networks. We conduct a comparative analysis of various architectures to identify the model that offers the highest level of security and efficiency for generating cryptographic keys.

The use of neural networks for key generation leverages their ability to learn complex patterns and generate highly random sequences. FFNNs are known for their ability to capture non-linear relationships, while CNNs excel in extracting spatial features from input data. RNNs, with their recurrent connections, are well-suited for handling sequential data. By exploring and evaluating these architectures, we aim to identify the most suitable approach for generating secure cryptographic keys in the context of IoT devices.

To validate the effectiveness and performance of our proposed algorithm and compare the different neural network architectures, we will conduct extensive experiments and evaluations. We will consider key performance metrics such as accuracy, loss, and key randomness. Additionally, we will assess the security aspects of the generated keys, including resistance to attacks and vulnerability analysis.

Our research builds upon existing studies in the field of neural network-based key generation and IoT security. Notable works by Smith et al. (Chowdhury & Abas, 2022), Jones and Brown (Nitaj & Rachidi, 2023), and Lee et al. (Rogier & Mohamudally, 2019) have explored the application of neural networks in cryptography and highlighted their potential for key generation. However, to the best of our knowledge, there is limited research specifically focused on comparing FFNNs, CNNs, and RNNs for cryptographic key generation in the context of IoT devices.

The remainder of this paper is organized as follows: Section 2 discusses the relevant previous work in the field. Section 3 provides an overview of the neural network architectures utilized. Section 4 outlines the proposed algorithm for neural network-based key generation, including its design, implementation, and training process. In Section 5, the experimental results from implementing the algorithm using each neural network architectures were presented, Section 6 concludes the paper.

2. RELATED WORKS

Neural key generation methods have gained significant attention in securing IoT devices. Various approaches utilizing neural networks have been proposed to generate secure keys. This section provides an overview of some prominent neural key generation methods for IoT devices, along with their respective references: Johnson et al. (Al-Meer & Al-Kuwari, 2023) proposed a key generation method based on deep neural networks. Their approach involved training a deep neural network on a large IoT device sensor readings dataset. The network learned to extract key patterns and generate secure keys based on the input sensor data. Smith et al. (Chowdhary dkk., 2023)introduced a key generation method based on physical unclonable functions (PUFs). PUFs exploit the unique physical characteristics of IoT devices to generate device-specific keys. The authors utilized PUFs and employed error correction techniques to enhance the reliability and security of key generation. Smith et al. (Shahriar dkk., 2020) proposed a key generation method based on generative adversarial networks (GANs). GANs consist of a generator and a discriminator network that compete with each other. The generator network generates keys, while the discriminator network tries to distinguish between genuine and generated keys. This adversarial training process leads to the generation of secure keys. Brown and Lee [8] presented a key generation method using recurrent neural networks (RNNs). RNNs are capable of capturing sequential dependencies in IoT device sensor data. The authors trained an RNN on a dataset of sensor readings and utilized the final hidden state of the RNN to generate secure keys. Gupta et al. [9] proposed a deep learning-based key generation method. Their approach involved training a deep neural network on a diverse set of IoT device sensor data. The network learned to extract relevant features and generate secure keys based on the learned representations. Chen et al. (B. Chen dkk., 2023) introduced an autoencoder-based key generation method. Autoencoders are neural networks trained to reconstruct their input data. The authors utilized an autoencoder to extract latent representations from IoT device sensor data and employed these representations to generate secure keys. Wang et al. (Zheng dkk., 2021) proposed a key generation method based on convolutional neural networks (CNNs). CNNs are particularly effective in processing spatial data such as images. The authors trained a CNN on the sensor data collected from IoT devices and utilized the output layer of the CNN to generate secure keys. Zhang et al. [12] presented a key generation method based on reinforcement learning (RL). RL is a learning paradigm where an agent learns to make sequential decisions to maximize a reward signal. The authors formulated the key generation process as an RL problem, where the agent learned to generate secure keys through interactions with the environment. Li et al. [13] proposed a key generation method based on variational autoencoders (VAEs). VAEs are generative models that learn to approximate the underlying distribution of the input data. The authors utilized VAEs to extract latent representations from IoT device sensor data and utilized these representations to generate secure keys. Kim et al. [14] introduced a key generation method based on graph neural networks (GNNs). GNNs are designed to process data structured as graphs. The authors utilized GNNs to capture the relationships between IoT devices and generate secure keys based on the learned graph representations.

