Improved Classification Algorithm for Restricted Coulomb Energy-based Neural Network

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***Abstract*— In this paper, we propose an improved classification scheme for the restricted coulomb energy neural network (the RCE NN). The core concept of our proposed algorithm lies in performing a K-Nearest Neighbor (KNN) search to determine the majority class among the neighbors in cases where the RCE network's decision is not reliable. Experimental results demonstrate that the proposed algorithm achieves higher classification accuracy compared to the standard RCE NN algorithm.**

Keywords—Neural network, Restricted Coulomb Energy, K-nearest neighbor, Artificial intelligence

I. INTRODUCTION

Due to the rapid advancement of artificial intelligence (AI) technology in recent years, research on applying AI to various fields is actively being conducted. In particular, with the emergence of large-scale neural networks such as Chat GPT, AI systems have exhibited exceptional processing capabilities in tasks such as search, translation, and text generation. As a result, they have already found applications in numerous domains.

Large-scale artificial intelligence systems require powerful computational capabilities and large memory capacity for data processing, and they are typically operated on server-grade processors. However, applying such massive AI systems to edge-level devices with limited memory, lower computational power, and power consumption constraints is practically impossible. Therefore, lightweight AI technologies with characteristics such as simplicity and minimal memory usage are primarily applied in these scenarios. One of the various lightweight AI technologies is the Restricted Coulomb Energy (RCE) based network, which forms clusters based on the characteristics of data and performs classification.[1] This algorithm has simple learning methods and the ability to construct dynamic networks, making it applicable to many fields. [2-4].

In this paper, an algorithm is proposed to improve the performance of the RCE-based neural network. This is enhanced version of our previous work [5] which merely targeted a single ambiguous classification case of the RCE network. When encountering a situation where input data is classified by a neuron with the minimum influence field, the algorithm analyzes the class statistics of K nearest neighbors (neurons) and performs classification. The proposed algorithm incorporates a majority voting approach based on neurons with similar characteristics to the input data in ambiguous regions where the distinction between neurons belonging to different classes is unclear. This allows for probabilistic classification of the input data into the class value with the highest likelihood. The performance of the proposed algorithm was measured on three benchmark datasets, demonstrating improved performance compared to existing algorithms.

II. THE PROPOSED RESTRICTED COULOMB ENERGY

In this chapter, the proposed algorithm to increase classification accuracy of RCE network is illustrated. The main idea of the proposed algorithm is that searching K-nearest neighbors and finding the majority category among them. We briefly illustrated the RCE-based neural network for better understanding of the proposed algorithm.

A. Restricted Coulomb Energy-based Neural Network

The RCE-based neural network is a supervised learning algorithm that performs classification by analyzing patterns between input feature data to form clusters [1]. The structure of the RCE network is shown in Fig. 1. The single prototype layer, comprised of neurons, compares the distance from the input feature set to determine whether it falls each neuron's influence field (IF).

To determine the category of the input, the RCE network examines all the firing neurons that have the input feature set within their influence field. Based on the analysis results, the RCE network performs its recognition process as illustrated in Fig. 2. The recognition process encompasses three possible scenarios: 'Unknown', 'Uncertain', and 'Identified'. If all the fired neurons belong to the same class, this case is called 'Identified' and the input is assigned the class of those neurons, resulting in the final classification outcome. If fired neurons have different classes, this case is called 'Uncertain'. In the 'Uncertain' case, where

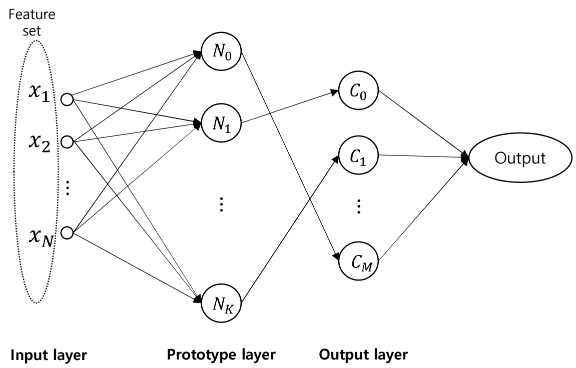

Fig. 1. The structure of the RCE network.

fired neurons have different classes, and in the 'Unknown' case, where no neurons fire, the class decision for the input typically follows the nearest neuron.

B. The Proposed Algorthm

As shown in the previous subsection, the RCE network outputs the classification result in three ways. Except for the 'Identified', the other two cases may cause an ambiguous result. In the 'Uncertain' case, if the fired neurons have the minimum IF which is set by the supervisor, it can be considered that the decision made by the neurons is not reliable. Also, in the 'Unknown' case, where no neuron is fired by the input, an appropriate decision scheme should be implemented.

The proposed algorithm applies the K nearest neuron-based decision scheme to above ambiguous decision cases to increase the RCE network's classification performance. The flowchart of the proposed algorithm is shown in Fig. 3. The basic operation of the proposed algorithm is similar to the RCE network, but it applies an algorithm to find the nearest neuron when a classification situation arises by a neuron with the minimum AIF value or in the absence of any firing neurons. This is done to probabilistically classify the input data into the class with the highest likelihood in ambiguous regions where the distinction between input data is unclear.

