



SUNSPOT PREDICTION WITH A NEURAL NETWORK: AN APPLICATION OF ADVANCED ARTIFICIAL INTELLIGENCE IN SECONDARY EDUCATION

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Abstract

Artificial Intelligence (AI) constitutes a central tool in contemporary education and science, as it enables the analysis of complex data, the development of predictive models, and the cultivation of 21st-century skills, such as computational thinking and critical evaluation. The integration of AI into learning environments allows students to gain an experiential understanding of how computers “learn” and adapt to data, strengthening inquiry-based learning and connecting theory with practice. Within the framework of the 5th “HERON” Summer School, implemented by the High Frequency, Metamaterials and Nonlinear Waves Research Laboratory (HERON LAB) of the University of Thessaly, Greece, the present study presents the implementation of a multilayer perceptron neural network (MLP) for predicting the number of sunspots, linking physics with computer science. Students experimented with real data, observing how the parameters of the system affect prediction accuracy and developing an understanding of both the potential and the limitations of AI in the analysis of natural phenomena.

Keywords: AI, solar observation, secondary education

INTRODUCTION

The observation of sunspots constitutes one of the most significant fields of solar physics, as it is directly linked to the understanding of the eleven-year solar cycle and its effects on Earth (Hathaway, 2015). Variations in the number of sunspots are associated with phenomena such as magnetic storms and disturbances in telecommunications, making their prediction crucial both for scientific research and for practical applications (Usoskin, 2017).

The prediction of such phenomena is particularly demanding, as they are characterized by nonlinearity, non-periodicity, and uncertainty (Kitiashvili, 2020). The development of artificial intelligence methods, and especially neural networks, has provided new tools for the analysis and prediction of space-related phenomena, in many cases going beyond classical statistical approaches (Asensio Ramos et al., 2018; Oloketuyi et al., 2019).

At the same time, the introduction of AI tools into education, through laboratory activities using real data, contributes substantially to the development of 21st-century skills, such as computational thinking, data analysis, and the critical evaluation of algorithms (Luckin et al., 2016). In this context, the prediction of sunspots using neural networks can serve as an authentic teaching scenario that connects physics with computer science and promotes inquiry-based learning.

The application of sunspot prediction through neural networks in the educational process offers a contemporary interdisciplinary approach that enhances students’ learning in secondary education. Through the use of real data and advanced artificial intelligence methods, students cultivate essential 21st-century skills, such as computational thinking, data analysis and interpretation, and the critical evaluation of algorithms (Luckin et al., 2016). Moreover, the connection between physics and computer science creates authentic inquiry-based learning environments, which promote active



participation and strengthen scientific understanding, making this topic a valuable educational application with both practical and theoretical significance (Holmes et al., 2019).

Thus, this study is not limited to a scientific engagement with the prediction of space-related phenomena, but also constitutes an innovative proposal for the application of artificial intelligence as a tool for instructional empowerment in secondary education.

Artificial Intelligence and Education

Artificial intelligence (AI) refers to the ability of machines to imitate cognitive functions traditionally attributed to the human brain, such as learning, planning, and creativity. Through AI, machines acquire the capacity to “perceive” their environment, solve problems, and act toward the achievement of specific goals. These are systems that perform cognitive processes such as learning, reasoning, problem solving, and decision making (Russell & Norvig, 2021). Unlike conventional computers, which process incoming data and respond on the basis of that data, artificial intelligence systems can adapt their behavior by analyzing the consequences of previous actions, demonstrating a certain degree of autonomy (European Parliament, 2025). Huang et al. (2019) distinguish three main categories of AI systems:

- Mechanical intelligence: focuses on the execution of repetitive tasks with consistency and reliability.
- Cognitive intelligence: is characterized by the ability to learn and adapt autonomously through data processing.
- Emotional intelligence: refers to future applications that will allow systems to interact with empathy.

In the field of education, AI is not regarded solely as a technological innovation, but as a pedagogical tool with the potential to reshape the way teaching is organized and learning is supported (Luckin et al., 2016). The application of AI in education is mainly implemented through Artificial Intelligence in Education (AIED) systems, which combine adaptive learning techniques, cognitive models, and data analysis in order to provide personalized learning experiences (Holmes et al., 2019). These technologies are capable of assessing students’ progress, predicting possible errors, providing targeted feedback, and adapting instructional content to their individual needs.