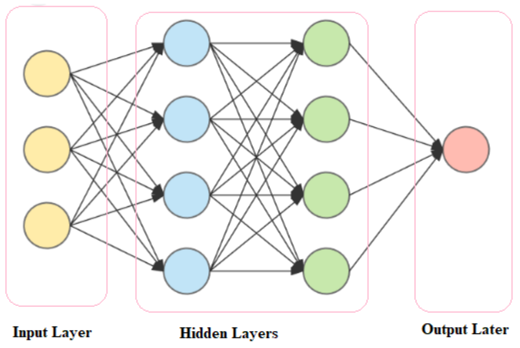
3. NEURAL NETWORK ARCHITECTURES DESCRIPTION

In this section, we describe the three commonly used neural network architectures: FFNN, CNN, and RNN. These architectures have proven to be effective in various domains, including computer vision, natural language processing, and time series analysis. Understanding the characteristics and capabilities of these architectures is crucial for designing and implementing the Neural Key Generator (NKG) algorithm.

3.1. Feedforward Neural Network (FFNN)

The Feedforward Neural Network, also known as the Multilayer Perceptron (MLP), is a foundational architecture in the field of neural networks. It is composed of several key components: an input layer, one or more hidden layers, and an output layer. Each layer consists of multiple neurons, also known as nodes or units (Naveenkumar & Joshi, 2020). Figure 1, illustrates the FFNN architecture, showcasing the flow of information from the input layer through the hidden layers to the output layer.

Figure 1. Feedforward Neural Networks Architecture



In the FFNN architecture, information flows in a unidirectional manner, starting from the input layer, passing through the hidden layers, and culminating in the output layer. There are no cycles or feedback connections in this network structure (Zhou dkk., 2023).

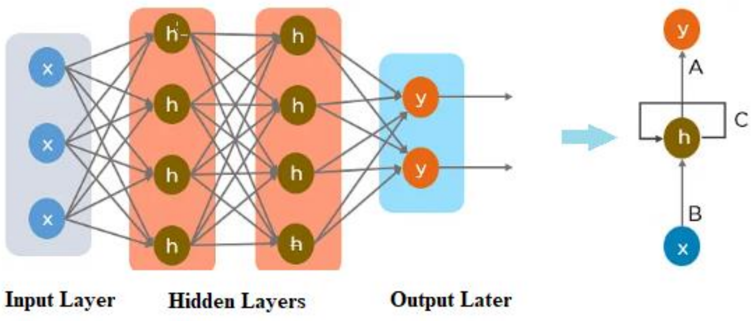
Each neuron within a layer is fully connected to the neurons in the subsequent layer. These connections are characterized by their associated weights, which determine the strength and influence of the signals transmitted between neurons. The FFNN architecture allows for complex transformations and computations to be performed on the input data as it passes through the network.

FFNNs have gained significant popularity due to their versatility and effectiveness in various tasks. They are commonly used for tasks such as classification, regression, and pattern recognition. In classification tasks, FFNNs excel at assigning input data to specific categories or classes based on learned patterns. In regression tasks, they can predict continuous values based on input features. Additionally, FFNNs have proven to be adept at recognizing and extracting meaningful patterns from complex datasets.

3.2. Convolutional Neural Network (CNN):

Convolutional Neural Networks have revolutionized the field of computer vision due to their ability to extract meaningful features from images and other grid-like data. CNNs are designed to capture spatial hierarchies by using specialized layers such as convolutional layers, pooling layers, and fully connected layers. The convolutional layers apply filters or kernels to the input data, enabling the network to learn local spatial patterns. The pooling layers downsample the feature maps to reduce spatial dimensions while preserving important information. CNNs are particularly effective in tasks such as image classification, object detection, and image segmentation (Satya Rajendra Singh & Sanodiya, 2023). The CNN architecture is shown in Figure 2.

