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Fire behavior prediction with artificial intelligence in thinned black pine (*Pinus nigra* Arnold) stand

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ABSTRACT

Modeling forest fire behavior is very important for the effective control of forest fires and the setting up of necessary precautions before fires start. However, studies of forest fire behavior are complex studies that depend on many variables and usually involve large data sets. For this reason, the predictive power and speed of classical forecasting models are lower than of artificial intelligence models in cases involving big data and many variables. Moreover, classical forecasting models must satisfy certain statistical assumptions, unlike artificial intelligence methods. Thus, in this study, predictions were made of surface fire behavior, especially the rate of fire spread and the fire intensity, at the location at which fires started using two artificial intelligence methods, an artificial neural network and a decision tree. The accuracy of the developed models was fitted and tested. Finally, the classical regression model for predicting surface fire behavior was compared with the two artificial intelligence methods. The accuracy measures of the artificial intelligence models were found to be better than those of the classical model.

1. Introduction

Forests are some of the most important natural resources in the world and play a key role in maintaining ecological balance, and forest ecosystems provide many ecological and economic services for human life. Forest fires are considered some of the most detrimental events that interrupt these services. Extreme meteorological conditions greatly increase the destructive effects of forest fires. The fires have complicated causes and are often very difficult to fight. Therefore, the prediction of fire behavior is essential for the successful management of fires, the effective planning of resources for fighting them, and the mitigation of the damage they cause (Mitsopoulos et al. 2017; Yavuz et al. 2018; Sevinc et al. 2020; Abid 2021). Various classical regression models have been developed to predict forest fire behavior (Fryer and Johnson 1988; Alexander and Cruz 2006; Sullivan 2007; Yassemi et al. 2008; Fernandes 2009; Matthews et al. 2012; Kucuk et al. 2012; Cruz et al. 2017; Kucuk et al. 2018; Bilgili et al. 2019; Alhaj-Khalaf et al. 2021; Cruz et al. 2022). Other models of forest fires based on the machine learning method of artificial neural networks (Pham et al. 2020) have predicted flame characteristics and fire spread (Chetehouna et al. 2015).

Fire detection and mapping, fire weather and climate change (Li et al. 2009; San-Miguel-Ayanz et al. 2012), fire probability and risk, fire hazard assessment, and fire behavior prediction have become very popular in recent years, driven by advances in fire sciences, digital and statistical information, the remote sensing technologies, including GIS, and the growing climate crisis (Vakalis et al 2004; Finney et al. 2011; Aricak et al. 2014; Rodrigues and Riva, 2014; Preisler et al. 2014; Goldarag et al. 2016; Lary et al. 2016; Huiling at al. 2016; Zhang et al 2018; Sivrikaya and Küçük, 2022). Probabilistic methods such as logistic regression, neural networks, and fuzzy logic regression are commonly used for forest fire studies (Jaafari et al. 2019). Traditional models for predicting fire risk and behavior include generalized linear models based on logistic, Poisson, and negative binomial distributions. However, these models cannot process multidimensional big data. Researchers have stated that artificial intelligence outperforms traditional statistical methods in solving the big data problem encountered in modeling forest fires. In addition, traditional statistical models must satisfy certain statistical assumptions, unlike artificial intelligence methods.

The traditional approaches generally lack the ability to combine data and evidence from various sources, and they also do not consider uncertainty or missing data. Therefore, new approaches, which consider

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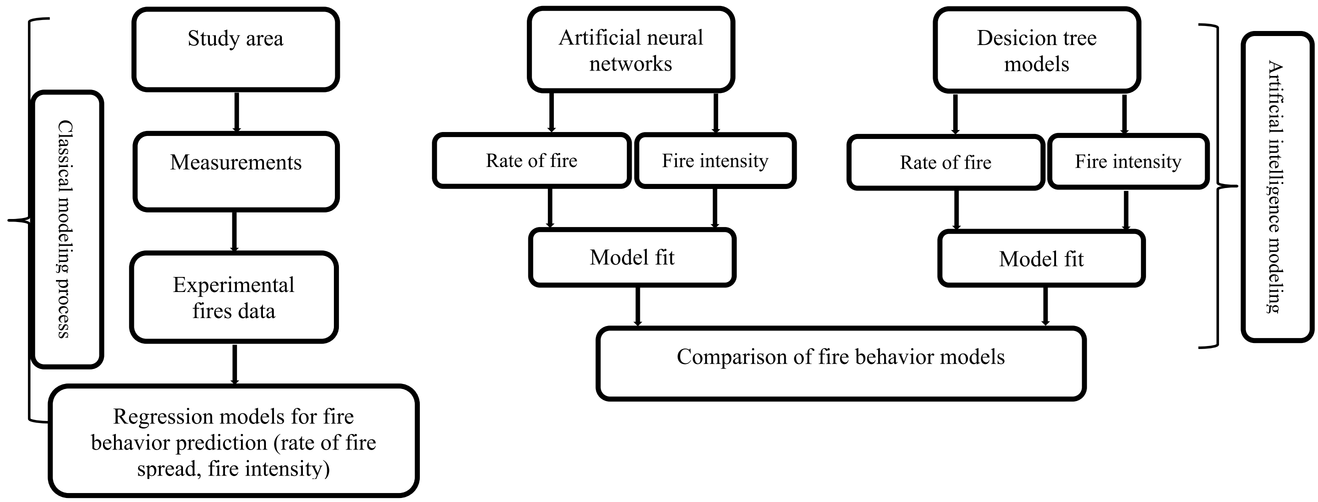