Thus, AI in the school environment is not limited to the simple automation of teaching, but contributes to the formation of a dynamic learning process in which the student is actively engaged. In addition, AI is associated with the development of meta-skills, such as critical thinking, digital literacy, and the ability to evaluate information. According to UNESCO (2021), education systems should prepare students not only to use AI technologies, but also to understand their social, ethical, and professional implications.

Therefore, AI in schools functions both as an instructional medium and as an object of learning, integrated into a human-centered and pedagogically grounded approach that promotes personalized learning and 21st-century skills, while maintaining the teacher’s central role. The teaching of the principles of AI themselves, and especially of neural networks, constitutes an innovative step toward cultivating the skills of the digital era (Holmes et al., 2022).

Within the framework of the laboratory activity that was implemented, neural networks were not presented as abstract concepts, but as practical tools that can be connected to real-world problems. The use of educational scenarios involving experimentation with data, such as sunspot data, enables students to understand how the parameters of a system affect the quality of predictions. In this way, students develop both computational thinking skills and scientific inquiry skills (Wing, 2006).

Furthermore, the connection with the teaching of STEM topics highlights how AI can be used to understand complex phenomena in physics and astronomy, strengthening the interdisciplinary character of education (Chassignol et al., 2018). In this way, neural networks can serve not only as



tools of analysis but also as objects of study, offering students an initial introduction to the technologies that are shaping the future.

Artificial Intelligence constitutes one of the most dynamic fields of contemporary science and technology, with applications extending from medicine and industry to education and everyday life (Russell & Norvig, 2021). At its core, AI concerns the development of algorithms and models that imitate human cognitive functions, such as learning, classification, and decision making.

One of the most significant approaches in AI is artificial neural networks (ANNs), which are inspired by the structure and function of the human brain. These networks consist of nodes, or neurons, which are organized into layers and connected to one another through “weights.” Each neuron performs a simple computation, but the collective operation of many neurons within a network can lead to complex data processing (Goodfellow et al., 2016).

The training of neural networks is carried out through the process of supervised learning. In this process, the network receives inputs and compares the outputs it produces with the desired values. The resulting error is used to adjust the network’s weights through optimization algorithms. In this way, the network “learns” to improve its predictions with each iteration, or epoch.

The present study focuses on the use of a Multi-Layer Perceptron (MLP), which constitutes one of the most fundamental forms of artificial neural networks. The MLP consists of an input layer, one or more hidden layers, and an output layer. Despite its simplicity, the MLP is capable of approximating nonlinear relationships and performing tasks such as regression and classification (Haykin, 2009).

An important issue that arises in the use of neural networks is overfitting, that is, excessive adaptation to the training data. This phenomenon occurs when the network “learns” the specific examples provided to it too well and fails to generalize to new data. It may be compared to rote learning in humans, where a student can reproduce what has been learned but struggles to combine it in new ways in order to generate new information. At the same time, when the training parameters, such as the number of iterations, the size of the input window, or the complexity of the architecture, are limited, the model may exhibit underfitting; that is, it may fail to capture the patterns present in the data. Finding the appropriate balance between these two conditions constitutes a central objective in machine learning (Goodfellow et al., 2016).

The use of real data in an educational scenario such as the one presented here allows students to experiment with AI models and investigate how different parameters affect model performance. In this way, students acquire not only knowledge related to neural networks, but also an understanding of the limits of prediction in physical phenomena characterized by complexity and uncertainty.

Sunspots and the Prediction of Solar Activity

Sunspots are dark regions on the surface of the Sun that are associated with intense magnetic activity. Their frequency follows an approximately eleven-year cycle, known as the “solar cycle,” which has significant consequences for space and Earth, such as geomagnetic storms and variations in cosmic radiation (Hathaway, 2015). Predicting their occurrence remains a scientific challenge, as it involves complex, nonlinear processes that cannot be adequately described by simple mathematical models (Usoskin, 2017).

Traditionally, the study and prediction of solar activity have been based on statistical techniques (Conway, 1998). However, in recent years, greater emphasis has been placed on more advanced machine learning methods and physics-based simulations, with the aim of improving prediction accuracy (Kitiashvili, 2020).

