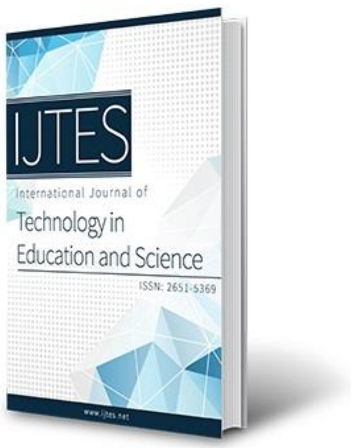

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To cite this article:

Seckin Kapucu, M., Ozcan, I., Ozcan, H., & Aypay, A. (2024). Predicting secondary school students' academic performance in science course by machine learning. *International Journal of Technology in Education and Science (IJTES), 8*(1), 41-62. https://doi.org/10.46328/ijtes.518

International Journal of Technology in Education and Science
2024, Vol. 8, No. 1, 41-62 https://doi.org/10.46328/ijtes.518

Predicting Secondary School Students' Academic Performance in Science Course by Machine Learning

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Article Info

Article History

Received:
23 August 2023
Accepted:
27 December 2023

Keywords

Artificial intelligence
Machine learning
Deep learning
Science
Academic achievement

Abstract

Our research aims to predict students' academic performance by considering the variables affecting academic performance in science courses using the deep learning method from machine learning algorithms and to determine the importance of independent variables affecting students' academic performance in science courses. 445 students from 5th, 6th, 7th, and 8th grades attending a school in Central Anatolian City in Turkey, participated in this study in the 2022-2023 school year. Data was collected with a. A deep learning method called deep neural network, one of the ways of machine learning, was used in data analysis. The average number of books read per year had the highest importance among the variables affecting academic performance in science courses. In addition, deep learning predicted students' final science scores with 90% accuracy. According to the results of this study, the percentage of the academic achievement prediction might be raised by reproducing the required data set for the data analysis method with deep learning. A forecast of the student's academic achievement with artificial intelligence and detecting the importance of variables' percentage might be researched for other courses in addition to the Science course.

Introduction

The notion of Artificial Intelligence (AI) has seemed so distant in our lives until recent decades. In his interview with BBC, Edward Fredkin, the director of MIT Computer Science laboratory, said, "There are three major events in history. The first of them is the formation of the universe. The second is the beginning of life. The third is the emergence of artificial intelligence (AI)" (Prim, 2006). Alan Turing, an important figure in AI (1950), addressed the question "Can machines think?" in his article "Computing Machinery and Intelligence". However, AI was first mentioned by John McCarthy at the Dortmund conference in 1956 (Arslan, 2017). Since then, AI applications have started to appear in our daily lives.

AI, which seemed to be distant and limitedly accessible only to professionals in technology until recently, is now used everywhere, including mobile phones, spam filters, suggestion mechanisms, chat robots, digital assistants, and GPS systems (Marr, 2019). AI has come into every area of our lives in the digitalized world. We use AI daily, from robot vacuum cleaners to shopping websites, vehicle navigation systems, and cell phone applications. It is possible to use AI in education, like in other areas, with machine learning, a sub-branch of AI, by analyzing complex data in the education systems and making faster and more reliable decisions in certain areas.

AI, resulting from imitating human intelligence, is specified as modeling human learning. In AI, computer systems exhibit human abilities such as thinking, learning, and problem-solving. AI could be used in many fields, including voice recognition, image recognition, natural language processing, games, finance, and health. It can produce solutions depending on the existing data and information using algorithms, data analysis, and calculation power. With smart forecasting, learning, and solving complex problems, AI is used directly in education or contributes to it. It entered the classroom and shifted education to different dimensions globally with its "smart, adaptable, or individualized learning systems" (Arslan, 2017).

The problems faced in mandatory distance education during the COVID pandemic that all countries had to cope with in 2019 showed that AI and educational technology must be used effectively. It is clear that the inconveniences in education cause long-term problems for future generations; thus, AI applications must be included in the education process (Coşkun and Gülleroğlu, 2021). Rodríguez-Hernández et al. (2021) analyzed the importance of some well-known determinants of academic performance in higher education. Questa, Cognii, and Kidaptive applications have been used for building AI systems, and AI-powered education platforms such as Knewton and Century Tech have been created (Raza, 2020).

The objectives set by the Ministry of National Education in Turkey for 2023 aim to use AI practices to improve education (İşler, 2021). With advancing technology, AI and its applications should be adapted to education more in Türkiye and around the world, since it may be used to prevent failure in courses for especially disadvantaged students. However, ethical standards should be followed strictly to protect students from the possible negative effects of labeling.

AI, machine learning, and cyber security concepts are primarily used in the digitalized world. Using the records kept in the notebooks before the computer age seems impossible now. Therefore, data mining has come up. Data mining analyses significant relationships in massive data (Savaş et al., 2012). It is impossible to use and analyze such data manually. For this reason, machine learning methods were developed to find the most suitable model for generating and processing new data using historical data (Diri, 2014). Despite the recent drops in dropout rates, it is still relatively high. The rates were 5 percent in the US (NCES, 2023) and while that 9.6 percent in the EU (Eurostat, 2023). Schools can increase their students' success while enriching their academic experiences. Moreover, schools need to keep some students in schools so that society can have a certain number of professionals in some critical areas (Campbell and Dickson, 1996).

Learning is a natural human behavior; it was made a fundamental feature of machines (Shinde and Shah, 2018). Machine learning is a computation algorithm designed to imitate human intelligence by learning from the surrounding environment (El Naqa and Murphy, 2015). Machine learning is a computer's ability to learn from data and then make predictions according to these data. These predictions are usually made by teaching a model. Machine learning methods direct a machine to learn from examples and/or low-level knowledge. What is learned is evaluated according to various criteria; its accuracy is measured, and this accuracy influences the accuracy of subsequent predictions. Machine learning can be used in different fields. However, it is primarily used in various prediction applications such as classification, regression, and artificial neural.

