Development of a neural network for neutron spectrometry with Bonner spheres.

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Abstract: The main objective of the current study is to develop a neural network for prediction of response matrix for neutron spectrometry with Bonner sphere. The Bonner multisphere spectrometry system, more commonly known as Bonner Spectrometer (EB) is a system that consists of a set of moderator spheres, where in the center of each sphere it is possible to accommodate a thermal neutron detector. However, in this system each sphere behaves as a different detector, so obtaining information from a neutron spectrum through the EB requires knowledge of the response of each sphere as a function of the neutron energy. This process introduces an imperative in obtaining the response of a set of spheres through the response function that must be determined in order to characterize the neutrons that pass through the system. This response function that allows access to the fluence values of the neutrons in the various energy ranges in practice is replaced by a response matrix. Obtaining this response matrix is not trivial and involves a complex calculation process that includes Monte Carlo simulation from experimental data. The present work seeks to circumvent this difficulty by using machine learning techniques with neural networks. The Laboratory of Neutron Metrology (LN/LNMRI) of the National Laboratory of Metrology of Ionizing Radiation (LNMRI) of the Institute of Radioprotection and Dosimetry of Brazil (IRD), which dominates the Bonner spectrometry technique where the development of the present work took place, has given particular attention to techniques for determining the response matrix, in particular the use of neural networks given the data set and experience it has accumulated with its Bonner sphere over the years. An MLP (Multi Layer Perceptron) network was developed in this work to obtain the response matrix. This network is tested by changing its different parameters and comparing its performances with other neural networks. The observed performances demonstrate that the developed technique serves as a solid alternative for obtaining the response matrix in neutron spectrometry.

Keywords: 1. neutron spectrometry 2. neural network 3. machine learning 4. Response matrix 5. Bonner sphere.

1. INTRODUÇÃO

The study of the atomic structure led to the discovery of a fundamental element of matter whose effects and interaction with matter continue to be the focus of many challenges: the neutron. This particle without charge can be generated by different processes and rearrangements of matter leading us to a continuous distribution of energy that makes the measurement of neutron fields complex [1]. The difficulty of measuring neutron fields is due in part to the complexity of its interaction with matter, for being electrically neutral, and in part to the wide variety of neutron energies that can be found because the way in which neutrons interact with matter depends largely on the energy of the neutron that presents a spectrum that extends from a few meV (thermal neutrons) in nuclear energy production, to hundreds of MeV in clinical accelerators and up to the GeV region for accelerators and cosmic rays [2].

Spectrometry is one of the main techniques that seeks to circumvent the difficulties linked to the characterization of neutrons of different energy ranges, and has even been used in the discovery of the neutron itself [2]. It has played and still plays an important role in the development of nuclear physics since the first works on the characterization of the elements of the atom in the early 20th century and has also become an important tool in several other fields, notably nuclear technology, fusion plasma diagnosis, radiotherapy and radiation protection. However, the use of this very useful technique when the energy range is well defined, becomes complex when one wants to characterize neutron over a wide and continuous energy range. For such situations a moderation system is used that makes it possible to obtain the characteristics of neutron spectra [3]. The Bonner multisphere spectrometry system, more commonly known as the Bonner Spectrometer (EB) is a system that meets this need. This system is composed of a set of moderator spheres, where in the center of each sphere a thermal neutron detector can be accommodated [4]. However, in this system each sphere behaves as a different detector, so obtaining information of a neutron spectrum through EB, requires a knowledge of the response of each sphere as a function of the neutron energy. This process introduces an imperative in obtaining the response of a set of spheres through the response function that must be determined in order to characterize the neutrons that pass through the system. This response function that allows access to the fluence values of the neutrons in the various energy ranges in practice is replaced by a response matrix [5]. Obtaining this response matrix is not trivial and involves a complex calculation process that includes Monte Carlo simulation from experimental data. These experiments and simulations are usually performed in metrology laboratories that have the technologies, techniques and skills adapted to the complexity of the procedure [6].