Artificial neural networks have proven particularly useful for the analysis of similar phenomena, as they are capable of capturing nonlinear patterns and complex correlations (Goodfellow et al., 2016). In applications related to sunspots, both simple Multi-Layer Perceptron (MLP) models and more



advanced architectures, such as recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) networks, have been used (Asensio Ramos et al., 2018; Oloketuyi et al., 2019).

The use of neural networks offers a promising framework for education and the study of such phenomena, as it enables the investigation of real data while also cultivating skills related to data analysis and the understanding of uncertainty in scientific predictions.

Methodology and Workshop Design

The methodological approach of the present study was based on an experimental scenario involving the application of a Machine Learning model for predicting the number of sunspots. The selection of this specific phenomenon was based on three main factors:

- The availability of extensive historical data related to the occurrence of sunspots (Ossendrijver, 2003).
- Its significance for understanding solar activity and its effects on Earth.
- The fact that solar observation is a key field of activity for the HERON LAB of the University of Thessaly, mainly through the operation of solar radiospectrographs, such as Artemis/Thermopylae.

Neural Network Design – Technical Specifications

The model selected was a Multi-Layer Perceptron (MLP), which constitutes a fundamental category of artificial neural networks. The architecture of the network included three hidden layers with 128, 64, and 32 neurons, respectively, using ReLU as the activation function. The choice of this architecture aimed to achieve a balance between adaptability and the risk of overfitting (LeCun, Bengio, & Hinton, 2015). The final layer included one output neuron for predicting the future value.

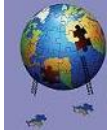
The Adam optimizer was used, with Mean Squared Error (MSE) as the loss function. Training was carried out with different numbers of epochs (20, 50, and 100) in order to identify the optimal balance between prediction accuracy and computational time. In addition, both the deviations observed during the use of training data (training loss) and those observed during the use of new data (validation loss) were recorded and analyzed.

The final evaluation was based on the calculation of MSE, as well as on the graphical representation of the actual values compared with the predicted values. The analysis focused on the model's ability to identify the peaks and troughs of the solar cycle, as well as the regions in which significant deviations were observed.

Workshop Implementation

The workshop was implemented within the framework of the 5th "HERON" Summer School, which took place at the premises of the Evening Junior High School with Lyceum Classes of Pyrgos and involved Lyceum students from the regional unit of Ilia. In order for the students to develop a more comprehensive understanding, prior to the implementation of the workshop, a Physics professor from Aristotle University of Thessaloniki presented to them the way in which Artificial Intelligence learns Physics. The students were introduced in detail to the theoretical background and the operating principles of a neural network.

In the second section, the practical application of what had been presented followed as a natural continuation. After a brief introduction and review of the main points of the theoretical model, as well as of solar phenomena, the activity was divided into two phases. In the first phase, students were shown how to create a neural network themselves using Python code, along with the parameters that can be modified. In the second phase, a more advanced and integrated neural network was used, with a practical application in the prediction of sunspots.



• Phase A

In order for students to become familiar with the basic principles and the creation of a neural network, we implemented a neural network in the Google Colab environment. Python code was used for its implementation. In order not to overburden or discourage the students, the code was provided to them ready-made, and we simply analyzed its mode of operation. For the students' first introduction, we selected the solution of the very simple equation $y = 2x + 1$.

The learning logic of a neural network is relatively simple. Initially, it is provided with the problem to be solved, as well as a set of data. In the case of $y = 2x + 1$, we provided six pairs of values as data: $x = 0, y = 1$; $x = 1, y = 3$; $x = 2, y = 5$; $x = 3, y = 7$; $x = -1, y = -1$; and $x = -2, y = -3$. The neural network takes these data values and attempts to learn from them through a series of trials. At first, with only a small number of iterations, the solutions it produces deviate considerably from the actual ones. However, by increasing the number of iterations and/or adjusting parameters such as the weights, the solutions produced by the network approach the actual solutions.

The students modified parameters in the code and identified their effect on the neural network. In such a simple equation, they observed that the neural network could easily “learn” after a small number of iterations.