People can predict the future using their education and experiences. However, humans are affected by their emotions and may fail to decide rationally. Also, omitted details may lead to wrong decisions in case of too much data. On the other hand, educated machines can decide rationally in a short time by analyzing millions of data and evaluating all the situations. Modeling human thinking and deciding ability is crucial (İnik and Ülker, 2017). In other words, machine learning is described as developing automated techniques to learn how to make accurate predictions based on past observations (Schapire, 2003).

As the essential element of machine learning is data, machine learning is used in all fields with available data, where it is desired to predict the behavior using previous data's features. Machine learning technology enhances many aspects of society. Machine learning systems are used to describe objects in images, transform speech into text, match news items, posts, or products to users' interests, and select the related search results. These applications increasingly use a technique called deep learning (LeCun, 2015).

The purpose of this study is to predict students' academic performance and determine the relative importance of the variables (gender, grade, father variable-1 father variable-2 (education level), mother variable-1, mother variable-2 (education level), living with parents, number of siblings, having a room, child's travel time to school, weekly study time allocated to science course, time spent on phone, tablet, and computer out of the lesson, having breakfast and lunch regularly, average sleeping time, having a hobby or out-of-lesson activity, the number of books read per year, spending quality time outside school, having friends, family helping students in their study, reviewing the subjects of the science course, having extra lesson for science course) affecting students' academic performance by using deep learning methods which is one of the machine learning algorithms. For this purpose, the following questions were addressed.

1. How is students' academic performance in science courses regarding independent variables?
2. Regarding the analysis made by deep learning, which independent variables predict students' academic performance in science courses?
3. Regarding the analysis made by deep learning, to what extent do independent variables explain/predict/affect students' academic performance in science courses?

Machine Learning and Deep Learning

Machine learning algorithms avoid common problems by classifying massive data appropriately. The hierarchical structure of machine learning algorithms is shown in Figure 1.

Rashidi et al. (2019) classified machine learning models as supervised, unsupervised, and reinforcement learning. Machine learning consists of different machine learning models that use various algorithmic technics. The most prevalent two are supervised and unsupervised learning. In supervised learning, a data set is given to help the model learn; however, in unsupervised learning, the model follows some procedures and learns alone (Alenezi and Faisal, 2020).

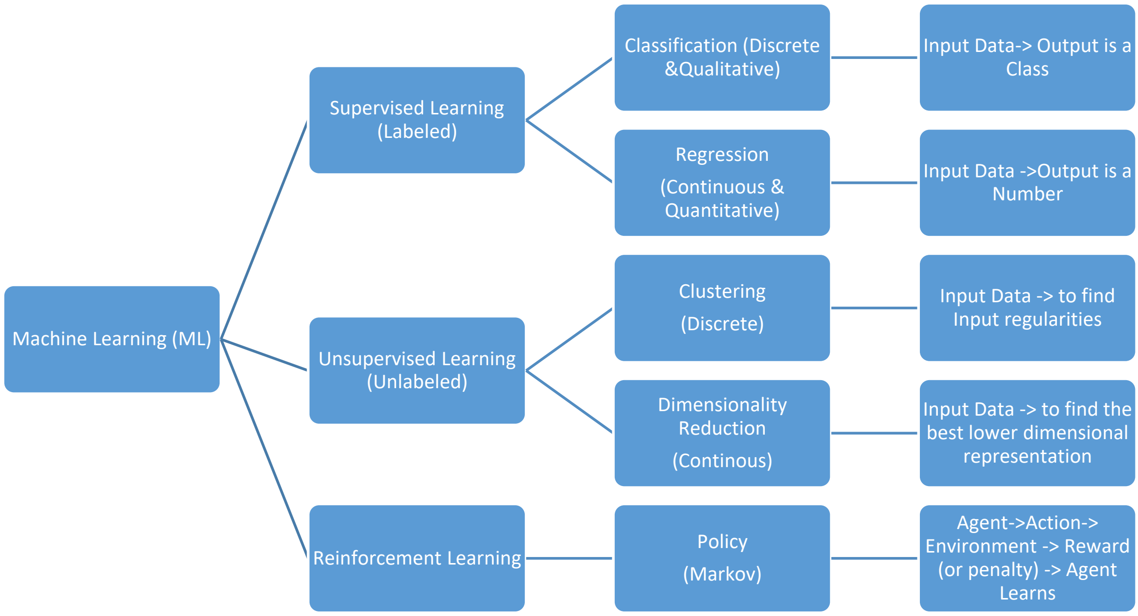

Figure 1. The Hierarchical Structure of Machine Learning Algorithm (Rashidi et al., 2019)

"Deep learning" term has been used for the first time in Machine Learning by Dechter (1986) and introduced in Artificial Neural Nets (NNs) by Aizenberg et al. (2000). Deep learning is one of the sub-branches of machine learning. It has supervised and unsupervised learning models (Aslankaya and Toprak, 2021). Deep learning is an advanced approach to artificial neural nets (Doğan and Türkoğlu, 2018). Deep learning networks are a revolutionary evolution of neural networks, as they are used to achieve more powerful deep learning predictions. (Sakarya and Yılmaz, 2019). Deep learning uses artificial neural networks with a structure similar to the human brain and consisting of neural cells. These neural cells process the data by interacting with each other and make predictions based on this data.

Deep learning context appeared for the first time in 2006 to efficiently train multi-layered artificial neural networks (Yılmaz and Yayın, 2021). It has started to be used in many fields, such as image analysis, voice analysis, robotics, autonomous vehicles, gene analysis, cancer diagnosis, and virtual reality. The main reason behind the widespread use of deep learning is its high accuracy in solving problems with data (İnik and Ülker, 2017). It enables computational models consisting of multiple processing layers to learn data representations at multiple levels of abstraction (LeCun et al., 2015).