Metrology is, according to the International Vocabulary of Metrology (VIM), the science of measurement and its applications [7]. One of the fields in which the implementation of metrology is fundamental is that of detection and dosimetry of ionizing radiation, among them the neutron whose detection and measurement involve complex instrumentation, theory and data processing. Neutron metrology is the science of measuring the intensity of neutron fields in different energy and intensity ranges. It is concerned with topics that include: quantities and their relations, the units for their measurements, techniques to produce and measure neutron fields, and reliability, that is, the uncertainties related to the measurements. Neutron metrology is indispensable for several areas including criticality dosimetry, nuclear reactor control and for providing input parameters for reactor design and radiological protection [8]. The Laboratório Nacional de Metrologia das Radiações Ionizantes (LNMRI) of the Instituto de Radioproteção e Dosimetria do Brasil (IRD) has a Neutron Metrology Laboratory (LN/LNMRI) that is responsible for neutron metrology in the country. The Laboratory of Neutron Metrology has and masters the Bonner spectrometry technique for the determination of neutron spectra that it uses for the quantification of radioprotection operational quantities [9]. The LN/LNMRI has given some attention to this alternative given the data set and experience it has accumulated with its Bonner spheres over the years and the possibilities offered by the use of neural networks. This work, which is in direct line with this particular objective of the LN/LNMRI, is presented here, in addition to this introduction, through the materials and methods used and the results achieved in the development of the neural network, and concluded with final considerations about the process..

2. MATERIALS AND METHODS

2.1. The LNMRI/IRD Neutron Metrology Laboratory

The Laboratory of Neutron Metrology (LN) is the site of this work. It is one of the research laboratories of the National Laboratory of Metrology of Ionizing Radiation (LNMRI) of the Institute of Radioprotection and Dosimetry (IRD). It was created in 1973 as a reference laboratory in the area of neutron metrology, being responsible for the custody and maintenance of the Brazilian Standard of Neutron Fluence, and for performing the neutron fluence magnitude. The LN has a laboratory structure that includes a Laboratory of Neutron Spectrometry (LEN) where the Bonner spectrometers are located, which were used to obtain experimental data in a first stage of the process of building the database used in this work. Figure 1 shows the basic scheme of the Bonner sphere model of LEN and figure 2 shows images of the LEN spheres.

Among the main research lines of the Computational Methods Laboratories (CMS) are mathematical simulations based on experimental or non-experimental data. In this sense, the LN/LNMRI has a database of data obtained both experimentally and by Monte Carlo simulations from the research carried out in these laboratories, which were the sites of this study. Thus, the works of Perreira (1999) [11] for character recognition and of Lemos (2009) [10] that uses a Monte Carlo simulation based on the MCNP code to develop a response matrix, which were developed in the scope of the activities of LN/LNMRI, provided the data that served as a basis for obtaining the response matrix that was used to train the neural network developed in this study.

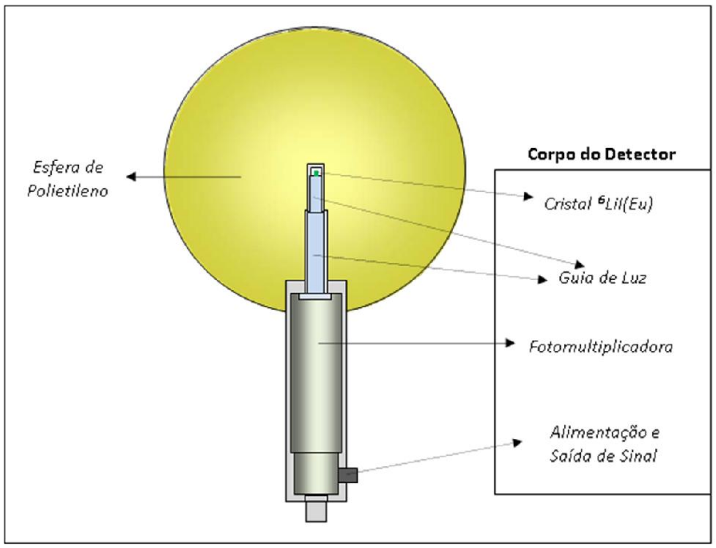

Figure 1: Schematic of a Bonner sphere with a source.

Figure 2: LN/LNMRI Bonner spheres.

2.2. Determination of the Response Matrix

To obtain information from a neutron spectrum through the Bonner Sphere (EB), one must know the response of each sphere as a function of the neutron energy, since each sphere is characterized as a different detector, for having the ability to register neutrons of different energy ranges. The response for a set of spheres can be obtained from the solution of the equation:

$$A_j = \int_{E_{min}}^{E_{max}} \alpha_j(E)\, \Phi_j(E) dE \qquad (2.1)$$

Where:

Aj is the count of the jth detector;

$\alpha_j(E)$ is the response function of the jth detector;

Φ_j(E) is the neutron fluence of the jth detector; and

M is the total number of detectors.

