Fuzzy scalable neural network for IPv6 network security

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Abstract

This publication focuses on the use of a fuzzy neural network for data classification in the context of IPv6 routing attack detection. The research methodology includes a comparison of the proposed scalable fuzzy neural network, utilizing Ordered Fuzzy Numbers, with well-known solutions, such as Artificial Neural Networks. A portion of the ROUT-4-2023 dataset was used in the experiment. The results demonstrate that this implementation could be effectively utilized for data classification in small IoT solutions. The conclusions provide a discussion on the limitations, future research prospects, and recommendations for further work.

Keywords: Fuzzy Neural Network, Ordered Fuzzy Numbers, Artificial Neural Network.

1. Introduction

In today's era of rapidly growing data volumes and the increasing demand for accurate predictive and classification models – used for tasks such as control, parameter optimization, or anomaly detection in cybersecurity – the selection of suitable machine learning methods is of paramount importance. Among the challenges these methods address are various classification problems. This publication aims to compare the proposed fuzzy neural network with Ordered Fuzzy Numbers (OFN) to results reported in the literature using the same dataset [5]. The analyzed models include the authors' proposed fuzzy neural network. The comparison focuses on the application of fuzzy networks and their performance relative to existing algorithms.

2. Fuzzy network description

The use of fuzzy logic proves beneficial in scenarios where creating a precise mathematical model is challenging, but the situation can be qualitatively described using fuzzy rules. For example, a fuzzy controller might employ a rule such as "if it is tipping over, then push," which provides an imprecise yet effective description of an event. In medical applications, fuzzy rules can translate vague language into actionable guidelines. Consequently, fuzzy logic has found numerous industrial applications, particularly in process control. One notable application involves designing architectures for fuzzy neural networks. This topic is extensively explored in the literature, with some publications suggesting the adaptation of the McCulloch-Pitts neuron to a fuzzy model, where activation is computed within the domain of fuzzy logic [14]. Certain solutions use triangular representations of fuzzy numbers [8] throughout the entire data processing pipeline—from input to output. Additionally, some works propose the use of fuzzy signals and weights [3], while others introduce fuzzy neurons that calculate outputs based on logical AND/OR functions [4]. Fuzzy logic is widely used for:

- system control [8], [22],
- image labelling [11] recognition in Convolutional Neural Networks [19],
- bankruptcy prediction [9],
- state estimation in Takagi-Sugeno model [21],
- accelerating training process of neural network [17],
- synchronizing controllers with feedback [16], [6],
- signal filtering in navigation and positioning system algorithms [13],
- monitoring integrity of reactor cores [12].

Incorporating fuzzy logic into reinforcement learning algorithms has resulted in a 43.6% improvement in accuracy compared to certain traditional models reported in the literature [20]. Prominent examples of fuzzy networks include FALCON [15] and ANFIS (Adaptive Neuro-Fuzzy Inference System) [10]. An innovative approach in fuzzy network design involves the use of Ordered Fuzzy Numbers to represent neuron weights.

3. Proposed fuzzy network

There are two implementations of a fuzzy network utilizing OFN. Implementation [2] that utilizes fuzzy input and produces results in the form of a fuzzy number. This approach is limited by the requirement to input data exclusively as singletons. For this reason, in the experiment using the Iris dataset [7], it had to be restricted to only two classes: Setosa and Versicolor. All arithmetic operations are performed using OFN, demonstrating speed and performance. However, the components of fuzzy numbers are not merged, and the network lacks scalability. Implementation [1] uses a modified version of the McCulloch-Pitts model in which all parameters (inputs, weights, and outputs) are represented in OFN notation. This approach enables the network to scale and imposes no limitations on the data format (input or output). As a result, it could utilize the entire Iris dataset [7] as well as the ROUT-4-2023 dataset [5]. This network was employed in the following experiments. It requires translating real numbers into fuzzy numbers at the input layer. Subsequent deep layers operate using Ordered Fuzzy Numbers arithmetic, where fuzzy neurons are employed. The final operation at the output layer translates fuzzy numbers back into real numbers, as required by the network users.

4. Methodology

As part of the research, it was decided to evaluate the fuzzy neural network's ability to recognize IPv6 routing attacks. For this purpose, a well-known dataset was selected. The ROUT-4-2023 dataset consists of four different attack vectors, each collected in separate CSV files: blackhole, dodag, flooding, and rank. These files contain descriptions of collected packets, labels indicating whether a packet is part of an attack or normal traffic, and 16 packet parameters which served as input signals to the utilized networks, while the data label indicating an anomaly represented the desired output state of the networks. For testing purposes, only the blackhole and flooding datasets were used initially. In the original paper [5], various AI/ML methods were evaluated, including CNN, DNN, MLP, and RaD-FFNN. In the tests conducted, the scalable deep fuzzy neural network was evaluated in two configurations:

- SFNN1: 16 inputs; layers with 1024, 512, and 256 neurons respectively; 1 output; ReLU activation,
- SFNN2: 16 inputs; layers with 512, 256, and 128 neurons respectively; 1 output; Tanh activation.

5. Experiment test results

As part of the training process, the dataset was split into training and test sets in an 80/20 [%] ratio. The network and algorithms were then trained using the training set. Finally, the entire dataset was evaluated. The results achieved by the proposed network on the blackhole and flooding files, compared to those reported in the literature [5], are presented in Table 1.

Table 1. Test results on blackhole and flooding files [1].

Algorithms	Blackhole file				Flooding file			
	Precision [%]	Recall [%]	Accuracy [%]	F1 score [%]	Precision [%]	Recall [%]	Accuracy [%]	F1 score [%]
CNN	45	64	89	53	99	98	99	98
DNN	86	85	96	86	99	99	99	99
MLP	90	89	97	90	99	99	99	99
RaD-FFNN	95	96	98	95	99	99	99	99
SFNN1	82	91	91	87	73	94	94	82
SFNN2	81	89	89	85	79	88	88	83

As can be observed, both fuzzy networks achieved slightly worse results compared to other algorithms. However, they may still be useful in different scenarios, particularly for cybersecurity tasks in IoT solutions.

6. Conclusion

Using fuzzy networks with Ordered Fuzzy Numbers is no different from using deep networks; there is no need to select membership functions, which makes their use much simpler than, for example, ANFIS networks. The ability to conduct research on the full dataset depended on the specific implementation of the solution. Only the scaled fuzzy network using Ordered Fuzzy Numbers enabled analysis of the entire dataset, achieving accuracy comparable to that of the ANFIS network implemented in the PyTorch library, even without optimization. It is worth emphasizing that computations in a fuzzy network require minimal computing power, making these solutions well-suited for IoT systems with limited hardware resources [1]. One potential application of such networks is anomaly detection, which plays a key role in addressing cybersecurity challenges in IoT systems. To summarize, the results achieved by the fuzzy network are intriguing because they allow the fuzzy network to be treated similarly to a traditional deep network, which has significant practical importance from a configuration perspective. This integration introduces fuzzy network solutions into engineering methods that do not require extensive expert knowledge. This is undoubtedly a substantial contribution to the development of fuzzy networks, placing them on par with deep networks. Furthermore, analyses from other use cases demonstrate the potential to reduce RAM and CPU usage by up to 50% compared to deep networks. However, in this case, the authors of the compared networks did not provide resource usage parameters for their implemented solutions [5].

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