Deep learning methods are used in classification, regression, and prediction. For example, voice, image, or text data could be processed using deep learning methods, and classification, regression, or prediction could be made based on these data. In their study, Sakarya and Yılmaz (2019) predicted the value of bist30 using deep learning. In another study, Gündüz and Cedimoğlu (2019) predicted the gender from images using deep learning. Deep learning refers to very deep neural networks (that is, they have many layers). This deep structure makes it possible to interact neural cells with each other. It gives the ability to process data, which allows deep learning methods to process massive complex data to make accurate predictions.

Machine Learning in Education

It seems that there are various variables affecting the academic performance in science courses in literature. Anıl (2009) examined PISA 2006 Turkey's scores and identified the factors affecting academic performance in science. Accordingly, the variable that primarily affects academic performance in science is the father's educational status. As the father's education level increases, students' academic performance in the science course also increases. Attitude is another variable affecting performance in science courses. There is a positive linear relationship between the attitude towards science and the performance in science courses; in other words, as positive attitudes toward science increase, so does science performance. The third factor affecting the performance in science courses is computer usage. The performance in science courses increases with internet access and educational computer programs.

According to a study based on PISA 2009 Turkey scores (Gürsakal, 2012), the scores differed based on gender, in favor of girls in reading and science and in favor of boys in maths. The age of entry into the school is also a significant risk factor regarding performance, which decreases as the age increases. The duration of computer usage at home and school, studying strategies, and parents' education level are important performance factors (Gürsakal, 2012).

Kaya and Kaya (2018) revealed a significant difference in science performance based on the frequency of assignments, the time spent on assignments, attending extra courses, and the duration of extra courses. Çubuk (2019) analyzed the relationship between secondary school students' internet addiction, physical activity, and academic performance and observed that students' academic performance decreases as internet addiction increases. In another study, Abazoğlu and Taşar (2016) studied the relationship between teacher characteristics and science course performance. They found that teacher's job satisfaction, usage of computers in lessons, and teachers' information technologies in-service training indices affected students' science course scores positively and significantly. Atchia and Chinapah (2019) concluded that students' socio-economic level and teachers had a significant impact on students' academic performance. Khan et al. (2015) found a positive and significant relationship between students' academic performance and their parents' education level.

Many factors have been affecting students' success in maths and language, i.e., family, demographics, and school. However, the factors affecting the most and directly have not yet been revealed (Gok, 2017). The factors that affect science course performance can be outlined as follows; student motivation (Tokan and Imakulata, 2019), teacher quality (Darling-Hammond, 2000), students' intelligence (Arbabisarjou et al., 2013), studying habits (Udeani, 2012), family support (Smith and Hausafus, 1998), self-awareness of learning style (Myers and Dyer, 2005), engagement in courses (McGarity and Butts, 1984), exam anxiety (Burns et al., 2021), technology usage (Papanastasiou et al., 2003). Even though these factors affect student performance, a single factor does not usually provide all the answers. A combination of them is needed to achieve sustainable success.

The studies showing which variable affects performance the most or whether it is possible to predict the students' science performance using the above variables have not been found. In addition, no other study used AI to determine the importance of variables that affect secondary school students' academic performance in science courses.

There are some studies on AI. Tosunoğlu et al. (2021) examined the trends in papers on machine learning methods in education. They concluded that studies are concentrated in this field because using AI and computer technology in education/training can improve education quality. In their study analyzing the data collected from vocational high school students, Aydoğan and Karcı (2018) found by machine learning that one of the most important factors affecting student performance and student achievement is family income. Gök (2017) conducted a similar study on language and mathematics course performance using data collected from 6th, 7th, and 8th-grade students, successfully predicting students' course performance using machine learning. Çırak (2012) classified the academic performance of higher education students using the artificial neural network analysis method, one of the sub-branches of AI. The high success of artificial neural network analysis showed that this method could be an alternative in educational studies.

Machine learning is a sub-brunch of AI that can be included in education using machine learning. A substantial amount of data on students, the primary components of the education system, is available. It is possible to use machine learning to predict students' academic performance on this data and determine the variables that affect it. To the authors' best knowledge, there are no deep learning analysis methods for predicting students' academic performance with machine learning in the literature. In this regard, our study is believed to contribute to the literature.

Method

Design of the Study

A correlational survey model was used in this study, aiming to determine the variables affecting secondary school students' science course academic performance. The correlational surveys aim to determine the change and/or its level between two or more variables (Fraenkel and Wallen, 2000; Karasar, 2005). It was aimed to reveal the relationship level between dependent and independent variables in the model.

Participants

The sample of this study was secondary school students from almost every socio-economic level attending a state school in Eskisehir, Turkey, during the 2022/2023 education year. 445 secondary school students were included in this study. Convenience sampling was preferred (Büyüköztürk et al., 2008). The descriptive statistics of the sample are shown in Table 1. Regarding the distribution of the students according to gender and grade, 233 of them (52.35 %) were girls, and 212 (47,65%) were boys. Regarding the grades, 151 (33.9%) were 5th grade, 118 (26.5%) were 6th grade, and 92 (20.7 %) were 8th grade.

