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Machine Learning Based Classification of the Halos in Light Nuclei Region

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ABSTRACT

Experimental and theoretical studies on halo nuclei, whose nucleon binding energies are extremely weak, are among the most interesting topics of nuclear physics studies. By better defining and understanding this unusual behavior of these nuclei, our understanding of nuclear structure can be further improved. Although there are already a few experimentally proven halo nuclei in the literature, many others have found their place in the literature as candidate halo nuclei. In this study, the classification of halo nuclei was carried out using an artificial neural network approach. In the light nuclei region, the properties of nuclei, including halo nuclei, were discussed and the existing halo nuclei were classified. The success of the obtained results indicates that machine learning methods can be used for identifying halo nuclei. Thus, these methods are considered as one of the alternative tools to confirm the existence of new or candidate halo nuclei.

Keywords: Nuclear structure, Halo nucleus, Machine-learning, Classification.

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Introduction

The halo nucleus has a very weak binding of the last one or two valence nucleons. While the separation energy for stable nuclei is around 6-8 MeV, for halo nuclei this value is much lower (in some cases less than 1 MeV). The main concept of the halo nucleus is a long tail in the density distribution of a nucleus due to the tunnelling of weakly bounded nucleons. It can be understood by the extremely small nucleon separation energy of the halo nucleus compared with that of stable nuclei [1]. The halo can be a proton halo or neutron halo These are confirmed and considered and has a very long tail of nucleon-density distribution. In 1985, Tanihata et al. [2] discovered ^{11}Li halo nucleus, and Hansen and Jonson [3] validated it. A neutron halo structure was discovered in this nucleus from the series of experiments including the interaction cross-section, the momentum distribution of the ^{9}Li fragment from ^{11}Li, and enhancement of the Electro-Magnetic Dissociation cross-section. The first halo nucleus ^{6}He made in the laboratory by using a neutron beam on a ^{9}Be target. The additional halo nuclei that have undergone experimental confirmation are ^{11}Li, ^{11}Be, ^{14}Be, ^{14}B, ^{15}C, and ^{19}C. Additionally, several potential halo nuclei exist but they are not confirmed experimentally. Some of them are ^{8}He, ^{12}Be, ^{17}B,^{16}B, ^{17}C, ^{22}C, ^{22}N, ^{23}O, ^{24}F, ^{26}F, ^{27}F, ^{29}F, and ^{29}Ne [4]. The chart of the confirmed and potential halo nuclei is shown in Figure 1. Neutron halo nuclei are shown by dark green square and candidates of neutron halo are shown by light green. Orange squares show the proton halos. Inside the figure, ^{11}Li halo structure has been shown as an illustration [5].

Figure 1. The chart of the confirmed neutron halo (dark green), candidates of neutron halo (light green) and proton halo (orange) [5].

Many theoretical studies exist to explain the properties of halo nuclei, including structure models [6-8] and reaction models [9-12]. To elucidate the structure of halo nuclei, Ryberg et al. [13] used halo effective field theory, in which a field-theoretic approach is used for the construction of the interaction and the calculation of observables. In this study, the classification of halo nuclei was carried out by using the machine learning approach. For this purpose, a feed-forward layered artificial neural network (ANN) model [14] was created and confirmed, and candidate halo nuclei were tried to be identified. Nuclei in the range of Z=2 to 10 and N=2 to 24 were taken into account and classified as halo or non-halo. 13 different parameters of the nuclei were determined, machine learning was performed with all and some of these parameters and the results were compared. ANN are widely used in the field of nuclear physics. Examples of studies carried out by our working group include: adjustment of non-linear interaction parameters for relativistic mean field approach [14], time-of-flight discrimination between gamma-rays and neutrons [15], construction of consistent empirical physical formulas for potential energy curves [17], determination of nuclear charge radii [18] and binding energy [19] and estimation of fusion reaction cross-section [20]. According to the results of the present study, machine learning approaches might be possible tool for the determination of the halo nuclei.

Materials and Method

Artificial neural network (ANN) is one of the powerful mathematical tool that mimics the human brain functionality. In the ANN structure, there are neurons in different layers, namely input, hidden, and output layers. Because of this type of structure, ANN is called as layered ANN. The processing units of the ANN are neurons, and they are connected to each other in different layers by adjustable synaptic weights. Input layer neurons receive data and transmit it to hidden layer neurons and then to output layer neurons by adaptive weighted connections. If the data flow forward in one-way, the ANN is named as layered feed-forward ANN. In the present study, layered feed-forward ANN has been used for the clasification of the halo nuclei.

