A Data-Driven Approach to Determining Safe Classroom Capacities During the Transition to Face-to-Face Education

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In this paper, different models have been developed to estimate how many students should be in the existing classrooms to be less affected and protected from the Covid19 virus during transition to face-to-face education. The factor that determines the risk of transmission of the Covid 19 virus is not only physical distance, but the duration of exposure. In this direction, model has been created by Fuzzy Logic method to evaluate the efficiency of classrooms in terms of physical sizes using the classroom and window sizes of existing primary schools. Various models have been developed by using the data obtained in line with the developed model. After the evaluation of the obtained models, it was concluded that deep neural networks model can be accepted as a more suitable approach for this estimation problem than other supervised learning methods. It is expected that the developed model will help the guidelines prepared for taking necessary precautions in educational structures and making arrangements to prevent the transmission of the virus. Developed with the data obtained by examining only the primary school classrooms, developed models can also be applied with the data to be obtained by examining the classrooms of different levels.

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Yüz Yüze Eğitime Geçiş Sürecinde Güvenli Sınıf Kapasitelerinin Belirlenmesine Yönelik Veri Odaklı Bir Yaklaşım

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Bu çalışmada, yüz yüze eğitime geçiş sürecinde mevcut sınıflarda kaç öğrencinin bulunması gerektiğini tahmin etmek amacıyla farklı modeller geliştirilmiştir. Covid-19 virüsünün bulaşma riskini belirleyen faktör yalnızca fiziksel mesafe değil, aynı zamanda maruz kalma süresidir. Bu doğrultuda, mevcut ilkokul sınıflarının ve pencere boyutlarının kullanılarak sınıfların fiziksel boyutlar açısından verimliliğini değerlendirmek için Bulanık Mantık yöntemiyle bir model oluşturulmuştur. Geliştirilen model doğrultusunda elde edilen veriler kullanılarak çeşitli modeller geliştirilmiştir. Elde edilen modellerin değerlendirilmesi sonucunda, derin sinir ağları modelinin bu tahmin probleminde diğer gözetimli öğrenme yöntemlerine kıyasla daha uygun bir yaklaşım olduğu sonucuna varılmıştır. Geliştirilen modelin, eğitim yapılarında gerekli önlemlerin alınması ve virüsün yayılmasını önlemeye yönelik düzenlemelerin yapılması için hazırlanan yönergelere katkı sağlaması beklenmektedir. Yalnızca ilkokul sınıfları incelenerek elde edilen verilerle geliştirilen modeller, farklı eğitim seviyelerindeki sınıfların incelenmesiyle elde edilecek verilerle de uygulanabilir.

Anahtar Kelimeler: Makine öğrenmesi, Derin öğrenme, Covid-19, Karar verme, Eğitim yapıları.

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1. INTRODUCTION

Corona virus (COVID-19) disease first appeared in Wuhan, China and has been described as a global epidemic by the World Health Organization as of March 11, 2020, as it began to spread rapidly around the world. Because of the transmission of the virus by contact and droplet (Huang et al.,2020; Liu et al., 2020), countries have taken various measures and applied some restrictions to be less affected and protected from this epidemic. The World Health Organization (2021) has stated that some simple precautions should be taken, such as maintaining physical distance, wearing a mask, well ventilating rooms, avoiding crowds, cleaning your hands, and coughing up bent elbow or tissue. In addition, in line with these measures and restrictions, some countries have implemented curfews with full closure or intermittent closure strategies to encourage people to stay home. Another of the measures taken was the closure of educational institutions. The United Nations Educational, Scientific and Cultural Organization (UNESCO, 2021) stated that on March 16, 2020, about 762 million students were affected by the closure of educational institutions. In addition, according to UNESCO (UNESCO, 2021) data, schools in Turkey were closed for a total of 47 weeks (**Figure 1**).

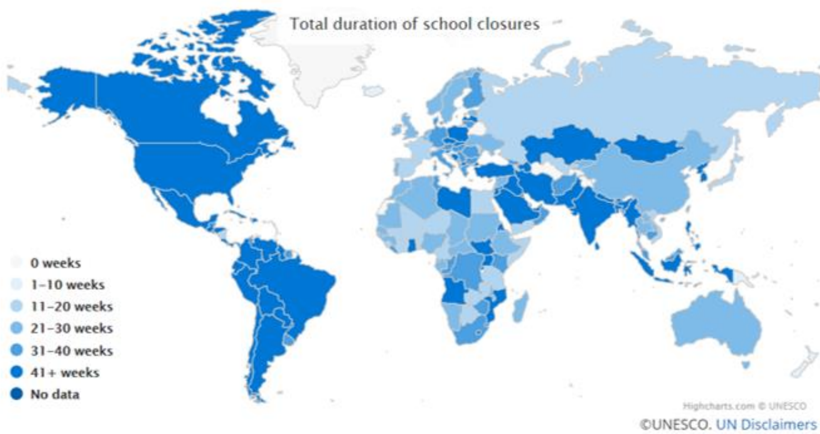


Figure 1: Total time schools were closed by country (UNESCO, 2021).

Although the purpose of closing schools was to prevent the virus from spreading within institutions and being transmitted to vulnerable individuals, these closures have had widespread socioeconomic consequences (Nicola et al., 2020). Keogh-Brown et al. (2010) noted that closing schools during an influenza epidemic will result in further reductions in labor supply, with lost working days as an indirect result of the disease, as parents (mostly) stay at home to care for their children.

The measures and restrictions made have affected many areas such as economy, education, health, art, entertainment. After the detection of the first case, the education was switched to the online education system conducted remotely. The transition to online learning instead of the traditional face-to-face learning mode in the Covid 19 epidemic has caused various effects on students' academic performance, physical and psychological health (Li and Che, 2022). Online teaching, which allows students to learn anywhere and with relatively flexible scheduling, is particularly suitable for mature students and has greatly benefited schools that have closed due to the Covid19 virus (Yu et al.,2021). During this transition, students need access to technology (internet connection, computer etc.), appropriate learning environment and parents who can support learning in online education especially for younger students. While this distance education has specific challenges for all students, it is more disadvantageous for students who do not have access to technology.

It is necessary to create an environment where all students in the class can share their ideas and experiences. It is especially important to introduce primary school students to different social environments and to allow them to discuss their feelings afterwards, to explain the importance of social interactions and develop trust and responsibility during peer-to-peer communication (Alsubaie, 2022). However, online education limits face-to-face interaction (Alsubaie, 2022) and may bring difficulties such as teacher-student compatibility, time management, motivation and technical problems in learning for primary school students (Gupta, 2021). Students face various problems during the transition from traditional education to online education. Some of these challenges are as follows (Neuwirth et al., 2021):

- ✓ The absence of a private area in the home environment or the absence of a quiet environment,
- ✓ Inability to have someone else watch their child/parent,
- ✓ Close enough to distract him/her with other family members at home,
- ✓ Domestic animals in the house etc.

A controlled return to social life has been initiated in countries with the discovery of various vaccines for this virus, which is a global epidemic. In this process, online education has gradually begun to transition to face-to-face education. Examining the precautions to be taken and the rules to be followed during the transition to face-to-face education in a controlled manner in educational buildings and, accordingly, evaluating the reuse is the most important way to combat the epidemic with architectural and engineering control (Yetiş and Kayılı, 2021). The COVID-19 virus is spread through liquid particles produced by breathing, speaking, shouting, singing, coughing, and sneezing, and therefore various measures must be taken to minimize the possibility of further transmission of the virus brought to school. The rapid precipitation rate of large droplets, physical distance, surface disinfection, ventilation and hand hygiene are the basis of the measures taken (Lordan et al., 2020). Therefore, in face-to-face education, measures such as keeping a distance, wearing masks in the corridors, hand hygiene and ventilation of classrooms have been taken to reduce the transmission of the virus to other people from the people who come to the school with the virus.

The concept of urban resilience against pandemics has come to the fore with the global prevalence of the COVID-19 disease, and a series of principles, starting from spatial levels, need to be addressed for urban resilience (Amirzadeh et al., 2022). Gaisie et al. (2022) argued that the evolution of the COVID-19 epidemic, which has become widespread since early 2020, proceeds through built environment features such as diversity, destination accessibility, travel distance, design and density. Urban mobility in the post-COVID-19 era is likely to depend on the prevalence and degree of acceptance of these remote online activities and social awareness of the future of cities, with several complex and interconnected factors related to urban form, spatial planning and decision-making (Mouratidis and Papagiannakis, 2021). Human mobility, a basic requirement of daily life, was most directly affected during the COVID-19 pandemic (Liu et al., 2023). Therefore, to control this interaction, there must be a certain distance between students in the classrooms.