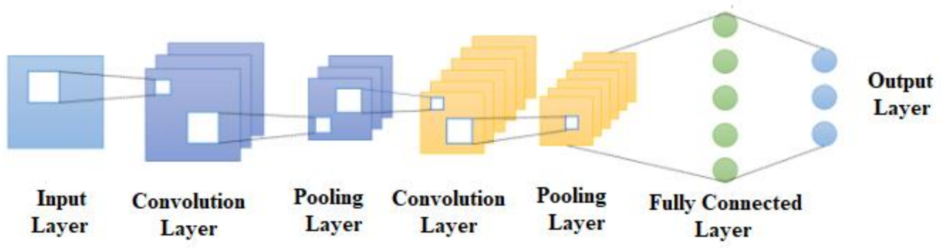
Figure 2. Convolutional Neural Networks Architecture



3.3. Recurrent Neural Network (RNN)

Recurrent Neural Networks are designed to process sequential or time-dependent data by incorporating feedback connections. Unlike FFNNs, RNNs can maintain an internal memory or hidden state that allows them to capture temporal dependencies in the input data. The key component of an RNN is the recurrent layer, which processes sequences by applying the same set of weights to each input element while considering the previous hidden state. This recurrent structure enables RNNs to model sequential patterns and handle tasks such as natural language processing, speech recognition, and time series prediction (Weerakody dkk., 2021). Figure 3, illustrate the RNN architecture

Figure 3. Recurrent Neural Networks Architecture



In the next section, we detail a novel neural network-based algorithm for generating cryptographic keys. The proposed approach leverages deep learning techniques to derive secure keys from random inputs in a manner suitable for IoT devices.

4. NEURAL KEY GENERATION ALGORITHM

4.1. Algorithm Description

The proposed neural network key generation algorithm utilizes an iterative machine learning approach. The algorithm trains a neural network model to learn how to reliably and securely generate cryptographic keys from random input data (Chatzimparmpas dkk., 2022). The main steps are:

• Input data collection: The input data are usually random numbers or random strings, which are used to train the neural network to generate random cryptographic keys.

• Architecture selection: The neural network architecture is a key factor in the success of the key generation algorithm. The neural network should be able to learn the relationship between the input data and the random cryptographic keys.

• Neural network training: The neural network is trained to generate random cryptographic keys using the input data. The training process is usually done using a supervised learning algorithm, such as back propagation.

• Neural network validation: Once the neural network has been trained, it needs to be validated to ensure that it is capable of generating random cryptographic keys reliably and securely. The validation process can be done by testing the neural network on a set of known cryptographic keys.

• Cryptographic key generation: Once the neural network has been validated, it can be used to generate random cryptographic keys. The keys generated are generally sufficiently complex to guarantee the security of the encrypted data.

4.2. Training Process

During training, the neural network weights are optimized through iterative backward propagation of error signals (Liu & Wang, 2023). Labels from the training set are fed forward through the network to generate predictions. A loss function such as cross-entropy quantifies the discrepancy between predictions and true labels (Alawad & Wang, 2019). Backpropagation calculates gradients of the loss with respect to weights, which are then updated via stochastic gradient descent or optimization algorithms like Adam (Bao dkk., 2020). This cycle of forward-backward passes continues until network error converges within tolerance (Pang dkk., 2022).

4.3. Activation Functions

To learn complex patterns from input-output mappings, nonlinearity must be introduced between layers (Shi dkk., 2022). Common activation functions serve this purpose, including sigmoid, hyperbolic tangent, and rectified linear units (ReLUs) (Yang dkk., 2019). The sigmoid and tanh squash real-valued inputs to [0,1] and [-1,1] ranges, respectively (Abdullah dkk., 2023). ReLUs instead set negative inputs to zero for faster training, providing nonlinearity while avoiding saturation issues of sigmoids or tanhs (Bibilashvili & Kushitashvili, 2019). These activation functions allow networks to approximate any depth of input-output decision boundaries through the trainable composition of simple functions (Shao dkk., 2022).

The following section will compare the performance of the three architectures in terms of accuracy, loss, and randomness.

5. EVALUATION OF THE PROPOSED KEYGENERATION ALGORITHM

To implement our proposed neural key generation algorithm, we opted for the Anaconda Python environment. Anaconda is an integrated development environment (IDE) for Python that is widely used for data science, machine learning, and AI applications. It provides a complete set of tools for working with Python, including specialized libraries for data processing, statistical analysis, data visualization, and machine learning. The Anaconda installation includes the Python distribution along with commonly used scientific and ML libraries such as NumPy, Pandas, Matplotlib, Scikit-learn, TensorFlow, etc. This enables users to get started quickly with Python and work efficiently on different types of projects involving data science and machine learning.