Table 1. Descriptive Statistics of Variables Affecting Student Academic Performance

Independent variables		**Frequency (f)**	**Percentage (%)**
Gender	Female	233	52.36
	Male	212	47.64
Grade	5	151	33.93
	6	118	26.52
	7	84	18.88
	8	92	20.67
Father Life Status	Alive	436	97.98
	Deceased	9	2.02
Mother Life Status	Alive	442	99.33
	Deceased	3	0.67
Father Education Level	Primary School	26	5.84
	High School	200	44.94
	Associate Degree	61	13.71
	Undergraduate or Postgraduate Degree	158	35.51
Mother Education Level	Primary School	70	15.73
	High School	179	40.23
	Associate Degree	58	13.03
	Undergraduate or Postgraduate Degree	138	31.01
Number of Siblings	None	91	20.45
	1	235	52.81
	2	82	18.43
	3 or more	37	8.31
Having a room	Yes	400	89.89
	No	45	10.11
Time spent on phone, tablet, and computer out of the lesson	0-30 min.	64	14.38
	30-60 min.	129	28.99
	60-90 min.	127	28.54
	90+ min.	125	28.09
Having a hobby or out-of-lesson activity	Yes	362	81.35
	No	83	18.65
Having Extra Lesson for Science Course	None	241	54.16
	School Course	33	7.42
	Private Teaching Institution	122	27.42
	Private Lesson	40	8.99
	Digital Platform	9	2.02

Independent variables		**Frequency (f)**	**Percentage (%)**
Weekly study time allocated to the science course	0-1 Hour	173	38.88
	1-3 Hours	197	44.27
	3 + Hours	75	16.85
Number of multiple-choice test questions solved	None	45	10.11
	30-50	194	43.60
	50-100	113	25.40
	100-250	73	16.40
	250-500	20	4.49
Number of books read per year	None	16	3.60
	Less than 10	130	29.21
	10-12	144	32.36
	More than 12	155	34.83
Reviewing the subjects of the Science course	Yes	290	65.17
	No	155	34.83
Travel time to school	0-15 min.	232	52.14
	15-30 min.	136	30.56
	30+ min.	77	17.30
Average Sleeping Time	Less than 6 hours	46	10.38
	6-8 hours	273	61.35
	More than 8 hours	126	28.31
Having lunch regularly	Yes	289	64.94
	No	156	35.06

436 (98%) students' fathers and 442 (99%) mothers were alive. 200 (45%) of fathers and 179 (40%) of mothers were high school graduates. 235 (53%) of the students had a sibling. In addition, 400 (90%) students had a room. Concerning the devices students own and technology usage, 129 used technological tools for 30-60 minutes during the day. 362 (81%) of the students had out-of-class activity. 241 (54%) do not have extra lessons out of class. Regarding students' studying and book reading habits, 197 (44%) students allocated 1-3 hours to the science course weekly. Again, 194 (44%) students solved 30-50 science questions weekly. 155 (35%) of these students read more than 12 books yearly. 290 (65%) of them repeated science course subjects.

Students’ eating and sleeping habits, and travel time to school; 329 students had breakfast in the morning regularly, and 289 (65%) had lunch. 232 (52%) students' travel time was 0-15 minutes. 273 (65%) students slept 6-8 hours daily.

Data Collection Tool

We developed the "Variables Affecting Student Academic Performance" scale in this study to collect data. First of all, the factors affecting the academic performance of secondary school students were identified by reviewing the relevant literature. Information about the student's family, studying environment, and teachers was included in the light of the findings in the literature. A draft form questioning the student's grade, characteristics of the parents and family, and studying and eating habits was prepared. The draft form has taken its final form after taking the expert opinion. A science expert and an expert in assessment and evaluation were consulted.

Data Collection Procedure

In order to administer the scale to the participants in the sample, permission was first obtained from the Human Research Ethics Committee of Eskişehir Osmangazi University Social and Human Sciences. Then, we applied to the school administration with this permission letter. An information letter was sent to the students' families who would participate in the study. The participation was voluntary, and the scale was administered to the children whose parents provided permission. On average, the application took about 15 minutes.

Data Analysis

The deep learning method, one of the machine learning methods, was used in this research. The deep learning is a multi-layered artificial neural network (see Figure 2). This method works well for solving complex problems because of the number of layers. This is where the term "depth" comes from. The model learns better as the number of layers in the artificial neural network increases (Çarkacı, 2018). Four hidden layers were used in this study, each consisting of 19 neurons. This number was preferred because the number of features given as input to the system was 19. Previous studies showed that the results are predicted more accurately when the number of neurons in the hidden layers is determined based on the number of inputs. The number of hidden layers is not limited. However, as each neuron in each layer performs mathematical operations with other neurons, too many layers will cause the operations to take too long, thus prolonging training. Generally, the number of layers is determined by analyzing previous studies and/or trial and error.

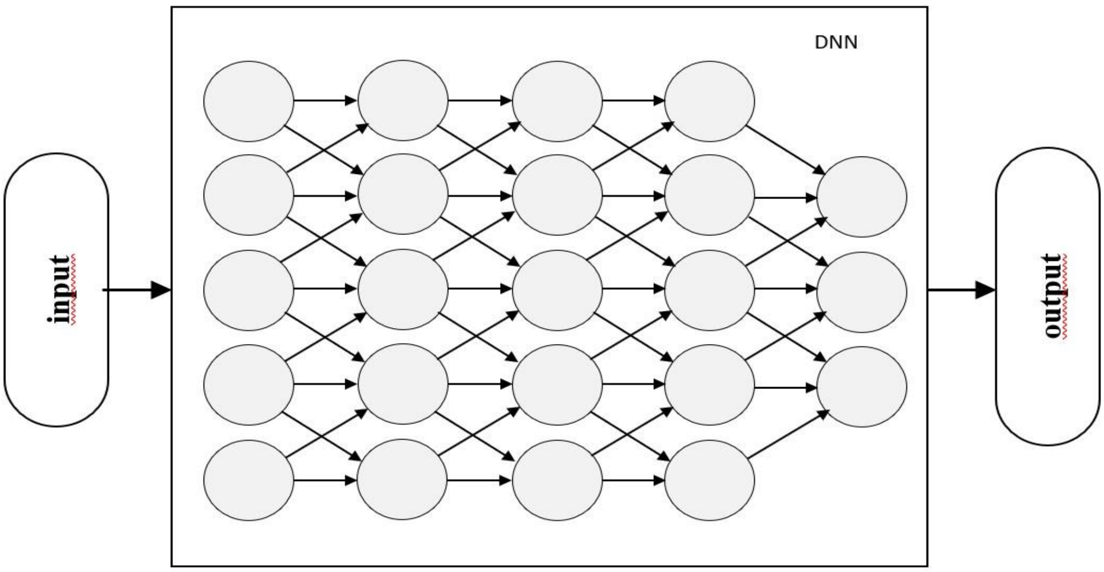

Figure 2. Deep Neural Network (Montavon et al., 2018)