Infection control and physical distancing measures are essential to prevent further spread of the virus and help contain the pandemic situation (Amir et al., 2020). The social distance recommended by the

CDC (Interim Guidance for Businesses and Employers Responding to Coronavirus Disease COVID-19) for physical distancing during the Covid19 pandemic is 6 feet, which is often visualized as a 3 feet radius circle with individuals at the center (American Institute of Architects, 2020). Since circles with a radius of 3 feet do not account for human movement, it is valid when people are standing in a row or sitting six feet apart from each other, and physical distance is violated when people move in space when the physical distance between each person is 6 feet (**Figure 2**) (American Institute of Architects, 2020).

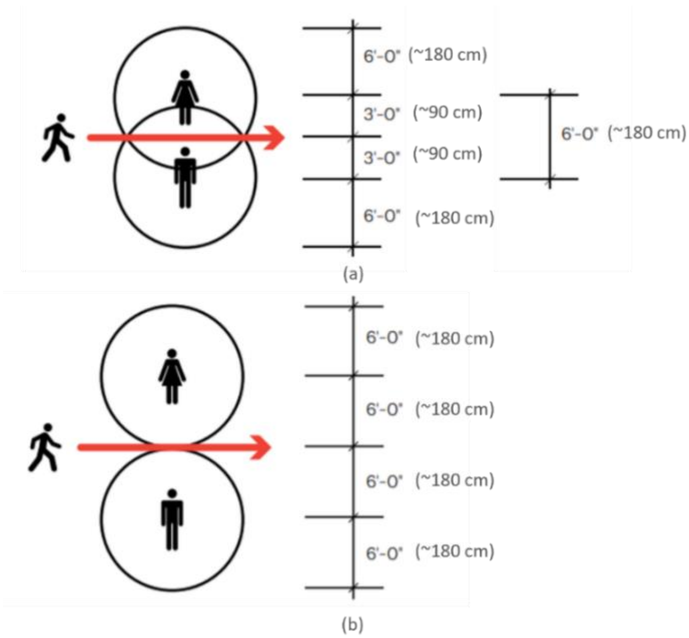


Figure 2: (a) Physical distance not allowing movement (b) Physical distance allowing movement (American Institute of Architects, 2020)

The number of people in the classrooms and the area per person are of great importance for physical distance in classrooms. In TSE's (Turkish Standards Institution) YÖK (2020), It is stated that the physical distance should be arranged according to a minimum 1 meter distance in the lessons, exams/practical exams, laboratories and classrooms where students will not interact with each other loudly, while the physical distance will be at least 1.5-2 meters if possible, especially in activities such as speaking loudly and debating, due to droplet formation indicated that it should be adjusted accordingly. In addition, it was stated that the capacity of the classrooms should be determined so that one person per 4 m^2, and at least 1 meter distance between people should be maintained in the seating arrangement. According to the American Institute of Architects (2020), the capacity should be determined to reduce the area of 20 sq. ft (1.85 m^2) per person in classrooms in educational structures, while 50 sq. ft (4.64 m^2) per person for technical units, library reading rooms and vocational training spaces.

Since the smaller liquid particles dispersed as aerosols remain in the air, it is not only the physical distance that determines the risk of contamination, but also the duration of exposure (Lordan et al., 2020). Therefore, although sufficient physical distance is provided in the classrooms, the classrooms should be ventilated frequently. Natural ventilation is the provision of air exchange through openings such as doors and windows to provide suitable and clean air from the outside environment instead of undesired substances such as temperature, carbon dioxide, moisture, and toxins in the indoor air at high levels. The ventilation principles according to the openings are shown in **Figure 3**.

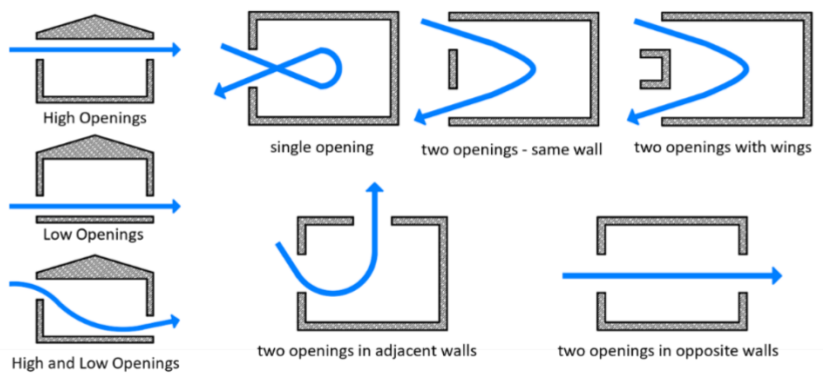


Figure 3: Ventilation principles according to openings (Dekay and Brown, 2013)

The COVID-19 pandemic has revealed the importance of flexible spaces with open plans and adequate spaces in primary and secondary school buildings for the continuity of educational environments (Güzelci et al., 2021). It has clearly emphasized the importance of face-to-face education, especially at the primary school level. During the transition from online to face-to-face education during the pandemic, classroom capacity was set at 4 m^2 per person. This measure, implemented for the health of students, offers a simple and practical solution. However, this solution did not consider the spatial characteristics of the classroom environment. Classroom capacity should be evaluated not only based on space size but also in terms of healthy ventilation, especially during pandemics. Therefore, the ratio of window area to wall and floor area should also be included in calculations. Therefore, there is a need to develop more comprehensive, scientific, and applicable standards for the sustainability of face-to-face education in potential new pandemic scenarios. The use of artificial intelligence and machine learning-based approaches in the design of classroom layouts in educational buildings not only saves time in the early design process but also contributes to the creation of more functional and adaptable spaces (Karadag et al., 2023).

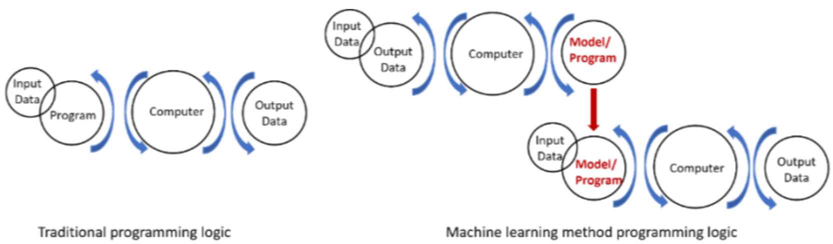
The aim of this study is to develop a method based on spatial parameters to determine the maximum number of students in existing primary school classrooms in the event of a potential pandemic. First, the study used fuzzy logic to calculate the design efficiencies of classrooms within a range of 5–18 students. Based on the data obtained, three basic rules were established, and the maximum number of students was determined based on these rules. Machine learning and deep learning methods were then developed to determine the maximum number of students, the width, length, ceiling height, and total window area of the classrooms. This developed method determines the student capacity of a given classroom based on data from existing classrooms.

The significance of this study is not limited to providing a response to the past Covid-19 pandemic. Its primary contribution is to provide a scientific basis for classroom planning in the event of a future resurgence or similar pandemics, and to guide the safe continuation of face-to-face education. At the same time, this study's application and comparison of different methods allows us to identify the advantages and limitations of each method, which is crucial for determining the most appropriate solution to the problem. It also goes beyond the simplified standards frequently used in existing literature and presents an innovative approach that evaluates classroom capacity through spatial design efficiency. This makes a significant contribution to both education and architectural planning.

2. MACHINE LEARNING AND DEEP LEARNING

Machine learning is a sub-branch of computer science that emerged from model recognition and computational learning theory studies in artificial intelligence. The term machine learning was defined in 1959 by the American computer scientist Arthur Samuel (1959) as the field of study that gives computers the ability to learn without being explicitly programmed. Machine learning deals with the question of how to create computer programs that automatically evolve through experience (Mitchell,1997). A machine learning algorithm is a computational process that uses input data to perform a desired task without being literally programmed (i.e. "hard coded") to produce a particular result, and these algorithms are, in a sense, a "soft-coded" because repetition architectures (i.e. experience) through changes automatically adapts to accomplish the desired task or so that they are becoming better and better (Naqa, I., and Murphy, 2015). The working logic of traditional programming is to obtain output data from the input data, and therefore, in order to obtain the output data, a program or software suitable for the problem type must be used, while in the machine learning working logic, the machine or software is trained with the input and output data to obtain the program or software suitable for the problem type (Figure 4) (Kavuncu, 2018) (**Figure 4**).