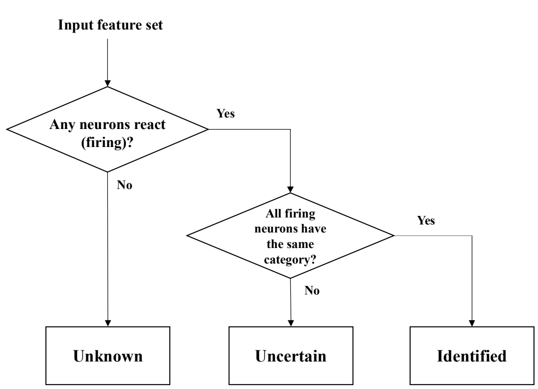

Fig. 2. The recognition process of the RCE network

As shown in Fig. 3, the classification of input data is performed based on three main regions. If the input data falls within the IF of a neuron in the network and the neuron has the minimum AIF value, the classification result is considered ambiguous, and an algorithm to find the nearest neuron is applied. When no neuron is fired by the input, the same decision process is applied. If the input data belongs to a neuron that does not have the minimum AIF value, it is classified into the class of the nearest neuron.

C. The Computational Complexity of the Proposed Algorithm comparing with the RCE network

Although the proposed algorithm utilizes the K-nearest neighbor method, which typically involves computing distances between data points, it should be noted that the increase in computational complexity is minimal. This is primarily due to the fact that the original RCE network already calculates distances between data points. In the proposed algorithm, the computed distances are simply utilized to identify the nearest neighbor. Consequently, the additional computational complexity introduced by the proposed algorithm is negligible.

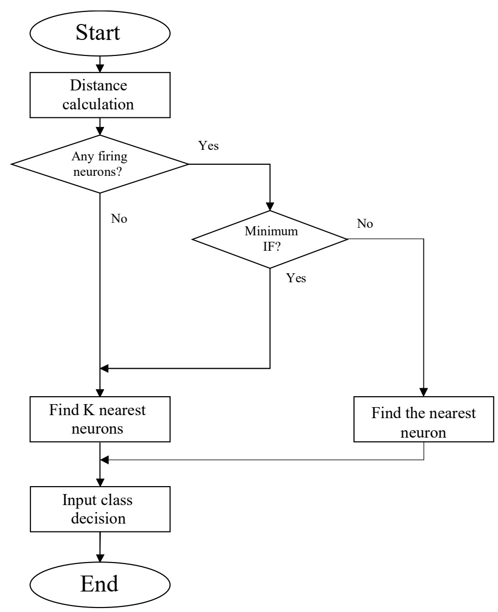

Fig. 3. The flowchart of the proposed algorithm

III. Performance Evaluation

To evaluate the performance of the proposed algorithm in this paper, performance measurements were conducted using benchmark datasets commonly used in the evaluation of performance, namely IRIS [6], WINE [7], and CatsDogs [8] datasets.

The configuration of hyperparameters applied for performance evaluation is presented in TABLE I. The results obtained by applying the parameter values in TABLE 1 and varying the value of K for the proposed algorithm are shown in TABLE II. It can be observed that the proposed algorithm exhibits a performance improvement of approximately 7% for the IRIS dataset, 8% for the WINE dataset, and 6% for the CatsDogs dataset compared to the RCE network.

Based on the results, it is evident that the ideal value of K differs among datasets. It is advisable to select a value of K below 7, as larger values negatively impact classification performance, as observed in the all cases.

TABLE I. HYPER PARAMETERS USED IN THE PERFORMANCE EVALUATION

Dataset	Hyper Parameter		
	Iteration	*MinIF*	*MaxIF*
IRIS	20	50	210
WINE	20	200	690
CatsDogs	20	500	760

TABLE II. PERFORMANCE COMPARION RESULTS FOR THREE DATASETS

Algorithm		Dataset		
		IRIS	*WINE*	*CatsDogs*
The RCE network		93.3%	94.4%	82.4%
The proposed algorithm	K = 3	100%	94.4%	88.2%
	K = 5	96.7%	97.2%	82.4%
	K = 7	96.7%	97.2%	76.5%
	K = 9	96.7%	94.4%	76.5%

IV. CONCLUSION

The proposed algorithm in this paper aims to enhance the data classification performance of the Restricted Coulomb Energy (RCE) network. It introduces an alternative algorithm by applying the nearest-neuron technique in situations where data classification is performed by neurons with minimum influence range or in the absence of any firing neurons . The proposed algorithm is particularly expected to achieve significant performance improvement in boundary areas where input data of different classes are complexly distributed.

The performance of the proposed algorithm depends on distribution of neurons. To attain an optimal distribution, it is necessary to employ a method for determining the optimal hyperparameters. This will be a focal point of our future work, aimed at enhancing the performance of the RCE network. By incorporating the K nearest neighbor-based classification algorithm in conjunction with the optimal hyperparameter selection method, we anticipate a significant enhancement in the classification performance of the RCE network.

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[7] https://archive.ics.uci.edu/dataset/109/wine

[8] https://www.timeseriesclassification.com/description.php?Dataset=CatsDogs