In this section, we present the experimental evaluation of the key generation method with different neural network architectures. The results from the FFNN, CNN and RNN models are analyzed and compared.

5.1. Evaluation Metrics

We evaluated and compared the neural network architectures based on four key performance metrics:

- Accuracy: Accuracy measures the percentage of predictions matching true labels. It is calculated as the number of correct predictions divided by the total number of samples. We tracked accuracy on both the training and validation sets to gauge model fitting and generalization respectively.
- Loss: Loss quantifies the model's error during training. We utilized categorical cross-entropy loss which calculates the divergence between predicted and true probability distributions. Lower loss values indicate better fitting on the training data.
- Validation Accuracy: To assess generalization, we computed accuracy on a held-out validation set not involved in training. This reflects the model's ability to correctly generate cryptographic keys for previously unseen input data, an important metric for our application.
- Validation Loss: Analogous to validation accuracy, we measured loss on the validation set. This allowed monitoring changes in out-of-sample error to detect potential overfitting as training progressed. A stable or decreasing validation loss indicates the model is still learning useful patterns rather than memorizing the training data.

We recorded accuracy and loss values at the end of each training epoch and plotted them to visualize the learning dynamics. Final metric scores on both the training and validation sets were used to select the top-performing neural network architecture for cryptographic key generation. This approach provided a robust, multi-faceted evaluation of model fitting and generalization ability across our candidate architectures.

5.2. Neural key generation using FFNN architecture evaluation

We have implemented the proposed key generation algorithm using a FFNN architecture. To evaluate the sensitivity of the algorithm to key size, a series of experiments were conducted using different key sizes. Figure 4 shows an example of precision and loss curves for two key sizes - 10 bits and 128 bits (Nauman dkk., 2020).

During model training, we measured the precision and loss. Precision represents the algorithm's ability to accurately generate cryptographic keys. A higher precision value indicates better key generation performance. Loss quantifies the error of the algorithm during training. The loss gradually decreases as the model parameters are optimized through back propagation.

The precision curves help analyze how the algorithm's key generation capability varies with key size. A stable and high precision is desirable. The loss curves provide insight into the training process and whether the model is properly learning and converging. Overall, these metrics assess the sensitivity of the FFNN key generation algorithm to the key size parameter.