Figure 4: Programming logic with traditional programming and machine learning method (Kavuncu, 2018)



According to the algorithm used, the accuracy of the results obtained from the model can vary. Therefore, better performance can be obtained from the model developed by using different algorithms or combining different algorithms. Different algorithms are used according to the type of machine learning (**Figure 5**).

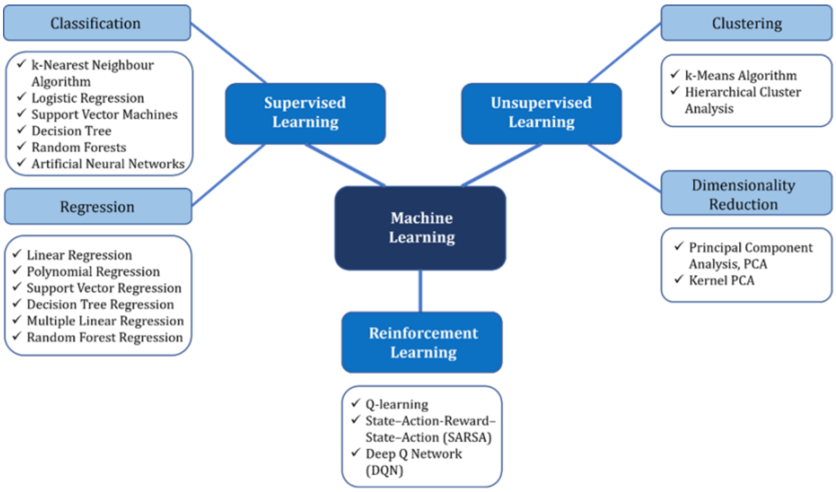


Figure 5: Machine learning types and most used methods

Machine learning is basically divided into three groups according to the learning method: supervised, unsupervised, and reinforced learning.

Supervised learning is a learning method that allows the machine to create a function from this information by teaching labeled data and the results obtained from that data. Thus, the machine learns the relationship between the data. In supervised learning, it is aimed to produce the closest result for unlabeled data. The difference between the result obtained with the model and the desired result determines the error rate and by minimizing this rate, the accuracy of the model is increased. It is widely used for classification and regression operations. In the classification process, a conclusion is drawn from the training data, and it is determined to which category the test data belongs. In the classification process, the system is trained by categorizing the data. Then, it is determined which class the data shown belongs to. In the regression process, the relationships between the input data (independent variable) and the output (dependent variable) data are estimated. A linear graph is created according to these relationships and the results of new data are estimated according to this graph.

With unsupervised learning, it is aimed to reveal the hidden relationships between unlabeled data in the data set. Unsupervised learning runs on more complex algorithms than supervised learning, as there is little or no information about the data. It is widely used for clustering and dimensionality reduction operations. The basic principle of clustering is based on the calculation of similarity measurement between class number unclear and unclassified data. While the similarity rate within itself is expected to be the highest, the similarity rate between different clusters is expected to be the least. Many data sets can contain large amounts of attributes and working with this type of data set makes operations that require high computational power, such as vectors and matrices, even more difficult. The size reduction process, on the other hand, preserves useful information to reduce such difficulties and transforms the dataset into a lower-dimensional space.

The purpose of reinforcement learning is to develop a system that increases its performance based on its interactions with its environment. In reinforcement learning, there is a reward-punishment system. In this system, inferences are made from errors made in the way that is being progressed to find the correct action, and then it tries to find the correct action with the least errors from its inferences made. The concept of deep learning first emerged when Hinton and Salakhutdinov (2006) proposed algorithms that can learn the properties of data hierarchically with deep neural networks. Deep learning, which is a method of artificial intelligence that uses multi-layer artificial neural networks and is one of the methods of machine learning, is growing rapidly today with the power of hardware (graphics processing units and increased processing power) that can process increasing data. Unlike traditional machine learning methods, it can learn from images, videos, audio and text data. In addition, unlike traditional machine learning, deep learning can perform feature extraction itself with little or no computer intervention.

3. METHODOLOGY

The proposed model consists of different stages: data collection, interpretation of data with fuzzy logic, development, implementation of machine learning and deep learning-based models, and evaluation of models (**Figure 6**).

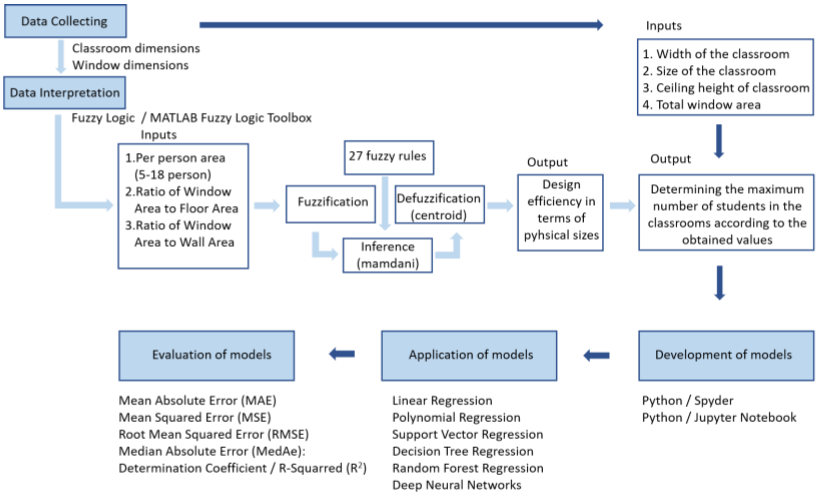


Figure 6: Flow diagram of the model

3.1 Data Collecting

34 primary schools affiliated to the Directorate of National Education of the Central District of Isparta were examined and measurements were made. Out of a total of 485 classrooms belonging to the first, second, third and fourth grades in primary schools (not including classrooms with approximately the same dimensions), 91 classrooms were examined. The width, length, ceiling height, width and length of the windows were measured by laser meters. The mean and standard deviation of the data obtained after the examination and measurement are shown in **Table 1.**

	Mean	Standard Deviation
Width of Classrooms (m)	6.30	0.95
Length of Classrooms (m)	6.86	1.20
Ceiling Height of Classrooms (m)	2.96	0.19
Area of Classrooms (m^2)	43.24	10.22
Volume of Classrooms (m^3)	128.54	33.40
Window Area (m^2)	6.73	1.91
Ratio of Window Area to Floor Area (%)	15.86	4.16
Ratio of Window Area to Wall Area (%)	33.45	8.31
Area Per Person (m^2) (10 persons)	4.32	1.02
Volume Per Person (m^3) (10 persons)	12.85	3.34

Table 1: The mean and standard deviation of the obtained data.

3.2 Data Interpretation

To achieve design efficiency in terms of physical sizes of the existing classrooms and to find out how many students are most suitable, the data obtained from the examined classrooms should be interpreted and inferences should be made accordingly. To determine the maximum number of students in classrooms, it is necessary to consider the dimensions of that classroom. There are many variables in the design of classes, and these variables make the decision-making stage difficult because they have different qualities (Diker and Erkan, 2021). Evaluating all the design criteria together makes this process more complex. To solve these problems, which have become complex in this process, fuzzy Logic method was used. The reason for using this method is that it can solve complex problems much faster and resembles the structure of human thought.

Modeling with the fuzzy logic method takes place in 5 stages (**Figure 7**).

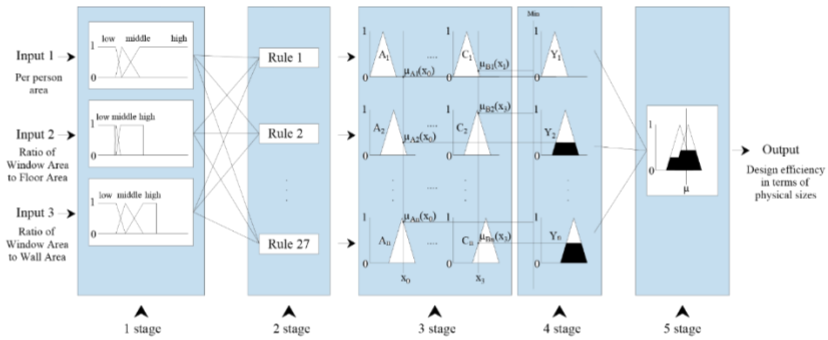


Figure 7: Modeling stages with fuzzy logic approach

These stages are:

1.Stage (Creating Membership Functions): First, membership functions are created for the inputs to be used for the model and the output variable to be created.