The main purpose of the ANN method is to determine the best weight values between neurons by using the given sample data in the training stage of machine-learning. The numbers of neurons in the input and output layers depend on the variety of the data belonging to the problem. Whereas, there is no rule to determine the number of hidden layer and its neurons between input and output layers. The number of hidden layer varies according to the nature of the problem, but generally one hidden layer is sufficient for almost all problems. However, the perfect neuron number in this layer is determined after several trials that give the best results for the problem. In this work, the numbers of hidden layer neuron are either 4 or 12 for different input parameters (Figure 2).

The ANN method is a perfect tool for both linear and nonlinear function approximations. It is composed of two main stages. The entire data belonging to the problem is divided into two separate sets for training and test stages. In the training stage of supervised training procedure, the first part of data is given to the ANN, including both input and desired output values. The weights are modified using the sample data in the training stage. The method generates its own outputs as close as possible to the desired output values. Comparisons between the desired output and the ANN output are made by root mean square error (RMSE) function given by Eq. (1). After an acceptable deviation between the ANN outputs and the desired outputs, the training stage is finally terminated. This means that the ANN is constructed for solving the problem with the modified final weights. However, it is still early to decide whether the constructed ANN is appropriate for the estimation of similar type of another set of data. The generalization ability of the ANN must be tested using the second set of the data that is never seen by the constructed ANN in the training stage. If the generated outputs in the test stage by using final weights are still close to the desired outputs, it can be confidently concluded that the ANN is appropriate for solving this type of problem. The performance of the results was evaluated by accuracy (AC), certainty (CR), sensitivity (SN) and error rate (ER) indicators. The descriptions of the indicators were given in Table 1 and Eqs.1-4. Here TP, TN, FP and FN are the numbers of true positive, true negative, false positive and false negative events.

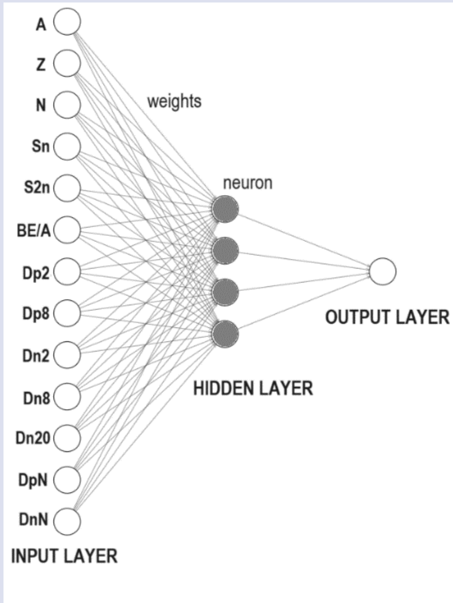

Figure 1. The used ANN structure for the classification of halo nucleus.

Results and Discussions

In order to determine the Halo nuclei for light nuclei region, we have applied artificial neural network method for the classification of the nuclei in the ranges of Z=2 to 10 and N=2 to 24. Because we have considered one and two neutron halos as ^{6}He, ^{8}He, ^{11}Li, ^{11}Be, ^{12}Be, ^{14}Be, ^{14}B, ^{17}B, ^{19}B, ^{15}C, ^{17}C, ^{19}C, ^{22}C, ^{22}N, ^{23}O, ^{24}F, ^{26}F, ^{27}F, ^{29}F and ^{29}Ne, we have interested in this region. These are confirmed and considered halo nuclei available in the literature in p and sd shell regions. Therefore, we have collected the available experimental data of the nuclei for the given range. The collected data parameters are mass number (A), proton number (Z), neutron number (N), one neutron seperation energy (S_n), two neutron seperation energy (S_{2n}), binding energy per nucleon (BE/A), distance of the proton number of the nucleus from closed core 2 (Dp2), distance of the proton number of the nucleus from closed core 8 (Dp8), distance of the neutron number of the nucleus from closed core 2 (Dn2), distance of the neutron number of the nucleus from closed core 8 (Dn8), distance of the neutron number of the nucleus from closed core 20 (Dn20), distance of the proton number of the nucleus from the closest core (DpN) and distance of the neutron number of the nucleus from the closest core (DnN). These parameters might the possible canditates of the inputs of the neural network. The output of the neural network was the 1 or 3 whose correspond to Halo or not Halo nucleus, respectively. In Figure 3, we have presented the correlation between the variables. As can be clearly seen in the figure that the strongest correlation between output and each input parameters are S_n and S_{2n} with the correlation degree of 0.31 and 0.32, respectively. The weakest ones are A and DpN.