ReLU (see Figure 3) was chosen as the activation function. The activation function converts the input signal of a node in the artificial neural network into an output signal by applying a transformation. In the ReLU (Rectified Linear Unit) function, negative values are valued as "0" (Agarap, 2018), allowing it to function faster and more efficiently than the Hyperbolic Tangent and Sigmoid functions. For this reason, the ReLU activation function was preferred in our model. Adam (Adaptative Momentum) optimization technique, a popular method used to get fast and accurate results in deep learning methods, was used. Mae was used as the Loss function. Loss functions measure success on the data set of deep learning models. If the success is high, the function is low, and vice versa.

The data collected via the "Variables Affecting Student Academic Performance" scale was loaded in the free GPU (Graphic Processor Unit) supported colab.researc.google.com medium provided by Google for researchers, in Excel format (with .xlsx extension) to be processed by the deep learning method. The processor could not do this alone because deep learning requires relatively high mathematics processes. Thus, carrying out the transaction in the Graphic Processor Unit (GPU) gives quicker results. The questions in the scale were coded as 0-1-2-3-4 before the analysis, and the codes are shown in Table 2.

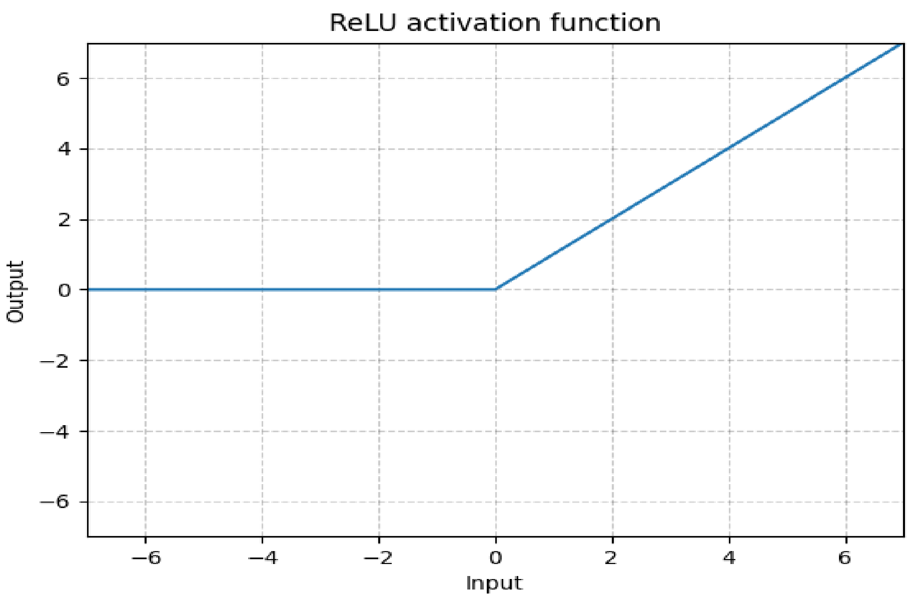

Figure 3. ReLU Activation Function

Table 2. Codes

Independent Variables	**0**	**1**	**2**	**3**	**4**
Gender	Female	Male			
Grade	5	6	7	8	
Father Variable-1	Deceased	Alive			
Father Variable-2 (Education Level)	Primary School	High School	Associate Degree	Undergraduate or Postgra	

Independent Variables	0	1	2	3	4
				duate	
Mother Variable-1	Deceased	Alive			
Mother variable-2 (Education level)	Primary School	High School	Associate Degree	Undergraduate or Postgraduate	
Number of Siblings	None	1	2	3 and more	
Having a Room	None	Yes			
Child's travel time to school	0-15 min.	15-30min.	30 + min.		
Weekly study time allocated to science	0-1 hour	1-3 hours	3+ hours		
Time spent on phone, tablet, and computer out of the lesson	0-30 min.	30-60min.	60-90 min.	90+ min.	
Having Breakfast Regularly	No	Yes			
Having Lunch Regularly	No	Yes			
Average Sleeping Time	<6 hours	6-8 hours	>8 hours		
Having a hobby or out-of-lesson activity	No	Yes			
Number of Books Read per Year	None	<10	10-12	>12	
Reviewing the subjects of the Science course	No	Yes			
Having extra lessons for the science course	None	School Extra Course	Private Teaching Institution	Private Lesson	Digital Platform

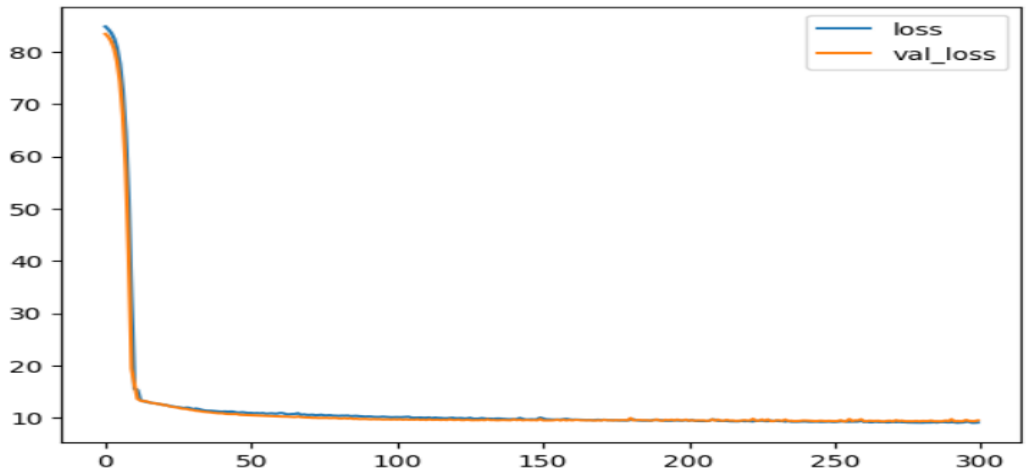

Figure 4. Loss Data Graph

The data set generated by the students through the scale was classified using the Scikit-learn library of the Python programming language, and these results were analyzed in detail. 70% of the collected data was used as training data and 30% as test data. After training, the training data is compared with the test data. If the loss curves of the training and test data are close, as shown in Figure 3, it can be said that the training was done correctly.