2. Stage (Rule Base): Logical if-type rules are created that link the input data to the output variable, which can affect the result of the model. All intermediate (fuzzy set) combinations must be considered in these rules.

3. Stage (Fuzzification): It is the process of converting the exact value of the input to fuzzy values by determining the fuzzy set or sets to which the input belongs and the degree of membership by using the membership function.

4. Stage (Fuzzy Inference): In the fuzzy rule base, by collecting all the relations established between the inputs and the output fuzzy sets, the inference corresponding to the input is made, like the human's abilities such as decision making, inference and proposition.

5. Stage (Defuzzification): The fuzzy inference results obtained as a result of fuzzy operations are defuzzification and converted into precise numerical output values.

"Fuzzy Logic Toolbox" in MatLab software was used to develop this model. In the fuzzy logic method, the degrees of belonging of the variables to different membership functions (e.g., low, medium, high) were determined by fuzzifying the crisp input values (**Figure 8**) and then 'If-then' rules were applied (**Table 2**).

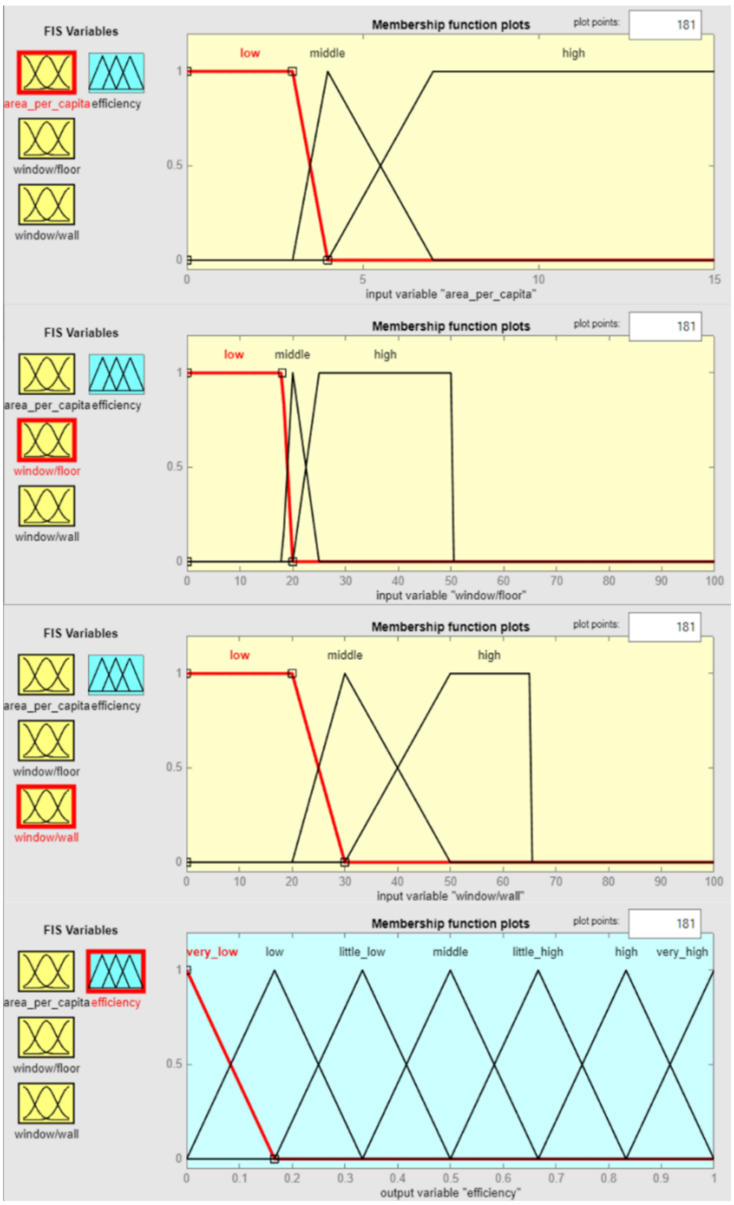


Figure 8: Membership functions of the inputs and outputs of the developed model

	If	and	and	then
Rule No	Area per Capita	Window-to-Floor Ratio	Window-to-Wall Ratio	Efficiency
1	Low	Low	Low	Very Low
2	Low	Low	Middle	Low
3	Low	Low	High	Little Low
4	Low	Middle	Low	Low
5	Low	Middle	Middle	Little Low
6	Low	Middle	High	Middle
7	Low	High	Low	Little Low
8	Low	High	Middle	Middle
9	Low	High	High	Little High
10	Middle	Low	Low	Low
11	Middle	Low	Middle	Little Low
12	Middle	Low	High	Middle
13	Middle	Middle	Low	Little Low
14	Middle	Middle	Middle	Middle
15	Middle	Middle	High	Little High
16	Middle	High	Low	Middle
17	Middle	High	Middle	Little High
18	Middle	High	High	High
19	High	Low	Low	Little Low
20	High	Low	Middle	Middle
21	High	Low	High	Little High
22	High	Middle	Low	Middle
23	High	Middle	Middle	Little High
24	High	Middle	High	High
25	High	High	Little High	Little High
26	High	High	Middle	High
27	High	High	High	Very High

Table 2: 27 rules created for the fuzzy logic method

The Mamdani approach was chosen for defuzzification due to its simplicity, interpretability, and widespread use in modeling fuzzy systems, making it particularly suitable for evaluating classroom design efficiency based on multiple spatial parameters. In the fuzzy logic method, the fuzzification of input values, their processing through 'If–Then' rules, and subsequent defuzzification reveal the effects of area per person, window-to-floor, and window-to-wall ratios on design efficiency (**Figure 9**).

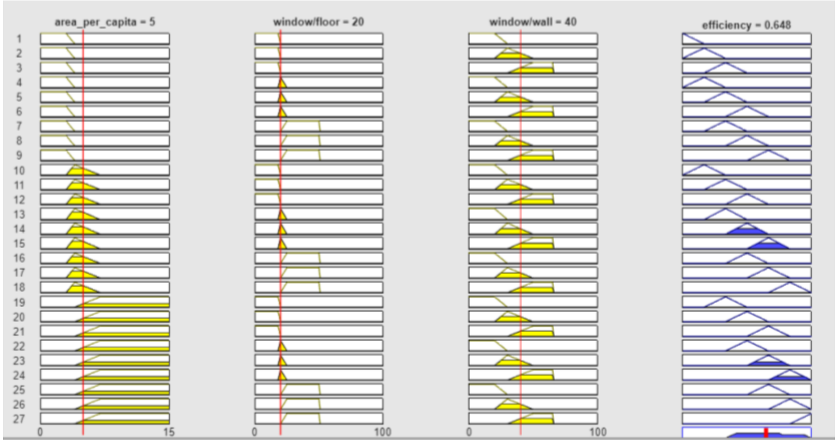


Figure 9: Effects of area per person, window-to-floor, and window-to-wall ratios on classroom design efficiency.

Design efficiencies obtained through fuzzy logic were not directly used in models developed using machine learning and deep learning methods. Design efficiencies for physical dimensions were determined using "if-then" rules using the per capita area, window area/floor area ratio, and window area/wall area ratio as input variables. The model's output is design efficiencies ranging from 0 to 1.

Values were calculated individually for each classroom, and design efficiencies corresponding to these student numbers were determined. Three rules were developed based on the results, and the maximum number of students in classrooms was determined based on these rules (**Figure 10**).