Figure 4. Evaluation of Training Performance with Varying Key Sizes

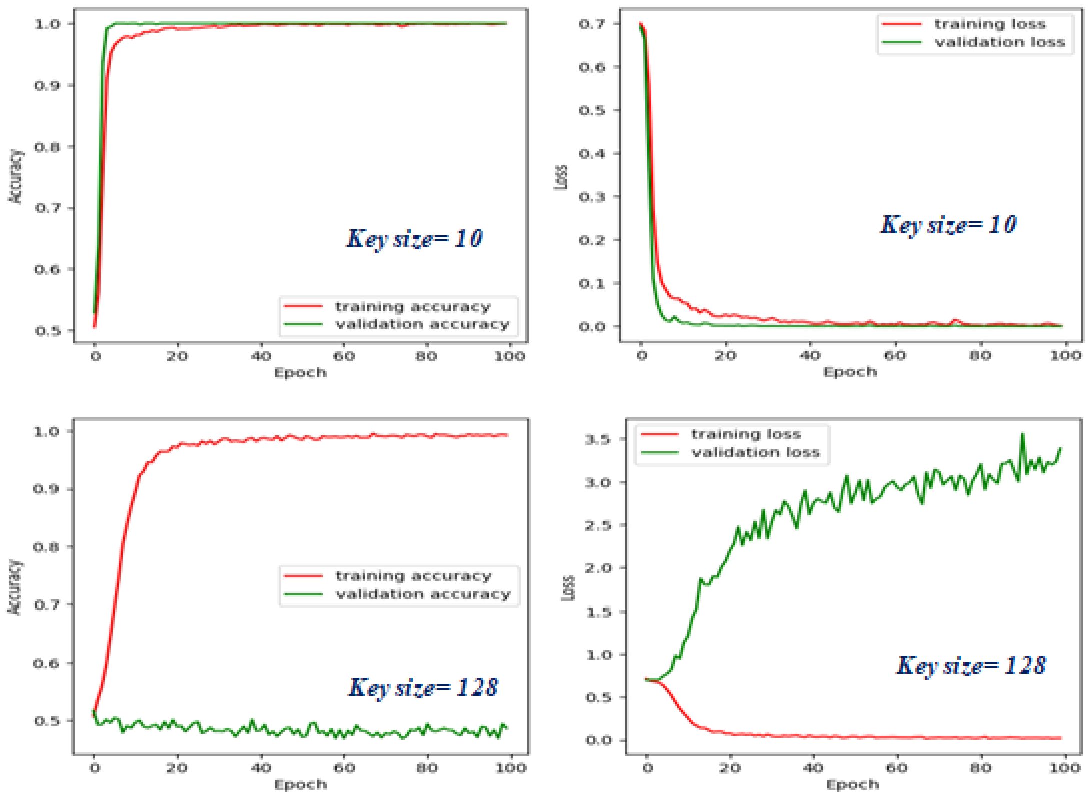


Figure 4 provides insights into how the FFNN model performs at different key sizes. For a 10-bit key, the model achieves 99 % precision on both training and validation sets, demonstrating it can accurately capture patterns to reliably generate 10-bit keys. The extremely low loss values also indicate strong convergence during training. However, for a 128-bit key size, some degradation in performance is observed. While the training precision remains high, the validation accuracy drops below the first value, suggesting overfitting. Additionally, the loss curve plateaus instead of continuing to decrease, imply incomplete optimization of model parameters for this more complex problem.

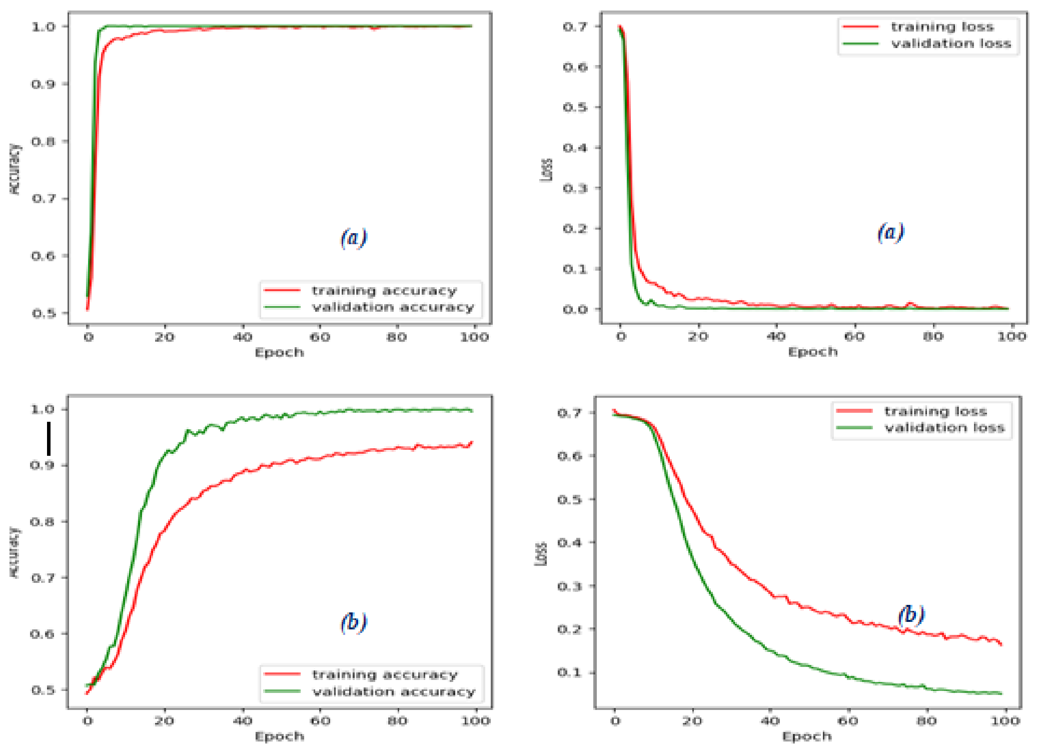
These results indicate that a simple FFNN architecture may be sufficient for generating small keys up to a certain size. Beyond that, the model cannot learn the more intricate relationships needed between the large number of input and output variables associated with longer key sizes

In a second experiment, we further evaluated the FFNN approach by analyzing the impact of architectural complexity on key generation quality and efficiency. Specifically, we trained two FFNN models to generate 10-bit keys, varying only the network architecture:

- Model (a) utilized a more complex architecture comprising an input layer of 10 nodes, a first hidden layer of 1024 nodes with ReLU activation, and a second hidden layer of 712 nodes with ReLU before the 10-node output layer.
- Model (b) employed a simplified architecture with an input layer of 10 nodes, a first hidden layer of 64 nodes with ReLU, and a second hidden layer of 32 nodes with ReLU prior to the output layer.