Equation (2.1) is known to be the first-order Fredholm integral. It could be solved if the response function (E) were an analytically known function; but this is not the case for practical neutron spectrometry systems. In practice, Equation (2.1) is replaced by a set of M linear equations dividing the energy range of that detector into several smaller regions, making the response and fluence of the detector constant over these small energy intervals. Therefore, Equation 1 can be written as follows:

$$A_j = \sum_{k=1}^{N} \alpha_{jk}\, \Phi_j(k) \qquad j = 1,2,\ldots, M\,, \tag{2.2}$$

Where:

α_{jk} is the jth detector response for neutrons in the kth energy interval; and

N is the total number of energy intervals.Therefore, the detector response function can be replaced by the matrix formed by the elements α_{jk}.

Obtaining the neutron spectrum from the detector responses is a rather complex process, since the count of each sphere has a characteristic spectrum due to the difference in diameter between them making necessary the use of computational methods like it's been studying in this work by neural network.

2.3. The implemented neural network

The mathematical model of Neural Network (RN) chosen in this work consists of a multilayer architecture of the "Multilayer Perceptron" (MLP) type, based on a totally interconnected network configuration with supervised learning, on a "Backpropagation" error back-propagation algorithm with "cross-validation" stopping criterion, based on the best result for the test set, and for determining and classifying the referential characteristics of the neutron spectra. As for the type of neuron connections, the "Feedforward" was adopted and the activation function chosen is the Linear Renormalization (ReLu) that can be changed to Sigmoid function or another function. The ReLu function was the one most used in the tests for its advantages because it allows faster and more efficient training of deep neural architectures such as MLP on large and complex datasets, and enables efficient gradient propagation, which means that no gradient problems disappear or explode, leading to efficient computation with only comparison, addition or multiplication of scales. The network was developed in Python language using the Google Colaboratory environment.

A draft of the structure of the neural network in this work is shown in figure 3 below with the input, hidden and output layers indicated.

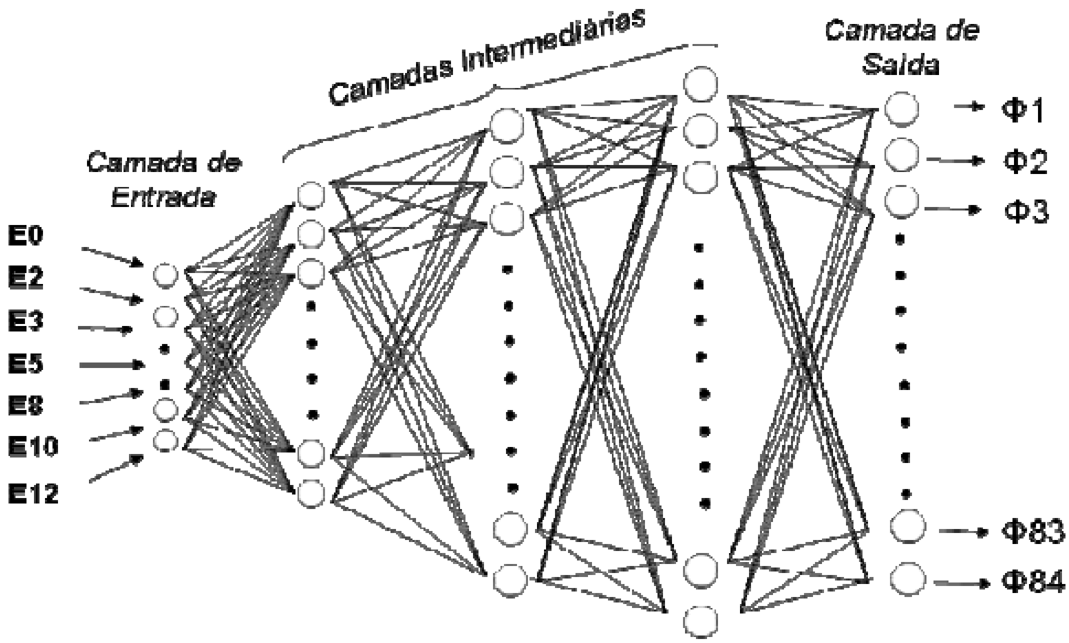

Figure 3: Schematic diagram showing the structure of the developed MLP neural network

With the methodology established and the database set up and defined, the next step was to set up and test the network to observe the results presented and discussed below.