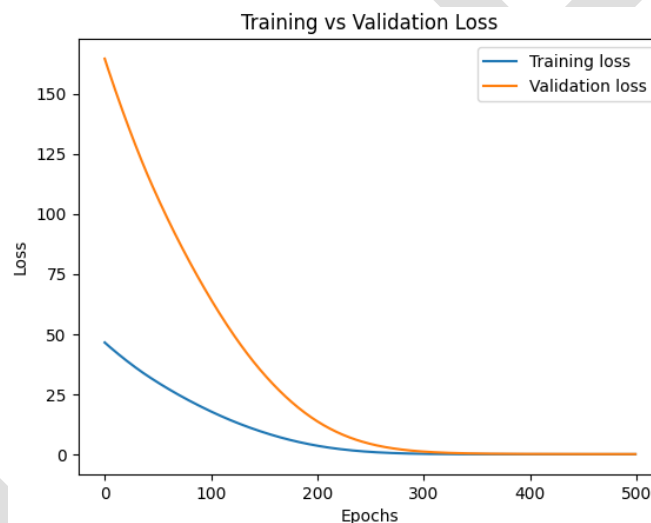
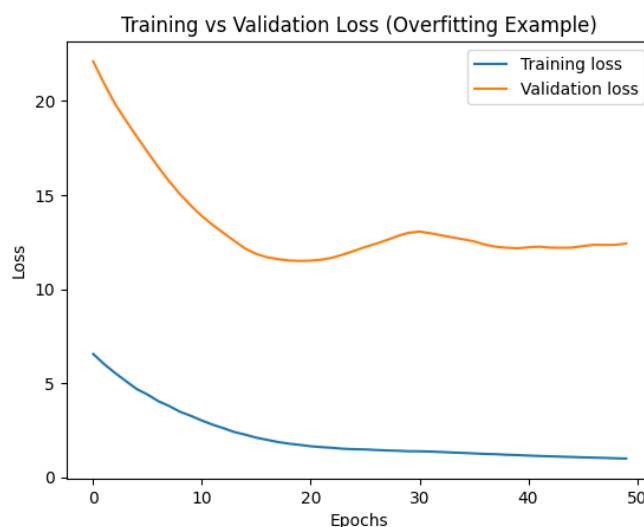


Figure 1. Example of the convergence of actual data (blue) and experimental data (orange) in the case of $y = 2x + 1$.

Figure 1 clearly shows that, with a small number of epochs, the neural network initially presents a significant error both in the data used during the learning process, represented by the blue line, and in real data/predictions, represented by the orange line. As the number of epochs increases, the model's predictions tend toward zero error (Loss = 0), indicating that the model has “learned” and can correctly combine the data.



Subsequently, a more complex model was selected, implementing the equation $y = x^3 + a$, where a corresponded to a noise parameter, so that students could also observe the case of underfitting; that is, the case in which the model had not learned correctly and whose solutions deviated from the actual



ones.

Figure 2. Example of divergence between actual and experimental data (overfitting).

In this case, students observed that the network encountered difficulties and that a series of modifications and adjustments had to be made in order to improve its performance. Figure 2 clearly shows that, although the orange line, which represents the model's actual predictions, initially begins to decrease and approach the blue line, at a certain point it changes direction and ceases to converge. This indicates that the model has not "learned" properly and, consequently, that its predictions will present significant errors.

• Phase B

After the students had become familiar with the logic and operating principles of a neural network, we proceeded to the second phase, using new and clearly more complex code. This code would "teach" a neural network how to predict sunspots. For the data required by the network, we used real data from the Solar Influences Data Analysis Center of the Royal Observatory of Belgium, corresponding to approximately 100 years of solar observations. This volume of data was necessary in order for students to identify the eleven-year cycle of solar activity.

In a network of this size, using a large volume of data, the difficulties involved in model parameterization became immediately apparent. After several trials, students were eventually able to observe that the optimal number of epochs was between 50 and 80. With these parameters, the network error remained at relatively low levels, indicating a satisfactory ability of the model to capture the basic trends in the occurrence of sunspots.

However, prediction accuracy varied depending on the phase of the solar cycle. More specifically:

- The peaks of the cycles were partially predicted, but not with absolute accuracy, a finding consistent with previous studies in which the prediction of maximum values is considered a particularly demanding problem (Hathaway, 2015).
- The troughs, corresponding to low sunspot values, were represented with greater consistency, as they exhibit smaller variation and are more "predictable."



- Regions of intense variability showed the greatest deviations, indicating that the MLP has difficulty capturing the nonlinear and chaotic dynamics of solar activity (Petrovay, 2010).

Figure 3 graphically presents the differences between the actual data and the model's predictions. The visual comparison between the actual and predicted values showed that, although the model captures the general rhythm of the fluctuations, it falls short in predicting sudden changes. This observation made by the students is fully consistent with the expected outcomes, as it was anticipated that the network would not be able to respond accurately in all cases.

