Learning the fusion evaporation cross-section by neural networks

Utkarsha Mishra,* Aman Sharma, Punit Dubey, Mahima Upadhyay, and Ajay Kumar†
Department of Physics, Banaras Hindu University, Varanasi 221005, India

Introduction

In the field of nuclear physics, heavy-ion fusion reactions play a pivotal role in advancing our understanding of nuclear reaction dynamics. Accurate data on fusion-evaporation reactions with low uncertainty is particularly important in the field of experimental nuclear physics. This precision has been essential for uncovering new reaction parameters and for synthesizing new heavy elements.[1]. Several theoretical models or empirical formulas have been proposed to study the fusion cross-section, which is one of the most important observable for studying heavy-ion reactions, such as the coupled channel calculations, the time-dependent Hartree-Fock (TDHF) theory [2–5].Theoretical models play a vital role in determining the cross-section data for specific reactions, which have limited experimental data. Despite using these models, the calculated cross-sections have a higher uncertainty.

In recent years, machine learning (ML) techniques have been extensively and effectively applied to data analysis across numerous scientific and technological fields, including physics [6] and geophysics. In nuclear physics, ML has shown significant potential in the study of heavy ion collisions [7].Using artificial neural networks in heavy-ion fusion-evaporation studies is a significant progress in nuclear physics, giving precise, data-based understanding of complex nuclear behavior.The current study focuses on applying artificial neural networks (ANN) to estimate the fusion evaporation cross-section in heavy ion-induced fusion reactions, with accuracy and validity based on existing experimental data.

Artificial neural network

The artificial neural network (ANN) model uses computing and mathematics to simulate human brain functioning. Recent advances in artificial intelligence research, such as image and voice recognition and robotics, frequently make use of artificial neural networks. These models have a design inspired by biological nervous systems, with neurons organized in a complex and nonlinear structure similar to the human brain. Weighted connections connect neurons, allowing them to learn. Every operation in an ANN model is computed using learning and training methods, including collecting information and network construction, hidden layer determination, network simulation, and weight and bias adjustment. ANNs are a useful mathematical tool for estimating values in a variety of scientific and technological disciplines, including nuclear physics. They consistently produce trustworthy findings, even when there are complex nonlinear interactions between dependent and independent variables. In recent years, ANNs have been used in a variety of nuclear physics disciplines, including the development of reliable detector count formulas. The present model is built on a feed-forward neural network structure [1].

Methodology

In this study, we focused on the fusion evaporation reaction cross-section. Through multiple trials, the optimal number of hidden layers was identified, with a 50-50-50-1 layer configuration producing the best outcomes for the current problem. The input layer consisted of 11 neurons.A feed-forward ANN was employed, using the 'ReLU' activation function for the hidden layers.The number of adjustable weights

*Electronic address: utkarshmishra22@bhu.ac.in
†Electronic address: ajaytyagi@bhu.ac.in

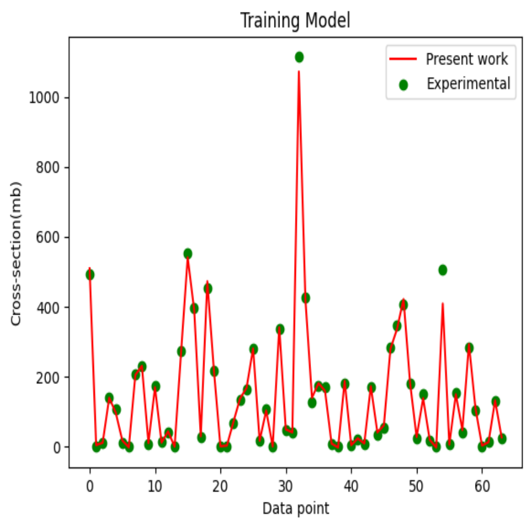

FIG. 1: Comparison of experimental cross-section values with ANN predictions for the training data in fusion reactions.

is 5600.The inputs to the ANN include beam energy, atomic charge and mass numbers, neutron numbers from the target, projectile, and compound nuclei, as well as the radius of the compound nucleus. The model's output is the fusion evaporation cross-section. Fusion evaporation cross-section data was sourced from the NRV experimental data sheet [8].For the ANN model, the data was split into two parts: 80% for training and 20% for testing. To train and test the model, we utilized 10 reactions involving compound nuclei with mass numbers ranging from 50 to 234, corresponding to 318 cross-section values. The reactions considered for the current work are as follows: ^{12}C+^{30}S, ^{40}Ca+^{40}Ca, ^{48}Ca+^{48}Ca, ^{58}Ni+^{58}Ni, ^{32}S+^{89}Y, ^{40}Ca+^{90}Zr, ^{40}Ca+^{96}Zr, ^{16}O+^{144}Sm, ^{16}O+^{208}Pb, ^{40}Ca+^{194}Pt.

Results

Experimental data, along with the predictions from the current study, are presented in FIG. 1. The green dots represent the experimental fusion evaporation cross-section data, while the red curve illustrates the predictions made by the present model. It is evident from FIG. 1 that the model has effectively learned the fusion evaporation cross-section. In this work, we analyzed experimental fusion evaporation reaction cross-section data using an artificial neural network (ANN). The current ANN model produced fusion evaporation cross-sections with errors of 0.145% and 7.83% for the training and test data sets, respectively. More details related to this work will be presented during the conference.

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