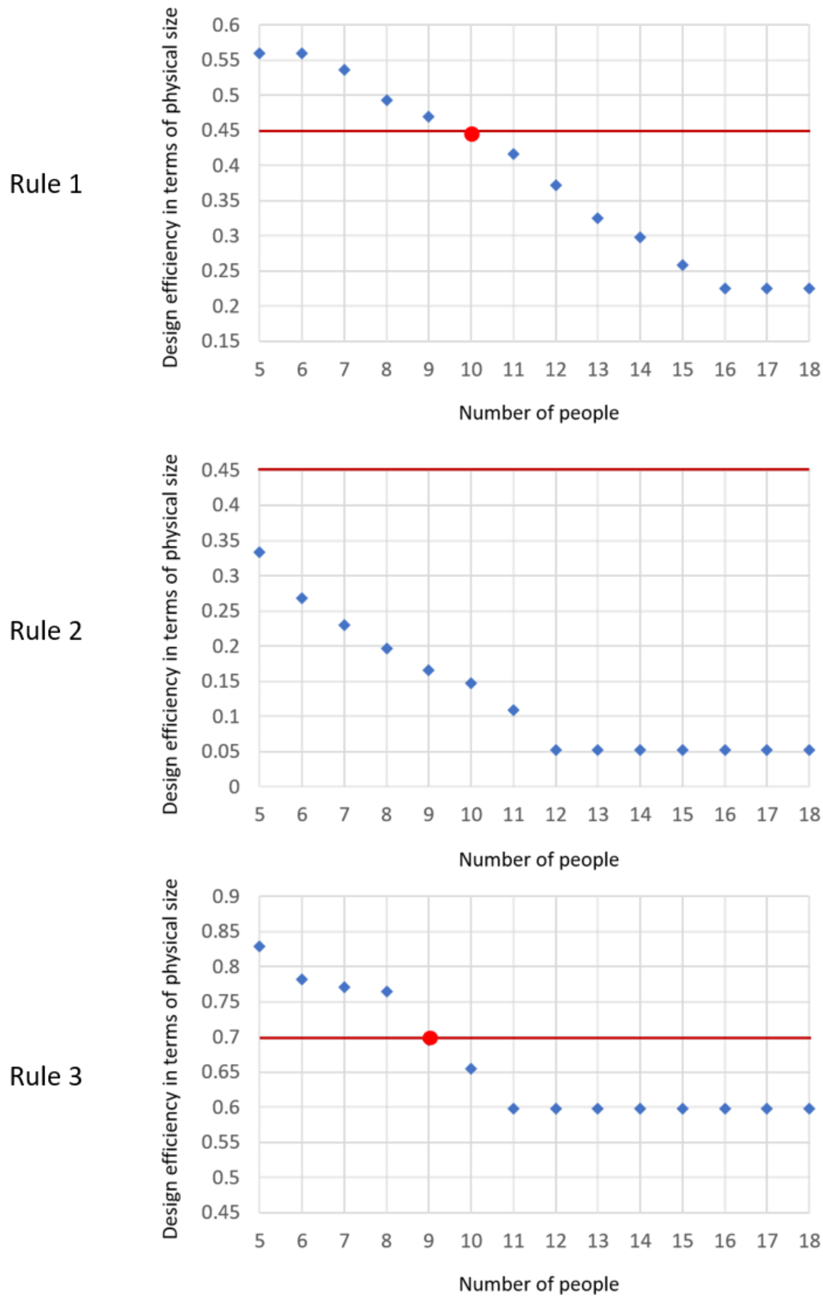


Figure 10: Rules for determining the maximum number of people in classrooms.

The maximum number of students in the classrooms is determined according to the following rules:

1. If the design efficiency, which varies according to the number of people, is at least 0.45, the number of students was selected as the maximum number of students.

2. If the design efficiency is less than 0.45 in 5 people, this classroom was not considered suitable and was determined as 0 people.
3. If the design efficiency is greater than 0.45 in 18 people, the number of students belonging to at least 0.70 was selected as the maximum number of students.

The design efficiency threshold values (0.45–0.70) used in this study were determined based on the seven membership functions generated in fuzzy logic and the expert opinions of the authors. Specifically, the value 0.45 corresponds to the "middle" membership function, while the value 0.70 corresponds to the "little high" membership function. Therefore, this range represents the fuzzy sets defined for design efficiency in terms of physical magnitude.

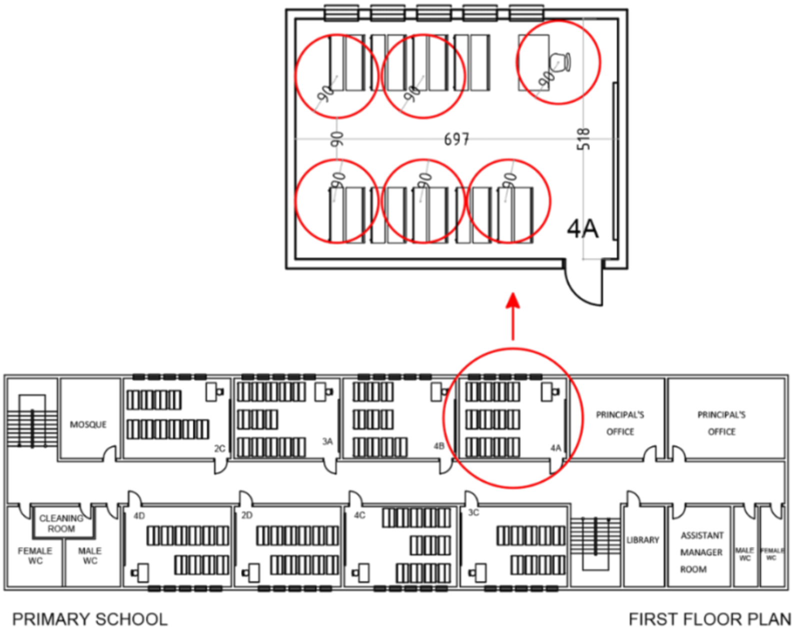
Since aerosols remain in the air, the factors that determine the risk of transmission are physical distance and exposure time to these aerosols. Ventilation is of great importance during exposure to aerosols. Therefore, in determining the capacity of the classrooms, it is necessary to determine the capacity by considering the window sizes and proportions for adequate ventilation of the classrooms in addition to the classroom dimensions, rather than determining the capacity to be 4 m^2 per person for physical distance only. In this direction, the data obtained were interpreted by the method of fuzzy logic. Some of the number of people obtained from the model results are shown in **Table 3**.

	Width of the classroom (m)	Size of the classroom (m)	Ceiling height of classroom (m)	Total window area (m^2)	Ratio of Window Area to Floor Area (%)	Ratio of Window Area to Wall Area (%)	Number of people obtained as a result of the model	Per person area (m^2)
1	5.12	10.32	3.27	2.86	5.42	8.48	0	-
2	5.09	6.95	2.74	2.19	6.18	11.48	0	-
3	6.92	6.65	3.24	10.61	23.05	49.23	12	3.83
4	6.59	6.63	2.93	8.18	18.73	42.12	11	3.97
5	5.52	6.03	3.17	8.18	24.57	42.78	8	4.16
6	6.83	7.22	2.98	8.48	17.19	39.40	11	4.48
7	6.76	6.94	2.92	7.38	15.73	36.42	10	4.69
8	6.95	6.98	2.9	6.65	13.70	32.83	9	5.39
9	6.8	7.81	3.06	6.98	13.15	29.22	8	6.64
10	6.93	7.87	3.11	6.70	12.28	27.36	7	7.79

Table 3: The number of people belonging to some classrooms obtained as a result of the model.

18 of the classrooms examined, it was concluded that there is no education in these classrooms, as adequate ventilation could not be provided in the classrooms due to the ratio of window area to floor area and the ratio of window area to wall area was very low. In 8 classrooms, since the ratio of the window area to the floor area and the ratio of the window area to the wall area is high, the area per person varies between 3.23 and 3.97 m^2, below 4 m^2. In the remaining 64 classrooms, the ratio of the window area to the floor area and the ratio of the window area to the wall area varies between 4.01 and 7.79 m^2, above 4 m^2 per person.

The floor plan (with pre-pandemic order) of one of the schools examined in **Figure 11** and, for example, the order of a classroom in accordance with the physical distance were created.



Width of the class-room (m)	Size of the class-room (m)	Ceiling height of class-room (m)	Total window area (m^2)	Ratio of Window Area to Floor Area (%)	Ratio of Window Area to Wall Area (%)	Number of people obtained as a result of the model	Per person area (m^2)
5.18	6.97	2.72	5.48	15.19	28.92	5	7.22

Figure 11: Floor plan of one of the schools examined

In this classroom, where 24 people were trained before the Pandemic, there should be 9 people to fall 4 m^2 per person in the gradual transition from distance education to face-to-face training, while as a result of the model, 5 people were proposed for this classroom. Considering the physical distance according to the row order, it is seen that it is suitable for 5 people. This situation indicates that it is not correct to determine only the area per person to be 4 m^2 in the determination of classroom capacities.

3.3 Development and Implementation of Models

Multivariate estimation is a problem of machine learning, and there are various algorithms that use different strategies to predict the variable that is dependent on the independent variables in a dataset. In this study, the goal is not only to estimate the maximum number of people who should be in the classrooms, but also to compare different machine learning models and deep learning models for subsequent stages.