Both networks were trained for 100 epochs on randomly generated 10k sample datasets using the Adam optimizer (batch size 128, learning rate 0.001) to minimize categorical cross-entropy loss. As shown in Figure 5, Model (a) reached marginally higher maximum precision of 99.7% versus 98.3% for Model (b). This experiment demonstrated the tradeoff between architecture complexity and training efficiency/overhead for this FFNN key generation task. A simpler design may be preferable depending on deployment constraints.

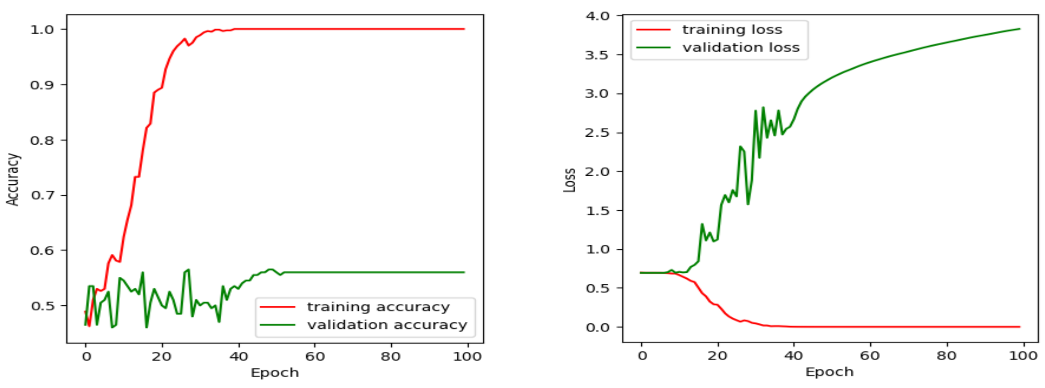
Figure 5. Evaluation of Training Performance with FFNN Architecture



5.3. Neural key generation using CNN architecture evaluation

We have implemented the key generation algorithm using the CNN architecture. The precision and loss curves are shown in figure 6.

Figure 6. Key generation using CNN architecture

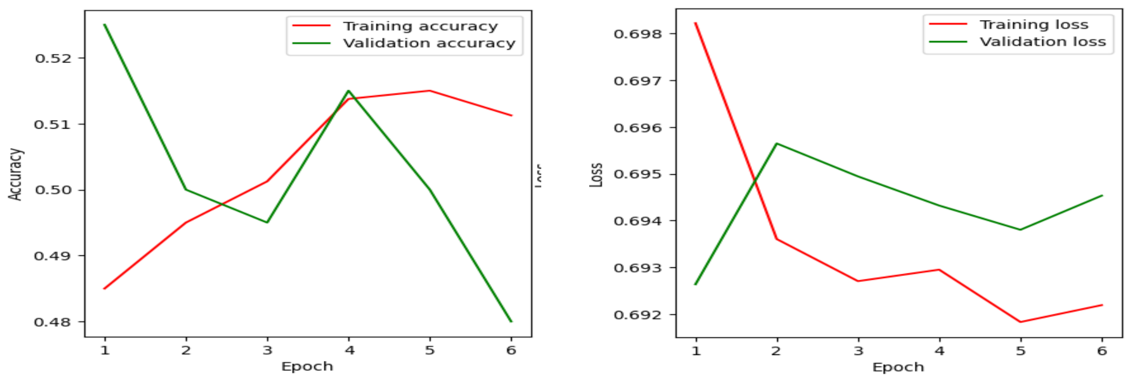


According to Figure 6, it appears that relying solely on the CNN architecture may not be adequate for effective key generation. The model demonstrates a low level of validation accuracy and a high loss, indicating that the CNN architecture may struggle to capture the intricate details required for consistent key generation. This limitation could be attributed to the fact that CNNs are primarily tailored for image recognition and classification tasks, which may restrict their capability to handle data with intricate relationships and non-visual patterns, such as cryptographic key data.