3. RESULTS

The neural network for neutron spectrometry in this work was structured using Python's Sequential Dense model library, which in addition to allowing condensing the layers, enables the structuring and operation of these in sequence. With the development of the neural network name "*Espectrometria de eutron-sinal-neutron*" for neutron spectrometry, several trainings and evaluations were performed to find the best configuration for structuring the layers. The configuration that showed the most stable behavior and the most interesting performances during the tests was a network structure with eight (8) layers arranged as follows:

- one input layer with seven (7) neurons;

- six intermediate hidden layers with a first layer of 50 neurons and the rest of the 5 with 25 neurons each;

- an output layer with eighty-four (84) neurons;

Thus, it was possible to evaluate the performance of the network by comparing the evolutions of the accuracy, which shows the quality of the approximation, and the loss function, which indicates the learning rate of the network and its applicability to other data sets with MNIST digit recognition neural network, and Lemos (2009) accuracy.

The net performance analysis, which was important for choosing the best network configuration, was carried out by monitoring the evolution of accuracy and the loss function "Loss" in relation to the number of training rounds "epochs". Accuracy allows the identification of the percentage of correct answers, as well as comparisons with other models. The loss function allows you to observe the learning level of the model. A reduced loss is an indication that the model has indirectly learned the function that maps input and output data and can make reliable predictions with new data.

This performance evaluation should involve both the loss function and the accuracy. As an example, one of the configurations (figure 4) tested with 7 layers (7-14-28-56-56-84) during the structuring of the network that had not shown any evolution of accuracy even showing an interesting evolution of the loss function keeping null was rejected as it shows that the network did not train.

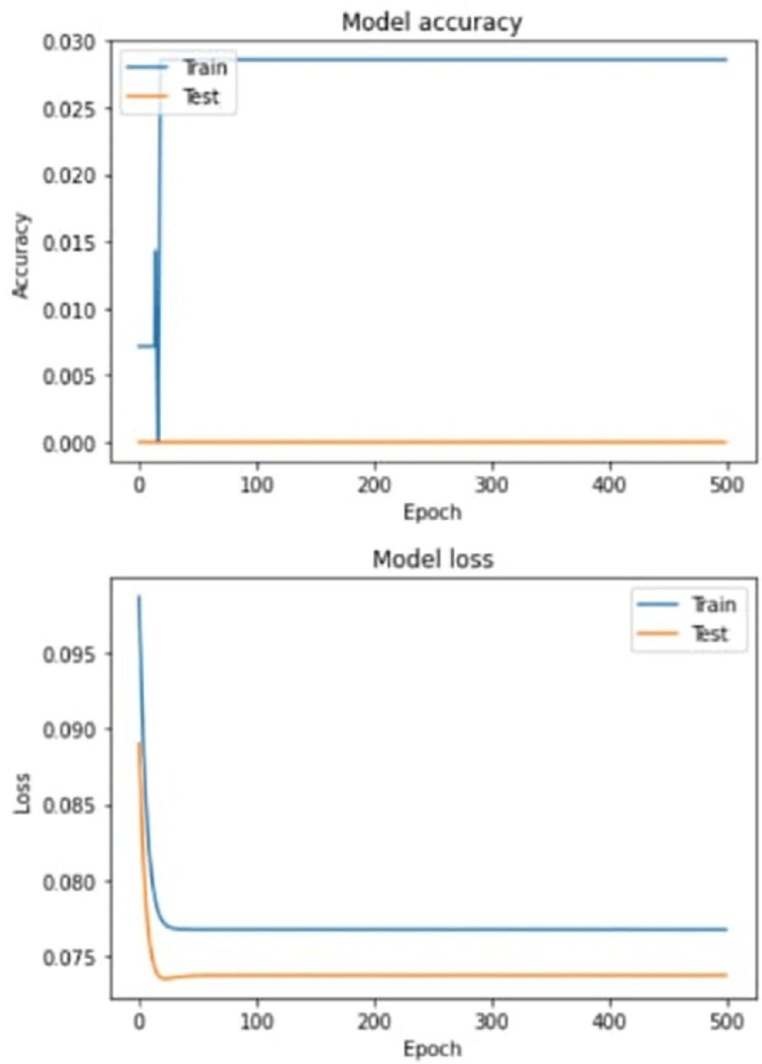

Figure 4: Network performance with misconfiguration

Another important aspect observed in the performance analysis is the number of training epochs. The analysis process showed that a number of epochs below 150 did not show interesting performances as it observed in figure 5 with the training of the chosen structure in 50 epochs.