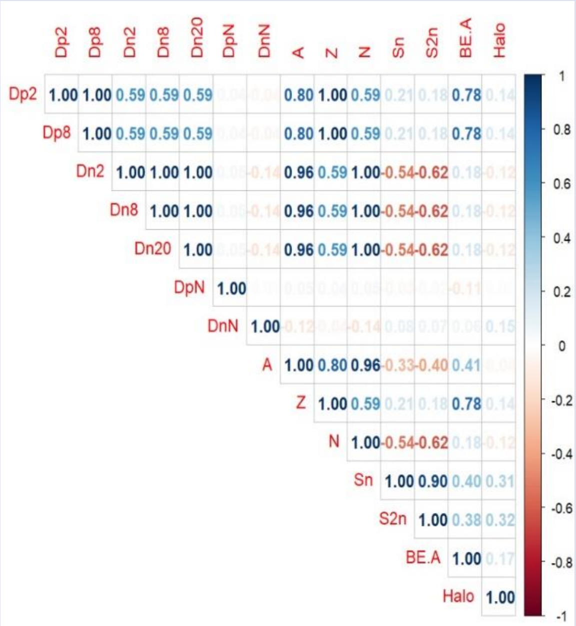

Figure 3. Correlation matrix between potantial input and output parameters for the classification of halo nuclei.

In the first step of the classification, we considered all the inputs. The number of the hidden neuron is 4 which gives the best result. According to the results, for the training dataset, the classification performance is obtained very high. In Table 2, we have presented the estimation on the training data of the trained neural network. For the total 87 nuclei, 14 halo nuclei were perfectly assigned as Halo and 73 not halo nuclei was assigned as not halo. The AC, CR, SN and ER values are obtained as 1.00, 1.00, 1.00 and 0, respectively. According to these values obtained from the performance indicators, it is seen that the method has a perfect success on the training data in classifying halo nuclei.

Table 2. The estimation of the machine-learning by all input parameters for the classification of the halo nuclei on the training dataset.

		True	
		Halo	Not Halo
Predicted	Halo	14	0
	Not Halo	0	73

In the training phase, we also performed machine training by limiting the input parameters as a second option. According to the correlation matrix, we only considered S_n and S_{2n} as two inputs, which were most strongly related to the output. The number of hidden layer neurons we used in this ANN structure was 12, which gave the best results. In Table 3, we have presented the estimation on the training data of the trained neural network. All the nuclei was classified correctly. The AC, CR, SN and ER values are obtained as 0.99, 1.00, 0.93 and 0.01, respectively. According to these values obtained from the performance indicators, it is seen that the method has a superior success on the training data in classifying halo nuclei.

Table 3. The estimation of the machine-learning by two input structure of ANN for the classification of the halo nuclei on the training dataset.

		True	
		Halo	Not Halo
Predicted	Halo	13	0
	Not Halo	1	73

In Table 4, we have given the predictions on the test dataset for 26 data points by including all input parameters in the input neurons. Clearly seen in the table that the desired 5 halo nuclei were assigned as halo and desired 19 not halo nuclei were assigned as not halo. Whereas, the desired 2 not halo nuclei were incorrectly assigned as halo nuclei. The AC, CR, SN and ER values are obtained as 0.92, 0.71, 1.00 and 0.08, respectively. According to these values obtained from the performance indicators, it was seen that the method was successful on the test data in classifying halo nuclei and that the method could be an alternative in determining unknown halo nuclei.

Table 4. The predictions of the machine-learning by all input parameters for the classification of the halo nuclei on the test dataset.

		True	
		Halo	Not Halo
Predicted	Halo	5	2
	Not Halo	0	19

In the study where we limited the input parameters to S_n and S_{2n}, the predictions obtained on the test data set are presented in Table 5. The desired 1 halo and 1 not halo nuclei were incorrectly assigned. The AC, CR, SN and ER values are obtained as 0.92, 0.83, 0.83 and 0.08, respectively. According to these values obtained from the performance indicators, again it was seen that the method was successful on the test data in classifying halo nuclei and that the method could be an alternative in determining unknown halo nuclei.

Table 5. The predictions of the machine-learning by two input structure of ANN for the classification of the halo nuclei on the training dataset.

		True	
		Halo	Not Halo
Predicted	Halo	5	1
	Not Halo	1	19

Conclusions

In this study, ANN, a machine learning approach, was used to classify possible halo nuclei identified in the literature. Parameters that may play a role in determining halo nuclei have been determined. Calculations and classification was made by considering the 13 determined parameters as the input of ANN. Then, the correlation between these parameters and the output value was examined and the number of input parameters was reduced to 2. It has been observed that there is no difference between the results of the calculations performed with the ANN in this structure and the results of the calculations using all input parameters. From this, it was concluded that only S_n and S_{2n} may be sufficient for the classification of the halo nuclei. Additionally, it has been observed that machine learning approaches can be an alternative tool in identifying halo nuclei. Thus, this approach can be considered as an alternative to confirm the existence of new halo nuclei or candidate halo nuclei. In ongoing studies, we will focus on the work on using different machine learning approaches in a wider nuclei region, confirming candidate halo nuclei, and identifying new possible halo nuclei, if any.

Conflicts of interest

There are no conflicts of interest in this work.

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