The linear regression method is a basic statistical approach frequently used in predictive analysis that reveals the linear relationship between the independent variable and the dependent variable. It is also one of the most fundamental regression methods, providing high interpretability of parameters and statistical significance testing of predictors (James et al., 2013). It was chosen in this study due to its strong interpretability and simplicity.

Polynomial regression is an extension of linear regression that allows for the modeling of nonlinear relationships by incorporating higher-order terms of the explanatory variables (Heiberger and Neuwirth, 2009). The relationship between the independent variable and the dependent variable is depicted with complex curves rather than linear lines. It was included in the analysis to capture potential nonlinear trends in the data. Different polynomial degrees should be applied to determine the optimal curve. In the model developed in this article, a value of 2 was used as the polynomial degree.

Support Vector Regression (SVR), developed by Vapnik (1997), is a kernel-based method used in both classification and regression problems, capable of effectively modeling nonlinear relationships by transforming inputs into high-dimensional feature spaces. In this study, SVR was chosen for its flexible and robust ability to capture nonlinear patterns.

Decision trees are methods that estimate the dependent variable by dividing the dataset into branches based on independent variables and can model nonlinear relationships and variable interactions. This model consists of decision nodes and leaf nodes created according to the features and target variables. At each split, it attempts to increase information gain by reducing the entropy value (degree of randomness) and selects the split with the lowest error. It also divides the independent variables into intervals based on the information gain; in the prediction phase, it uses the mean learned during the training process for the value in the relevant interval. Therefore, unlike other regression methods, it has a non-continuous prediction structure. Decision trees are widely used in machine learning because they are easy to understand, require minimal data preparation, and can handle both numerical and categorical data (Dehghani et al., 2023). This algorithm has been evaluated for its ability to capture complex feature interactions.

Random Forest is an ensemble learning method that combines multiple decision trees to increase prediction accuracy and reduce overfitting. This method is based on a structure where each tree is based on independently sampled random vectors, and all trees have the same distribution (Breiman, 2001). While the optimal split of each node in a single tree is achieved using all predictors, in the Random Forest approach, each node is split using only a randomly selected subset of predictors. This allows for the creation of multiple trees (forests), reduces variance, and reduces correlation between trees, resulting in higher accuracy predictions (Suchetana et al., 2017). It was chosen for this study due to its robustness against overfitting, its ability to model complex relationships, and its relative flexibility in addressing missing data and variable selection issues.

Deep Neural Networks are models capable of automatically extracting features and modeling highly complex, high-dimensional nonlinear relationships. The training phase is crucial for DNNs with more than two hidden layers, as when error values propagate across multiple layers, the model's performance is directly affected. Advances in both machine learning algorithms and computer hardware have made it possible to train DNNs with numerous nonlinear hidden layers and large output layers more efficiently (Hinton et al., 2012). Therefore, they were included in this study due to their robust representation learning capabilities.

The resulting data was split using a 5-fold cross-validation method for model development and performance evaluation. In this approach, the dataset is divided into five equal parts; in each iteration, one part serves as the test set, and the remaining four parts serve as the training set. This method allows for a more reliable assessment of the model's generalizability.

Different models have been developed to estimate the maximum number of students in the classrooms by using the width, size, ceiling height and total window area of the classrooms. All models were developed using the Python programming language, and the implementation was carried out in the Jupyter Notebook environment.

3.4 Performance Metrics for Model Evaluation

It is necessary to evaluate the performance of the models to measure the success of the developed models or to decide whether the model is a good model. Different performance evaluation methods are used for prediction in supervised learning. In this paper, the following were used as performance evaluation criteria:

Mean Absolute Error (MAE): It is found by summing the absolute values of the differences between the actual values and the predicted values in the data set and dividing the value obtained by the number of samples (**Equation 1**).

$$MAE(y, h_0(x)) = \frac{1}{n}\sum_{i=0}^{n-1} |\mathrm{y_i} - \mathrm{h_0}(\mathrm{x_i})| \tag{1}$$

Here, yi represents the actual value of the ith sample in the data set, and h0(xi) the predicted value, and n represents the number of samples in the data set. It takes values in the range of 0 to ∞. However, the lower the value, the better the performance of the model.

Mean Squared Error (MSE): It is found by dividing the value obtained by the sum of the squares of the differences between the actual values and the predicted values in the data set by the number of samples (**Equation 2**).

$$MSE(y, h0(x)) = \frac{1}{n}\sum_{i=0}^{n-1}(\mathrm{yi} - \mathrm{h0}(\mathrm{xi}))^{2} \tag{2}$$

Root Mean Squared Error (RMSE): It is found by taking the square root of the mean square error value (**Equation 3**).

$$RMSE(y, h0(x)) = \sqrt{\frac{1}{n}\sum_{i=0}^{n-1}(\mathrm{yi} - \mathrm{h0}(\mathrm{xi}))^{2}} \tag{3}$$

Median Absolute Error (MedAe): It is found by taking the median of the absolute differences between the actual and predicted values in the data set (**Equation 4**).

$$MedAE(y, h0(x)) = Medyan(|\mathrm{y1} - \mathrm{h0}(\mathrm{x1})|, \dots, |\mathrm{yn} - \mathrm{h0}(\mathrm{xn})| \tag{4}$$

Determination Coefficient, (R-Squarred, R^2): It is found by subtracting the value obtained from the division of the sum of the squares of the error by the sum of the mean differences from 1 (**Equation 5**).

$$R^2\big(y, h0(x)\big) = 1 - \frac{\sum_{i=0}^{n-1}(yi - h0(xi))2}{\sum_{i=0}^{n-1}(yi - \bar{y})2} \tag{5}$$

Here, $\bar{y}$ represents the mean of the samples. It is an indication of the extent to which samples that are not in the dataset can be accurately estimated by the model. It takes values in the range of 0 to 1. However, the closer the value is to 1, the better the performance of the model.

4. RESULTS

In this study, the performances of different regression models (linear regression, polynomial regression, support vector regression [SVR], decision tree, random forest, and deep neural network [DNN]) were compared using five-fold cross-validation. Each model predicts the given data using a different mathematical method and therefore exhibits different performance. The performance of the developed models was examined with various evaluation criteria using a five-fold cross-validation method. The results show significant differences between the models.

The results of the model developed with the linear regression method are shown in **Figure 12**.

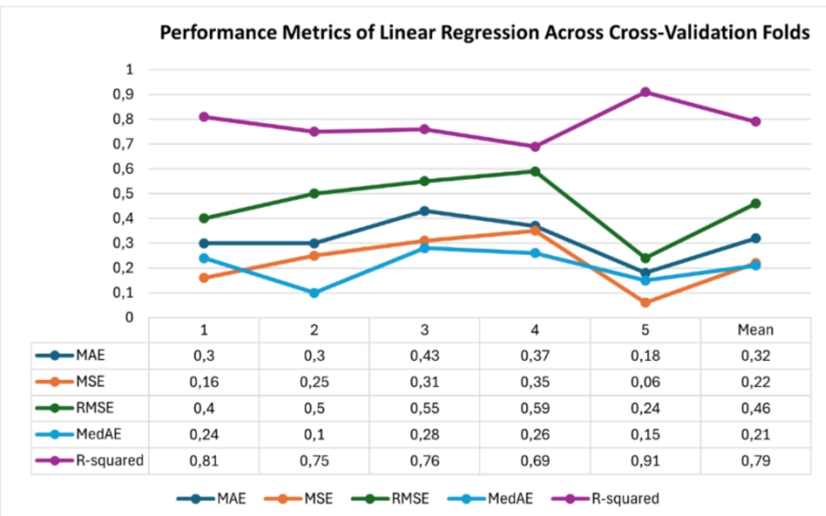
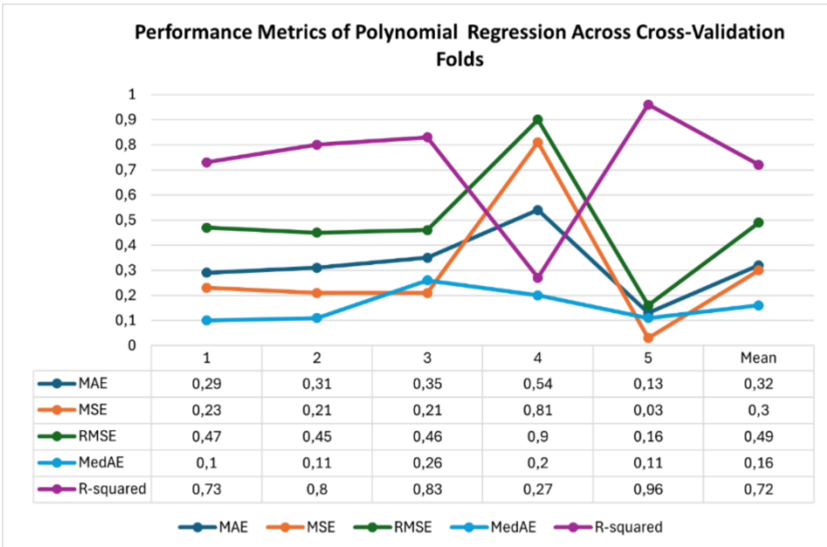