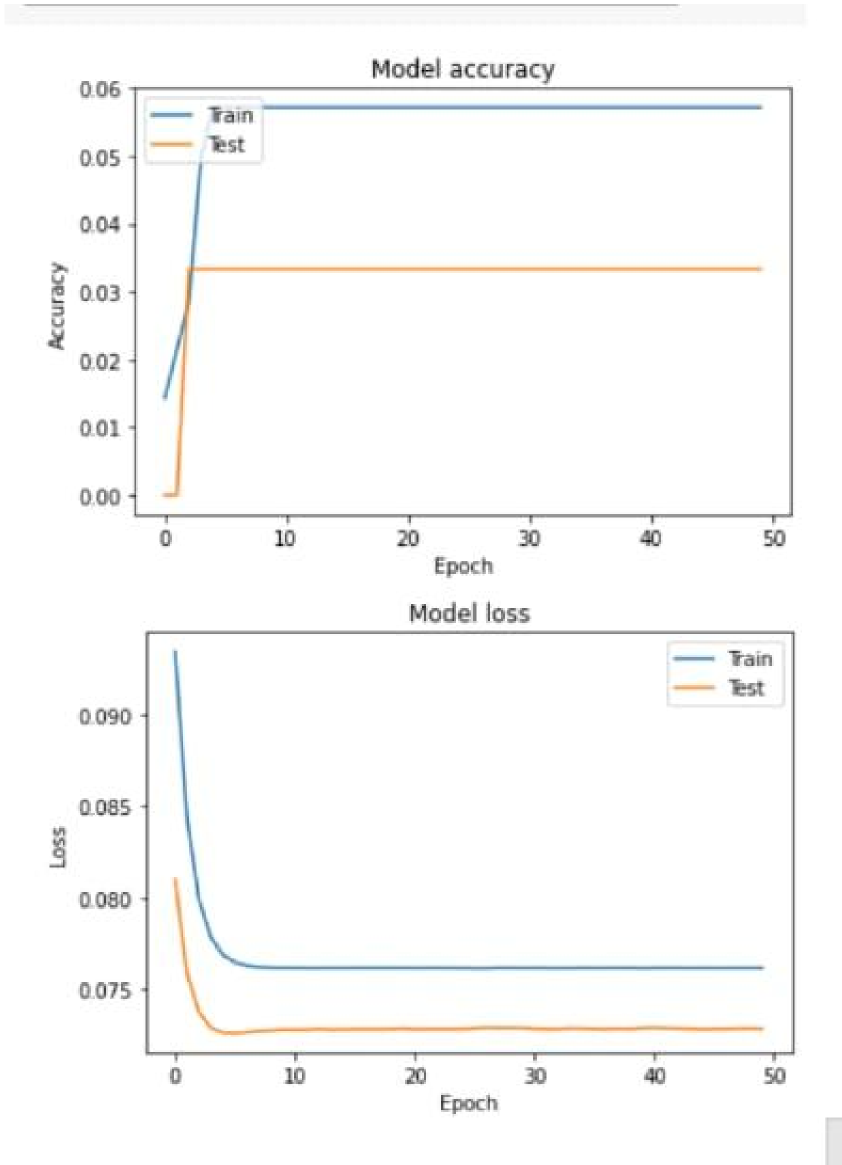

Figure 5: Training with 50 epochs

As it can be seen by figure 5 , despite the interesting performance of the network, there is a difference between the training loss and the test loss, indicating that the network does not replicate its performance well with other data. Then, the maintained structure was then trained with five hundred (500) epochs and presented a behavior of accuracy and Loss function similar to the MNIST digit recognition model, which is a network already classic for being used in many applications and in the teaching of neural networks, thus confirming the quality of the network assembled within this work. Figures 6 , 7, 8 and 9 below highlight the performance curves of the two networks for comparative purposes.