Findings

This section presents the findings from the data analysis according to the sub-objectives.

Students' Academic Performances in Science Courses Based on the Independent Variables

First, descriptive statistics of the independent variables affecting the academic performance of secondary school students (gender, grade, father variable, mother variable, parents' togetherness, number of siblings, having a room, child's travel time to school, weekly study time allocated to science, time spent on phone, tablet, computer out of the lesson, having breakfast and lunch regularly, average sleeping time, having a hobby or out of lesson activity, the number of books read per year, spending quality time outside school, having friends, family helping students in their study, reviewing the subjects of the science course, having an extra lesson for science course) were analyzed. The results are shown in Table 3.

Table 3. Descriptive Statistics Regarding Academic Performance of the Groups

Independent Variables		**min**	**max**	**avgscore**	**sd**
Gender	Female	30	100	85.96137	13,31622
	Male	30	100	83.20283	16,09072
Grade	5	40	100	88.95364	12,85786
	6	30	100	83.05085	14,86742
	7	30	100	81.55952	16,36581
	8	40	100	82.44565	14,59141
Father Alive/ Deceased	Alive	30	100	84.63532	14,72046
	Deceased	45.00	100	85.22222	17,13752
Mother Alive/ Deceased	Alive	30	100	84.66968	14,76803
	Deceased	65	90	81.33333	14,15392
Father Education Level	Primary School	35	100	75.80769	18,33253
	High School	30	100	83.445	13,60635
	Associate Degree	40	100	85.36066	15,95831
	Undergraduate or Postgraduate	30	100	87.3481	14,40671
Mother Education Level	Primary School	35	100	82.82857	15,52368
	High School	30	100	82.44134	14,5363
	Associate Degree	40	100	86.37931	14,95587
	Undergraduate or Postgraduate	40	100	87.7029	14,05381

Independent Variables		min	max	avgscore	sd
Number of Siblings	None	30	100	81.48352	16,69688
	1	40	100	86.45957	13,50916
	2	40	100	85.5	13,44054
	3 and above	30	100	79.02703	17,69728
Having a Room	Yes	30	100	85.06484	14,17448
	No	35	100	80.84091	19,01033
Child's travel time to school	0-15 min.	30	100	84.37931	15,07365
	15-30 min.	30	100	84.06618	15,83957
	30+ min.	42	100	86.48052	11,43357
Having a hobby or out-of-lesson activity	Yes	30	100	84.74586	14,31972
	No	30	100	84.21687	16,59051
Having extra lessons for the science course	No	30	100	83.78008	15,75904
	School Course	40	100	79.18182	15,98721
	Private Teaching Institution	40	100	86.22951	12,8319
	Private Lesson	60	100	90.375	9,300365
	Digital Platform	55	100	81	20,10926
Weekly study time allocated to science	0-1 Hour	30	100	81.0578	16,72267
	1-3 Hours	35	100	85.95431	13,40358
	3 + Hours	45	100	89.49333	11,01274
Number of Multiple-Choice Test Questions Solved	No Solving	30	100	77.48889	19,63487
	30-50	30	100	82.10825	15,25852
	50-100	45	100	87.43363	12,44909
	100-250	40	100	89.79452	9,976304
	250-500	45	100	90.85	12,67934
Time spent on phone, tablet, and computer out of the lesson	0-30 min.	30	100	85.90625	15,29988
	30-60 min.	35	100	85.28682	13,90829
	60-90 min.	45	100	87.3622	12,46116
	90+ min.	30	100	80.584	16,65261
Number of Books Read per year	None	45	95	77.0625	15,85126
	Less than 10	30	100	79.35385	17,46619
	10-12	30	100	85.80556	13,38263
	More than 12	50	100	88.79355	13,78704
Reviewing the subjects of the Science course	Yes	30	100	85.65172	13,38263
	No	30	100	82.76774	11,5262
Regular Breakfast	Yes	30	100	85.11585	13,78704
	No	45	100	83.33333	16,28473

Independent Variables		**min**	**max**	**avgscore**	**sd**
Average Sleeping Time	Less than 6 hours	45	100	81.5	14,74157
	6-8 hours	30	100	85.02564	14,7619
	more than 8	30	100	84.97619	14,91718
Regular lunch	Yes	30	100	84.67474	14,62105
	No	30	100	84.59615	14,9519

Predicting Students' Test Score Data

In this study, the mean absolute error (MAE) was 9.97, meaning that the accuracy of predicting the academic performance score was 90%. Predicted scores were very accurate for some students. For example, Student #10's actual score was 90, while the predicted score was 92. Some students' actual and predicted scores were even the same, i.e., students #78, #85, #106, and #108.

Deep learning predicted scores between 0-70 higher than actual. The actual score of student #10 was 64, and the predicted score was 95. The actual score of student #15 was 40, and the predicted score was 99. The actual score of student #120 was 65, and the predicted score was 82 (Table 4). This is due to the method used by deep learning to train the data. In deep learning, learning occurs using the data loaded for training. In this dataset, the loaded data was predominantly in the 85-100 points range. After the completion of the learning process, the score prediction tended to be in the 85-100 range.