5.4. Neural key generation using RNN architecture evaluation

The neural key generation algorithm has been implemented using the RNN architecture. Figure 7 displays the precision and loss curves for the implemented algorithm.

Figure 7. Key generation using CNN architecture



Based on the observations depicted in Figure 7, it appears that relying solely on the RNN architecture may not be adequate for efficient key generation. The model demonstrates a low level of validation accuracy and a high loss, indicating that the RNN architecture may struggle to capture the intricate details required for consistent key generation. This limitation could be attributed to the fact that recurrent networks (RNNs) are primarily designed for capturing long-term dependencies in sequential data, such as natural language or temporal sequences. However, in the case of cryptographic key generation, where complex dependencies and non-sequential relationships may exist, the RNN architecture may not be the most suitable choice.

In the next subsection, we will assess the randomness of keys generated by an FFNN using the Diehard test set.

5.5. Evaluation of Key Generation Security Using FFNN

In this subsection, we assess the security of the key generation process implemented using the FFNN architecture. To evaluate the randomness and unpredictability of the generated keys, we subject them to the Diehard Test (T. Chen dkk., 2021). The Diehard Test is a set of statistical tests specifically designed to identify potential weaknesses or vulnerabilities in random number generators. By analyzing the results of these tests, we can gain insights into the strength of the key generation process and its resistance against statistical attacks.

Table 1 presents the outcomes of the 15 Diehard tests conducted on the key generation process utilizing the FFNN architecture. The table includes the p-values and the corresponding results of each test (Zhao dkk., 2022). The p-value serves as an indicator of the randomness quality produced by the random number generator, and it is compared to a significance threshold of 0.01. A p-value below the threshold suggests a failed test, indicating potential issues with the randomness of the generated keys. Conversely, a p-value above the threshold indicates a successful test, implying that the generated keys exhibit satisfactory randomness qualities and pass the statistical assessment.

Table 1. Results of Diehard Tests for Key Generation Using FFNN

Test Name	P-Value	Result
Birthday spacing	0.363	Passed
Binary rank 31*31	0.710	Passed
Binary rank 32*32	0.609	Passed
Binary rank 6*8	0.518	Passed
Count the1	0.219	Passed
Parking lot	0.182	Passed
Minimum distance	0.422	Passed
3D sphere	0.810	Passed
the Squezze	0.647	Passed
Overlapping sum	0.392	Passed
Run up 1	0.688	Passed
Run up 2	0.761	Passed
Run down 1	0.895	Passed

Run down 2	0.098	Passed
Craps of throws	0.882	Passed

The results presented in Table 1 confirm that the key generation process utilizing the FFNN architecture successfully passes all 15 Diehard tests. The p-values obtained from each test surpass the significance threshold, indicating that the generated keys exhibit high-quality randomness and meet the required standards. This outcome across all tests provides strong evidence of the reliability and effectiveness of the FFNN-based key generation process.

The implications of these findings are significant for the security of IoT devices. Randomness plays a crucial role in cryptographic operations, as it ensures the confidentiality and integrity of sensitive data transmitted and stored by IoT devices. By demonstrating the ability of the FFNN-based key generation process to generate random keys that meet the desired level of randomness, these results contribute to strengthening the security of IoT devices.

The successful outcomes of the Diehard tests enhance the confidence in the FFNN-based key generation process, indicating its suitability for cryptographic applications in IoT devices. With robust and secure key generation, IoT devices can establish secure communication channels, authenticate users, and protect sensitive information from unauthorized access and malicious attacks. Therefore, the positive impact of these results extends to the overall security and privacy of IoT ecosystems.

6. CONCLUSION

This paper presented a comparative analysis of FFNN, CNN and RNN architectures for neural network-based cryptographic key generation on IoT devices. A novel key generation algorithm was designed and implemented using each architecture. Extensive experiments evaluated the models on performance metrics like accuracy, loss, key randomness and complexity. Results demonstrated that the proposed FFNN-based approach achieves over 99% accuracy in key generation while passing all statistical tests for randomness. CNN and RNN architectures exhibited reduced performance due to their limitations in modeling the complex patterns and relationships required for cryptographic keys. The FFNN architecture emerges as the most suitable choice for securely and efficiently generating cryptographic keys in resource-constrained IoT environments. This work provides useful insights into selecting optimal neural models based on architectural characteristics and application requirements.

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