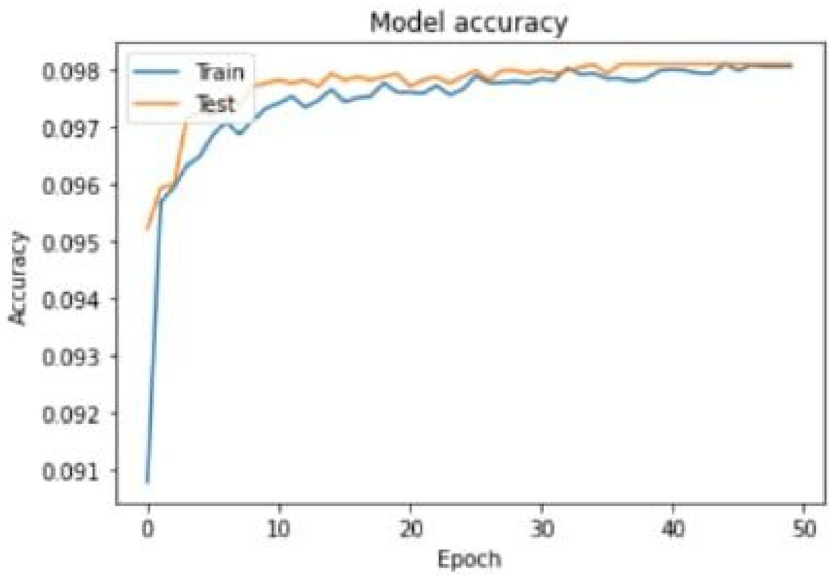

Figure 6: MNIST Network accuracy Evolution

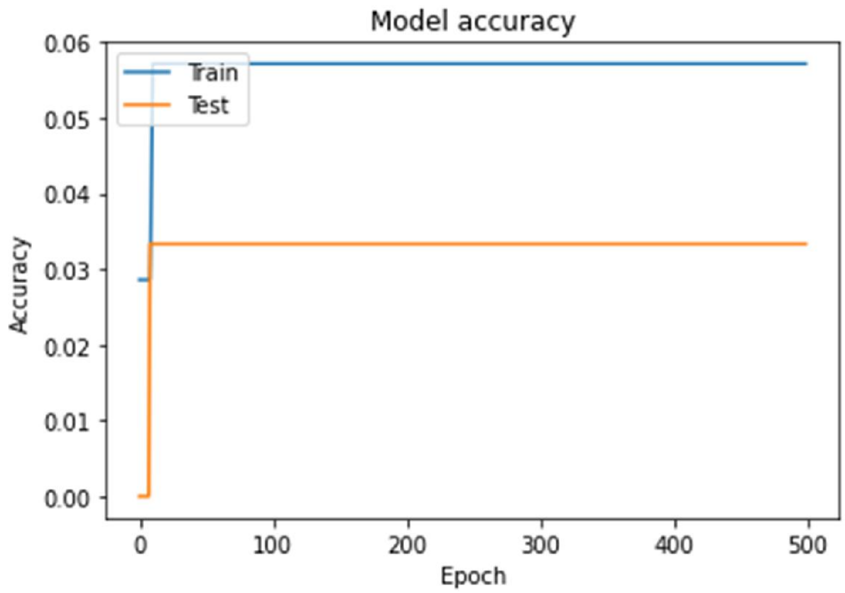

Figure 7: Evolution of accuracy of the Neural Network “spectrometria de neutron-LN”.