Figure 12: Performance measures in cross-validation folds of the linear regression model

According to the 5-fold cross-validation results of the Linear Regression model, the MAE, MSE, RMSE, and MedAE values show significant fluctuations across folds. The R^2 value ranges from 0.69 to 0.91. While the model provides high accuracy in some folds, its performance is relatively low in others. For example, it provides high performance in the 5th fold, but low performance in the 4th fold. This suggests that linear assumptions are not fully valid across all data subsets. When average metrics are considered, the Linear Regression model provides acceptable accuracy and stability across the dataset. Due to the model's linear assumption-based structure, it struggles to capture the complex relationships between variables. Consequently, occasional increases in error metrics are observed.

The results of the model developed with the polynomial regression method are shown in **Figure 13**.



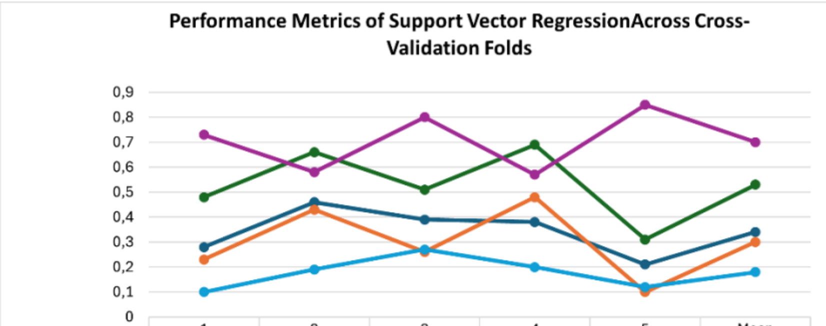
	1	2	3	4	5	Mean
MAE	0,29	0,31	0,35	0,54	0,13	0,32
MSE	0,23	0,21	0,21	0,81	0,03	0,3
RMSE	0,47	0,45	0,46	0,9	0,16	0,49
MedAE	0,1	0,11	0,26	0,2	0,11	0,16
R-squared	0,73	0,8	0,83	0,27	0,96	0,72

Figure 13: Performance measures in cross-validation folds of the polynomial regression model

Five-fold cross-validation results of the Polynomial Regression model show that MAE, MSE, RMSE, and MedAE values reach particularly high levels in the fourth fold, while the R^2 value varies between 0.27 and 0.96. This indicates that the model exhibits more sensitive and variable performance to data subsets. For example, the highest R^2 value (0.96) and very low error metrics in the fifth fold indicate that the data distribution in this fold provides an excellent fit to the model, while the increase in the error metrics in the fourth fold and the decrease in R^2

to 0.27 indicate that the model is inadequate for some data subsets. When considering average metrics, the Polynomial Regression model generally exhibits acceptable performance on the dataset. However, it can produce more inconsistent results when nonlinear relationships are present. The average performance was lower than that of linear regression.

The results of the model developed with the support vector regression method are shown in **Figure 14**.



	1	2	3	4	5	Mean
MAE	0,28	0,46	0,39	0,38	0,21	0,34
MSE	0,23	0,43	0,26	0,48	0,1	0,3
RMSE	0,48	0,66	0,51	0,69	0,31	0,53
MedAE	0,1	0,19	0,27	0,2	0,12	0,18
R-squared	0,73	0,58	0,8	0,57	0,85	0,7

Figure 14: Performance measures in cross-validation folds of the support vector regression model

Five-fold cross-validation results of the Support Vector Regression model show that MAE, MSE, RMSE, and MedAE values vary significantly across folds, while R^2 varies between 0.57 and 0.85. Considering the average metrics, the Support Vector Regression model demonstrates stable and satisfactory performance on the dataset. However, despite offering a more flexible structure compared to linear and polynomial models, SVR's average performance remains relatively low. Particularly poor results were obtained in some folds (e.g., Fold 2 and Fold 4). This demonstrates that SVR is highly sensitive to hyperparameter selection and data distribution.

The results of the model developed with the decision tree regression method are shown in **Figure 15**.

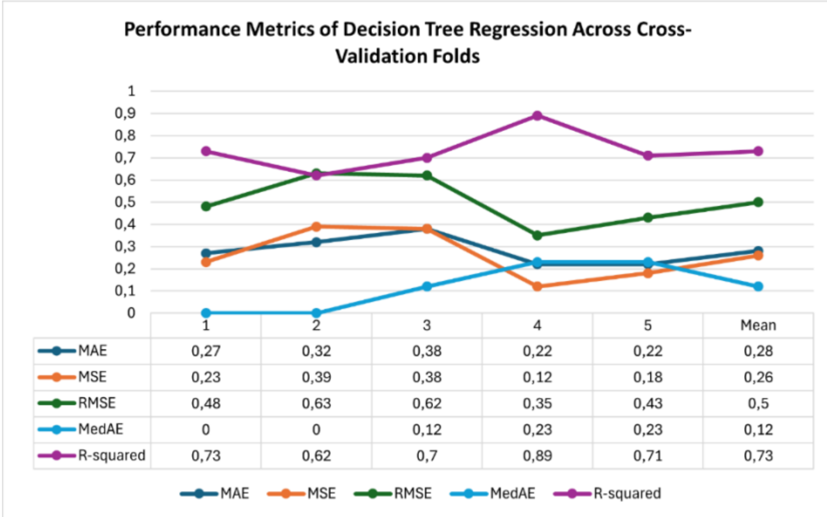


Figure 15: Performance measures in cross-validation folds of the decision tree regression model

The five-fold cross-validation results of the Decision Tree Regression model show that MAE, MSE, RMSE, and MedAE values vary significantly across layers, with R^2 varying between 0.62 and 0.89. This suggests that the model experiences performance degradation in some layers. The fourth layer exhibits the highest R^2 value (0.89), while the error metrics drop to their lowest levels. Conversely, in the second layer, the increase in the error metrics and the decrease in R^2 to 0.62 indicate that the model performs less well on some data subsets. This result reflects the high-variance nature of decision trees. When average metrics are considered, the Decision Tree Regression model also demonstrates stable and acceptable performance on the dataset. Although decision trees offer a more flexible structure compared to linear models, their average performance remains relatively limited. Particularly weak results were obtained in Folds 2 and 3. This shows that the Decision Tree Regression model is quite sensitive to the hyperparameter selection and data distribution.

The results of the model developed with the random forest regression method are shown in **Figure 16**.

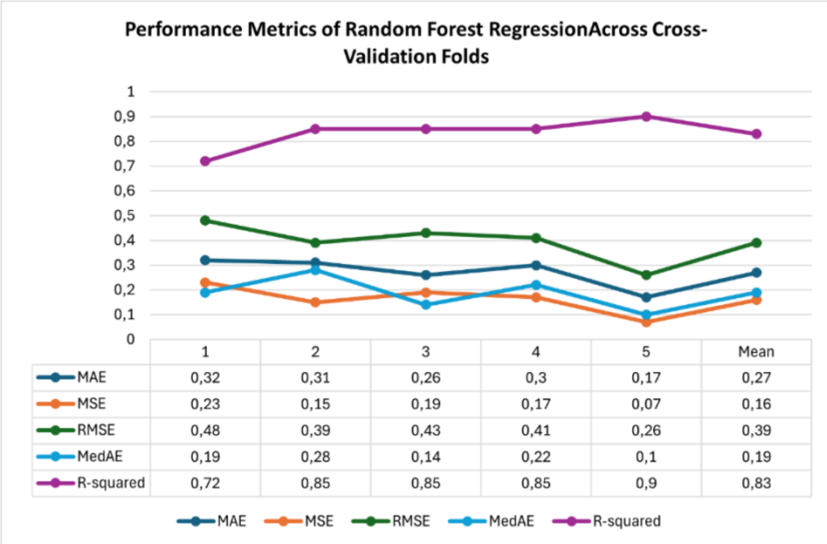
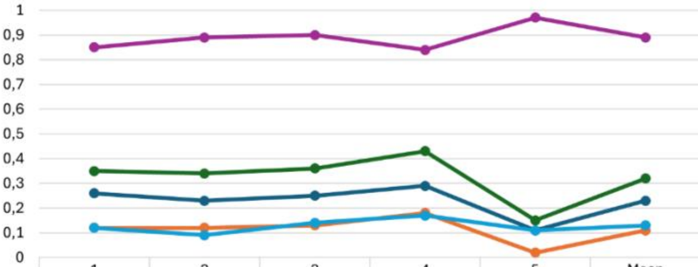