In any case, however, the real objective was not the optimal performance of the model, that is, the absolute convergence of the curves, since this would require code adjustments at a level that would be completely difficult for students to understand. Rather, the aim was for students to be able to improve the performance of their network, gradually approaching the actual values more closely each time.

These observations demonstrate that the students not only understood the process of machine learning, but also developed critical thinking regarding the capabilities and

limitations of predictive models. Their engagement with real data strengthened their awareness that Artificial Intelligence is a tool for analysis and not a panacea, thus contributing to the development of a scientific attitude toward knowledge..

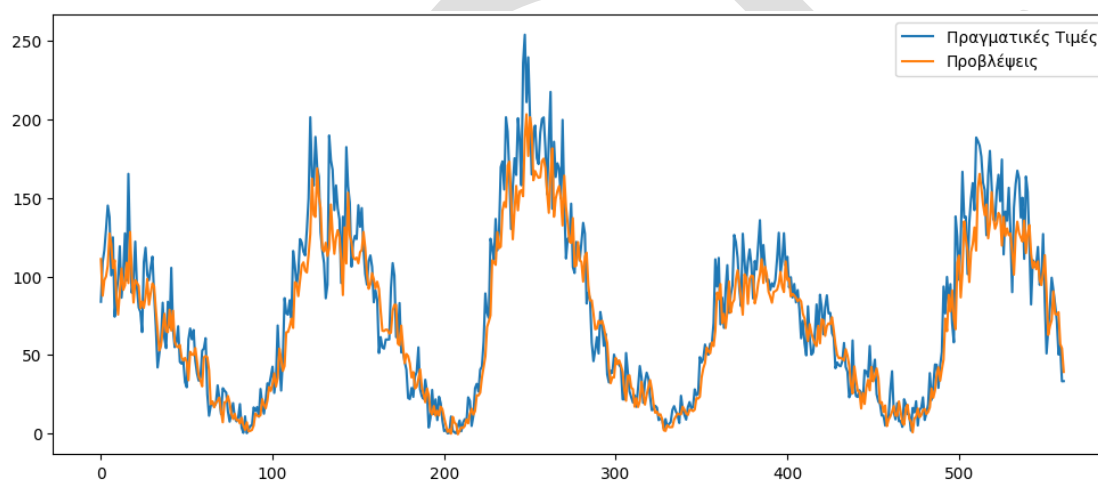


Figure 3. Example of sunspot prediction using real data

DISCUSSION and CONCLUSIONS

The present study highlighted the potential of using a simple Multi-Layer Perceptron (MLP) neural network for the prediction of sunspots. The results showed that, although the model was able to represent the general trends of the phenomenon with relative accuracy, its predictions presented weaknesses mainly at points of intense variability and at the peaks of the cycles. This finding is consistent with previous studies that emphasize the complexity and chaotic nature of solar activity, which makes accurate prediction difficult (Petrovay, 2010; Hathaway, 2015).

From a pedagogical perspective, the workshop enabled students to experiment with real data and to understand basic principles of Artificial Intelligence and neural networks. Their observations revealed that students perceived both the usefulness of AI tools for the analysis of natural phenomena and their limitations. The realization that “there is no perfect prediction” reflects the development of scientific thinking, which is based on the recognition of uncertainty and the multifactorial nature of physical processes (Mitchell, 2019).



Furthermore, the implementation of the workshop connects the teaching of fundamental concepts of Physics with contemporary tools of Computer Science, strengthening interdisciplinarity. This approach is aligned with current directions for education in the digital era, where data skills and algorithmic thinking constitute essential competences (Luckin et al., 2016). The integration of such workshops into school curricula can enhance not only science learning, but also the development of critical thinking, collaboration, and problem-solving skills.

In summary, this study shows that Artificial Intelligence can function both as a scientific tool for the analysis of complex physical phenomena and as a pedagogical means that enhances the learning experience.

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Ethics and Conflict of Interest

All ethical rules were observed at each stage of the research. The author declares that he acted in accordance with ethical rules in all processes of the research. The author declares that they do not have any conflict of interest with other persons, institutions or organizations.

Data Availability

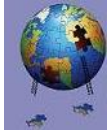
The data that support the findings of this study are available on request from the author.

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