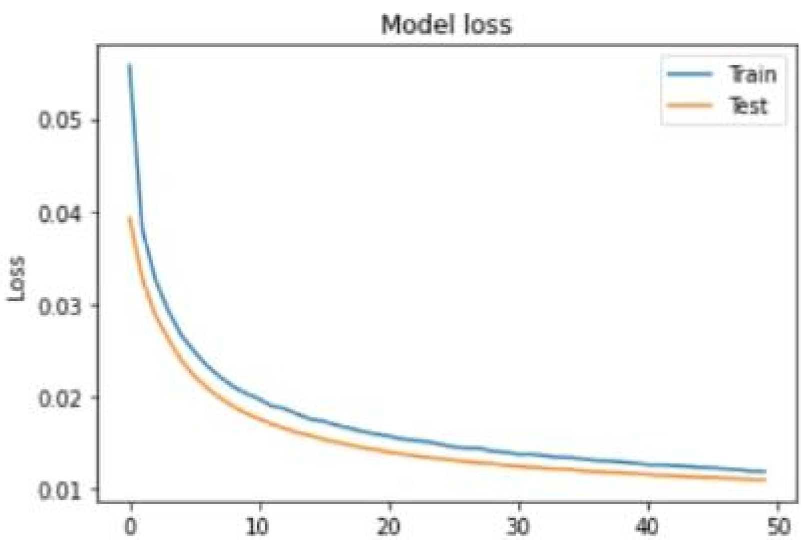

Figure 8: MNIST Network Loss Function Evolution

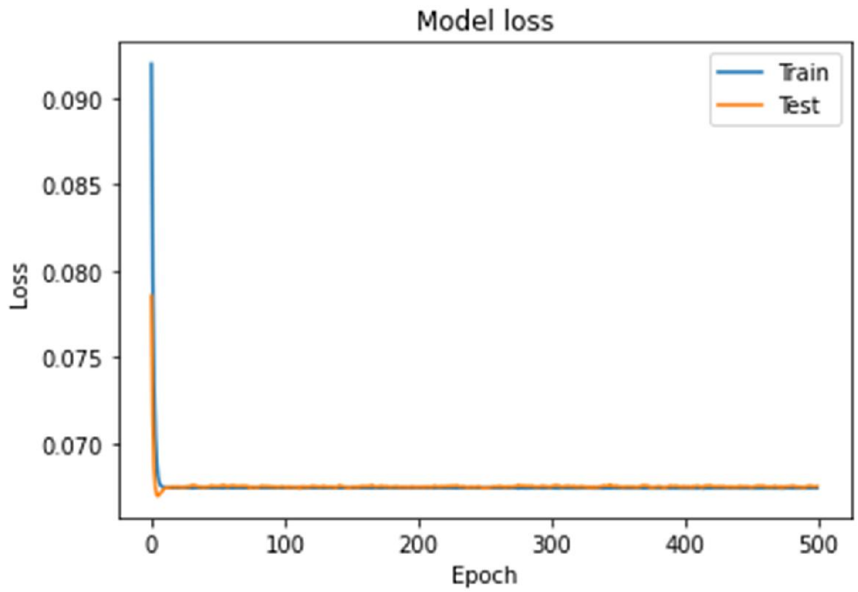

Figure 9: Evolution of the Loss Function of the Neural Network “spectrometria de neutron-LN”.

The above figures indicate an identical behavior of the network for spectrometry developed in this work with a classic network, but with a better refinement of the network for neutron spectrometry between training and testing both in accuracy and Loss function. This is explained in part by the quantities of epochs used for the MNIST network being smaller, but consolidates the efficiency of the neutron spectrometry network showing that it is an effective network for predicting the response matrices of Bonner spheres. This is confirmed by the observed accuracy of 97% with an uncertainty of 3%, the same range as in the work of Lemos,2009 [9]. The Loss function that remained at 0.06 for both training and testing shows on one hand that the network can handle new data with the same efficiency as known data, and on the other hand that the network is stable during the learning process. Further tests showed the possibility of reaching 98% accuracy, showing that the network settings can be improved to obtain more refined results.

4. CONCLUSION

The general objective of this work that sought the development of a neural network for determining the response matrix of a set of data obtained from measurements made with Bonner spheres was achieved with the construction of the neural network in MPL (Multi Layer Perceptron) "Neutron Spectrometry". This process was accomplished after conducting a literature review that allowed to have theoretical foundation and knowledge of the state of the art of techniques, theories and equipment to distinguish the Python and Google Colaboratory tools with the most adapted to perform this task. With the determination of the tool, procedures were implemented for the selection and treatment of the database for the implementation of the neural network in spectrometry with Bonner spheres at the LNMRI's Neutron Spectrometry Laboratory. With this it was possible to assemble, train and test the neural network "Neutron Spectrometry" and show through an evaluation process of its efficiency by comparison between trained and tested data as well as comparison with literature data such as MNIST and Lemos,(2009).

This study demonstrated the possibility of using neural networks for prediction of response matrix in spectrometry with Bonner Spheres and allows improving the knowledge about machine learning and neutron spectrometry through the use and application of the results in different areas related to neutron metrology. These applications can be extended to other aspects of metrology like the estimation of uncertainties and classification of standards. The results achieved by the development of this work finally open paths for future works with other neural network models such as the Convolutional Neural Network (CNN) in neutron spectrometry.

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