Table 4. Predicted Students' Score in Test Data.

Index	**Actual Score**	**Predicted Score**	**Index**	**Actual Score**	**Predicted Score**	**Index**	**Actual Score**	**Predicted Score**	**Index**	**Actual Score**	**Predicted Score**
0	64	95.0	34	60	99.0	67	90	74.0	100	100	93.0
1	75	83.0	35	45	77.0	68	85	89.0	101	93	91.0
2	95	96.0	36	100	97.0	69	94	89.0	102	70	93.0
3	95	88.0	37	78	88.0	70	98	97.0	103	100	95.0
4	75	80.0	38	60	91.0	71	75	78.0	104	98	87.0
5	40	99.0	39	79	89.0	72	95	97.0	105	100	90.0
6	100	75.0	40	100	91.0	73	90	94.0	106	100	100
7	90	92.0	41	92	98.0	74	98	83.0	107	100	98.0
8	95	87.0	42	90	94.0	75	95	88.0	108	100	100
9	80	83.0	43	98	99.0	76	50	75.0	109	90	76.0
10	90	89.0	44	75	81.0	77	88	88.0	110	85	80.0
11	95	80.0	45	92	91.0	78	100	100	111	85	80.0
12	95	83.0	46	98	100	79	90	85.0	112	95	93.0
13	80	75.0	47	95	88.0	80	75	77.0	113	90	93.0
14	88	89.0	48	85	89.0	81	45	66.0	114	85	97.0

Index	Actual Score	Predicted Score	Index	Actual Score	Predicted Score	Index	Actual Score	Predicted Score	Index	Actual Score	Predicted Score
15	95	98.0	49	50	89.0	82	80	95.0	115	85	86.0
16	82	83.0	50	94	95.0	83	80	84.0	116	55	84.0
17	100	100	51	85	95.0	84	85	89.0	117	90	92.0
18	80	91.0	52	80	78.0	85	75	75.0	118	97	85.0
19	86	91.0	53	100	91.0	86	60	77.0	119	70	93.0
20	65	82.0	54	90	91.0	87	85	87.0	120	85	82.0
21	70	75.0	55	95	83.0	88	100	99.0	121	100	98.0
22	80	88.0	56	88	96.0	89	100	88.0	122	60	74.0
23	50	81.0	57	70	83.0	90	80	68.0	123	60	75.0
24	65	85.0	58	56	70.0	91	80	95.0	124	95	77.0
25	52	84.0	59	85	83.0	92	95	85.0	125	92	84.0
26	70	81.0	60	100	89.0	93	85	67.0	126	85	73.0
27	96	95.0	61	92	74.0	94	86	100	127	95	91.0
28	79	83.0	62	96	94.0	95	86	85.0	128	82	83.0
29	85	79.0	63	95	85.0	96	75	93.0	129	85	92.0
30	90	88.0	64	80	80.0	97	96	96.0	130	92	92.0
31	77	98.0	65	70	86.0	98	45	60.0	131	85	85.0
32	90	90.0	66	90	84.0	99	92	93.0	132	92	94.0
33	72	86.0									

Regarding the distribution and percentiles of the scores, 3.6% of them were in the range of 0-45, 2.92% in the range of 45-55, 10.56% in the range of 55-70, 27, 64% in the range of 70-85, and 55.28% in the range of 85-100.

The importance of variables affecting secondary school students' academic performances

Table 4 shows the effect of the variables that affect secondary school students' academic performances in science courses. Some variables have a negative effect because academic performance is negatively affected as the numerical value of these variables increases. Regarding the variables that positively affect academic performance, the number of books read has the highest effect, with 27%. The number of practice test questions solved is the second most effective variable, with 21%.

Another important finding of the study was that secondary school students' science course performance increased as the father and mother's educational level increased. Other dependent variables that positively influenced academic performances were studying time, extra lessons (private lessons, courses), having a room, having regular breakfast, and sleeping time. The independent variable that most negatively affected secondary school students' academic performance in science was the grade. As the grade increases, academic performance decreases. Boys had lower academic performance than girls did. In addition, a high amount of time spent on the telephone and

Internet caused a decrease in their academic performance in science courses.