Figure 16: Performance measures in cross-validation folds of the random forest regression model

The 5-fold cross-validation results of the Random Forest Regression model show that MAE, MSE, RMSE, and MedAE values exhibit relatively less variability across layers, while the R^2 value ranges from 0.72 to 0.9. This demonstrates that the model generally achieves high accuracy and exhibits more consistent performance across layers. When average metrics are considered, the Random Forest Regression model demonstrates a balanced, reliable, and satisfactory performance on the dataset. The Random Forest Regression model demonstrated a more successful and stable performance compared to Decision Tree Regression. Thanks to the k-fold crossover method, Random Forest significantly reduces the risk of overfitting compared to single decision trees and produces more consistent results across different subsets.

The results of the model developed with the deep neural network regression method are shown in **Figure 17**.

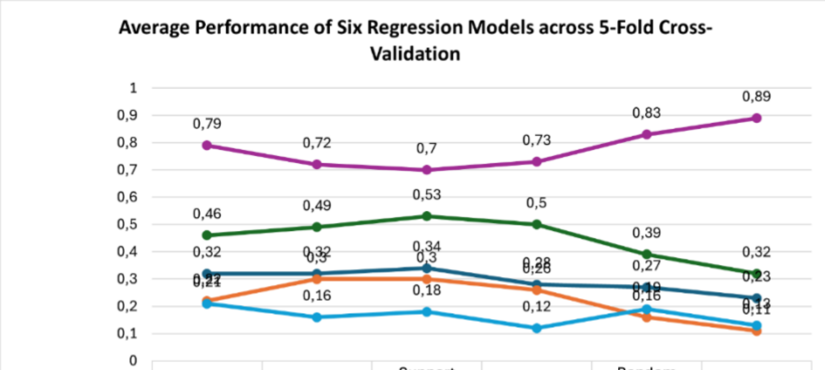


	1	2	3	4	5	Mean
MAE	0,26	0,23	0,25	0,29	0,11	0,23
MSE	0,12	0,12	0,13	0,18	0,02	0,11
RMSE	0,35	0,34	0,36	0,43	0,15	0,32
MedAE	0,12	0,09	0,14	0,17	0,11	0,13
R-squared	0,85	0,89	0,9	0,84	0,97	0,89

Figure 17: Performance measures in cross-validation folds of the deep neural network regression model

According to the 5-fold cross-validation results, the MAE, MSE, RMSE, and MedAE values of the Deep Neural Network Regression model show relatively less variability across layers. The R^2 value ranges between 0.84 and 0.97. This demonstrates that the model generally achieves high accuracy and exhibits consistent performance across layers. When average metrics are considered, the Deep Neural Network Regression model demonstrated stable, reliable, and satisfactory performance on the dataset. Capable of capturing complex relationships between variables, the model achieved more consistent results across different subsets thanks to its deep learning architecture. However, while performance was slightly lower in some layers, the overall trend was toward higher accuracy and lower errors.

Figure 18 illustrates the comparison of six regression models using the average performance across 5-fold cross-validation.



	Linear Regression	Polynomial Regression	Support Vector Regression	Decision Tree Regression	Random Forest Regression	Deep Neural Networks
MAE	0,32	0,32	0,34	0,28	0,27	0,23
MSE	0,22	0,3	0,3	0,26	0,16	0,11
RMSE	0,46	0,49	0,53	0,5	0,39	0,32
MedAE	0,21	0,16	0,18	0,12	0,19	0,13
R-squared	0,79	0,72	0,7	0,73	0,83	0,89

MAE MSE RMSE MedAE R-squared

Figure 18: Comparison of six regression models based on the average results of 5-fold cross-validation

As a result, the Deep Neural Network Regression model demonstrated better and more consistent performance compared to classical regression methods. This clearly demonstrates that deep learning-based methods offer higher accuracy and generalizability due to their ability to capture nonlinear relationships. While the Random Forest Regression model also demonstrated consistent performance across layers, the Deep Neural Network Regression model stood out with its higher accuracy (especially in R^2) and lower error metrics.

5. CONCLUSION

Some measures and restrictions have been made to be less affected and protected from the Covid 19 virus, which is a global epidemic. One of these measures was the closure of educational institutions and online training. In the process of gradually transitioning to normal life with developed vaccines, the trainings are gradually transitioning to face-to-face training. During this period, classroom capacity needed to be reduced. Classroom capacity should be evaluated not only in terms of physical space but also in terms of ventilation facilities that will ensure student safety during pandemic conditions. In this context, within the scope of the study, recommendation models were developed to determine the maximum number of students that primary school classrooms can accommodate in possible epidemic situations based on spatial parameters.

In this context, a model has been created by Fuzzy Logic method to evaluate the efficiency of existing primary school classrooms in terms of physical sizes. From the data obtained by examining the existing primary school classrooms, the area per person (m^2) in the classrooms, the ratio of the window area to the floor area and the ratio of the window area to the wall area and the efficiency of the classrooms in terms of physical sizes were obtained. According to these values obtained, it was determined how many students should be present in the classrooms. Due to the lack of sufficient windows according to classroom sizes in most existing classrooms, changing the area per person for each classroom according to classroom and window sizes, rather than the standard (4 m^2), will reduce the risk of virus transmission. In addition to the physical distance, the dimensions of the classrooms and row sizes should be determined by considering the minimum area per person.

To increase the generalizability and reliability of the models, a 5-fold cross-validation method was applied. This method divided the dataset into five equal parts. Each part served as test data, while the remaining four were used for training, and the results were average. This reduced the bias that could arise from a single training-test split, allowing the average performance of the models across different data splits to be evaluated. This approach reduces the risk of overfitting the model, particularly when working with limited data, and allows for more reliable comparisons.

According to five-fold cross-validation results, the Deep Neural Network regression model demonstrated the highest overall performance and consistency compared to conventional regression approaches. While the Random Forest regression model also exhibited relatively consistent performance across layers, the Deep Neural Network regression model outperformed the other methods with higher accuracy and lower error metrics. These findings demonstrate the ability of deep learning-based approaches to capture complex and nonlinear relationships in data and demonstrate higher generalizability compared to conventional regression models. Therefore, the Deep Neural Network regression model can be considered a more suitable method than other supervised learning algorithms for this prediction problem.

During the gradual transition to face-to-face education following the COVID-19 pandemic, six different regression models were developed to estimate the maximum number of students required in classrooms, considering existing classroom sizes and window area. The study findings indicate that the Deep Neural Network method provides higher accuracy compared to other methods in estimating student numbers based on spatial parameters. However, rather than setting a definitive standard, the model developed here is considered a tool that serves as a recommendation for implementing necessary precautions in educational structures and reducing the spread of infectious diseases. In this respect, it is expected to guide decision-makers by providing quantitative input to the prepared guidelines. Furthermore, expanding the scope of the dataset could further enhance the model's performance and generalizability. The developed models are limited to data obtained only from primary school classrooms; therefore, studies at middle school, high school, and university levels will provide the opportunity to test the model's applicability at different educational levels. This methodology has the potential to be used not only to determine student capacity for a safe return to face-to-face education under pandemic conditions, but also to determine optimal class sizes in terms of student achievement, health, and spatial comfort in the post-pandemic period. In future studies, it is recommended to examine school typologies in different climatic zones, including more comprehensive spatial parameters (acoustics, lighting, indoor air quality, etc.) in the model, and verify with field applications.

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We would like to thank all school administrations and teachers who contributed to the measurement and evaluation of the classrooms examined in this study.

Conflict of Interest Statement

The manuscript is entitled “A Data-Driven Approach to Determining Safe Classroom Capacities During the Transition to Face-to-Face Education” has not been published elsewhere and that it has not been submitted simultaneously for publication elsewhere.

Author Contribution

All authors contributed equally to this article.

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