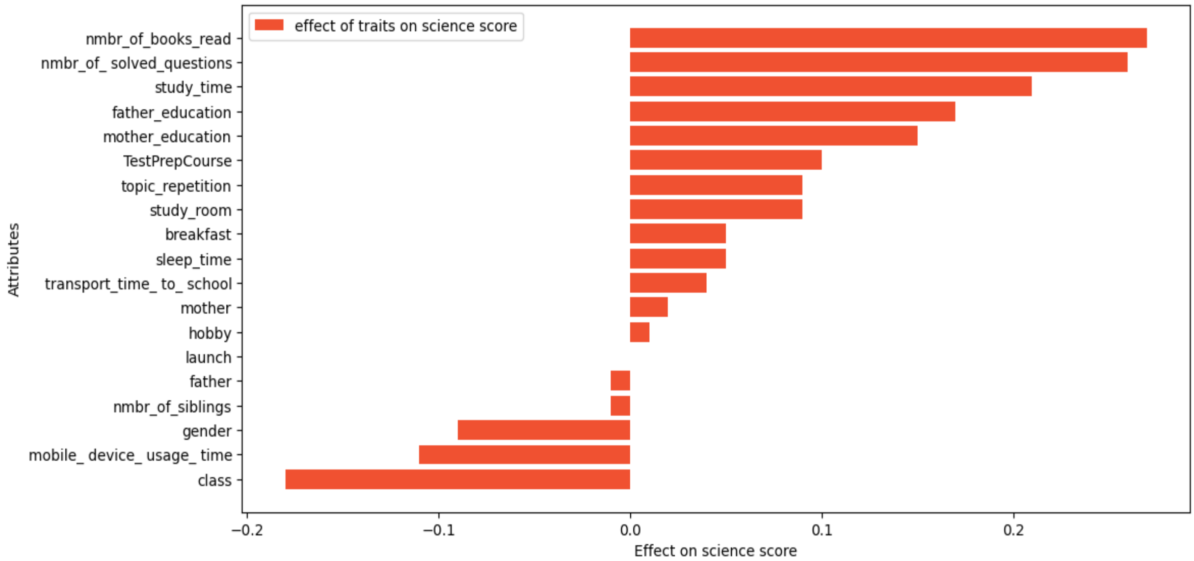

Figure 5. Importance of Variables

Discussion and Conclusion

This study aimed to determine the variables that affect the academic performance of secondary school students in science courses using machine learning and deep learning methods, one of the sub-branches of machine learning. For this purpose, the "Variables Affecting Student Academic Performance" scale was administered to 445 students, and the data obtained were analyzed using Python programming language. 70% of the data obtained from 445 students was used as training data, and 30 % was used as test data. According to the analysis results, the academic performance of secondary school students in science courses was predicted with an error margin of 9.95%.

According to Inik and Ülker (2017), the main reason for the widespread use of deep learning is the high accuracy in solving the problem using available data. Ahmad and Shahzadi (2018) used machine learning methods to investigate whether students are at risk regarding academic performance. They achieved 85% classification accuracy in predictions using students' learning skills, studying habits, and academic interactions as variables. Cruz-Jesus et al. (2020) used machine learning methods (logistic regression, random forest k-nearest neighbor, and support vector machines) to predict students' academic performance using 16 demographic variables, including age, gender, class attendance, Internet access, computer ownership, and the number of courses. As a result, they could predict student performance with an accuracy ranging from 50% to 81%. In the current study, the prediction accuracy of deep learning using data collected from students in a secondary school in Türkiye was 90%.

The study revealed the importance of variables that affect students' academic performance in science courses. Regarding the importance of the independent variables, the most positively influential factor was the number of books read, with 27%, followed by solving questions, with 21%. The increase in the time spent on technology usage, higher grades, and the number of siblings negatively affected students' academic performance in science courses. In addition, another finding of the study was that girls were more successful in science than boys. Unlike other studies, the importance of the number of questions solved, subject repetition, and number of books read per year were quite high on the academic performance of secondary school students in science courses. All the variables contributed, the majority of the study variables (13) contributed positively while some (5) variables related negatively to predicting the academic performance of students.

Studies since the 1960s (Coleman et al., 1966) consistently found that parental educational level is the most important factor in predicting student achievement. ML assessment could increase the validity and reliability of teacher assessments (Hilbert et al., 2021). Campbell and Dickson (1996) in their meta-analysis of 162 studies found that GPA in science and nursing courses was the main predictor while the parental educational level was the most important demographic predictor. Miguéis et al., (2021) predicted that university students' performance students with an accuracy of 95 %. Selwyn (2022) argued that if planned and used correctly, AI wouldn't have any biases for students concerning their gender, SES, race, and personality. Moreover, AI will help teachers as assistants freeing them from bureaucratic work, routines, and duties, and providing intelligent support for students for a personalized education. AI-driven tools may nudge students to make decisions so that they can get more advantageous educational outcomes. These tools could also be used to support students who require special education with "socially assistive" programs to enhance social and emotional skills, and communication so that they can learn better (Selwyn, 2022).

On the other hand, there are critics of AI. For example, Davies et al,. (2021) caution about techno solutionism using AI in educational problems. Fullan et al., (2023) argue that we should not make assumptions about the future of AI since no one knows about the future looks like. Rather we should how we can position the education system around AI. And then, we should invest in the development of social intelligence of all individuals collectively in school. While there is no "quick fix" in education, technology constantly changes the power and control in education (Selwyn, 2011).

Based on the results of this study, the following suggestions can be made: The accuracy of the predictions for students' academic performance can be improved by extending the data set of the deep learning data analysis method. Students' academic performance can be predicted, and the importance of variables can be determined in courses other than science. With the changing and developing technology, AI can be used in education for predicting performance and in other studies. In particular, AI can reduce the routine and bureaucratic workloads of school administrators, teachers, and other school staff. As a result, all administrators, teachers, and school staff may spend their time to improve student learning. This research is limited to the variables covered by the "Variables Affecting Student Academic Performance" scale. Future studies can repeat the study by including other variables (student motivation, teacher quality, student intelligence, studying habits, family support, student learning style, student attendance, test anxiety, technology use) that are related to student performance. This study used the Python programming language, which has an extensive library, for deep learning. In future studies, other machine learning techniques, such as Polynomial Regression and Random Tree, can be used in data analysis, and the results can be compared with this study. This study was conducted on secondary school students. It can be repeated with students at different grade levels and with different samples.

This study is limited to the following variables: gender, grade, father variable-1 father variable-2 (education level), mother variable-1, mother variable-2 (education level), parents' togetherness, number of siblings, having a room, child's travel time to school, weekly study time allocated to science, time spent on phone, tablet, computer out of the lesson, having breakfast and lunch regularly, average sleeping time, having a hobby or out of lesson activity, the number of books read per year, spending quality time outside school, having friends, family helping students in their study, Reviewing the subjects of the Science course, having extra lesson for science course). It is also limited to 445 secondary school students from a state school in Eskisehir in the 2022-2023 education year. In addition, it is limited to the "Variables Affecting Student Academic Performance" scale prepared by the researchers. Finally, we are not sure of all the consequences of AI yet. However, we can think and discuss the ways in which we can position our educational systems around AI. Machine learning can be used to predict students' engagement or disengagement levels (or possible drop-outs) in other courses. Knowing these possibilities may help the teacher or the system provide extra help for students who may likely fall behind with ethical considerations such as not labeling or classifying students. This may help the completion of other courses and schools. Future research may focus on how to improve student achievement based on family as well as classroom data.

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