Fig. 1. Comparison of artificial intelligence models and classical regression model in predicting fire surface behavior.

uncertainty and link the various long-term effects of factors to each other, are needed. Such methods should be capable of being integrated into multiple system operations. Artificial intelligence techniques have been very useful in meeting this need (Jain et al. 2020). They allow for modeling analysis to support decision making within an adaptive management framework (Cencerrado et al. 2014; O'Connor et al. 2017; Sayad et al. 2019).

In recent years, artificial intelligence methods have proven to be very effective in predicting environmental disasters (Hart et al. 2019; Tan et al. 2021). However, there are difficulties in predicting the behavior of forest fires because they are very complex paradoxical events that are influenced by many environmental factors. One of the most effective methods of overcoming the difficulties of prediction is the use of artificial intelligence techniques. The artificial neural network, which is a mathematical software simulation, is used to expand the data and to provide new and unknown data. In practice, the artificial neural network is used as an alternative to traditional methods and is very helpful in producing satisfactory solutions for difficult problems. Artificial intelligence is especially useful in solving problems that are rich in data but weak in modeling and that no traditional method can solve (Kotsiantis et al. 2006; Kinaneva et al. 2019; Liang et al. 2019; Razavi-Termeh et al. 2020; Wu et al. 2022). This makes the use of artificial intelligence advantageous in predicting forest fires. Data based on wildfires and experimental fires are usually not sufficient for accurate predictions and cannot encompass every situation. Artificial intelligence not only prevents data loss in fire behavior predictions, but also contributes to the solution of many data problems in making predictions.

Studies using artificial intelligence to predict fire behavior are quite limited (Kozik et al. 2013; Zheng et al. 2017; Hodges and Lattimer, 2019). In this study, for the first time in the literature, we propose a new approach to predicting fire behavior using artificial intelligence. We explain the structure of an artificial neural network and decision tree, the advantages and disadvantages of each, and the differences of each from classical regression models. We show how forest fire behavior can be predicted using artificial intelligence.

Forest fuel characteristics and weather conditions are two factors that determine the ecological and economic impacts of a fire. In the extreme weather conditions experienced in 2021, the biggest forest fires in the history of Turkey occurred, and a total of 139.503 ha of forest area was burned (GDF 2022). The Manavgat forest fire (~55000 ha) was recorded as the largest forest area burned in a fire (Bilgili et al. 2021).

Forest fires occur in different stand types, but the fuel types and the forest management plan applications in a stand determine to what degree a fire will directly and indirectly affect the forest. In young stands with no interventions, a fire can easily turn into a crown fire because of the characteristics of the fuel and the stand's horizontal and vertical continuity. For this reason, silvicultural interventions are made to delay and make it difficult for fires that start on the surface to reach the crown, to increase the crown base height, and to decrease the crown bulk density within the scope of forest fuel management (Kucuk et al. 2021). However, slash fuels that accumulate in a stand as a result of silvicultural interventions pose a great danger for fires. For this reason, it is important to know how a fire will develop when slash fuels have accumulated in the surface layer of such stands. Kucuk et al (2012) stated that forest fires first started in the litter layer and turned into larger fires depending on environmental conditions.

This study was the first study conducted in Turkey using the two different artificial intelligence methods of an artificial neural network and a decision tree, instead of the classical regression model, to predict the fire behavior of *Pinus nigra* slash fuels. Artificial neural network models were originally developed to solve problems that linear regression models failed to solve. Problems of regression models, in which nonlinear relationships are represented, are not always solvable. The search for solutions to such problems has been one of the starting points in the development of artificial neural networks. Another feature that makes this study very different from others is that it uses the results of experimentally obtained fire behavior models and the results of models developed using artificial intelligence. In other words, it shows that artificial intelligence, which is used successfully in many fields for its ability to go beyond the classical modeling approach, can also be used in the prediction of fire behavior. This point brought the innovative aspects of this study to the fore. The decision tree model used in the study, which makes the innovative aspects of this study even stronger, is another alternative artificial intelligence model. Decision trees are some of the most practical methods for revealing the relationships between variables. The results of the artificial neural network model and decision tree model developed for predicting the rate of fire spread and the fire intensity, which are fire behavior parameters, are compared with the results of the traditional regression models. This study showed that artificial intelligence can be used in fighting the mega forest fires increasingly seen in recent years, especially those due to the effects of the climate crisis.

2. Methods

In this study, the surface fire behavior at the location where the fire started was predicted using artificial intelligence, especially the rate of fire spread and the fire intensity. The suitability of the developed models was fitted and tested. Finally, the classical regression models developed for predicting surface fire behavior were compared with the two

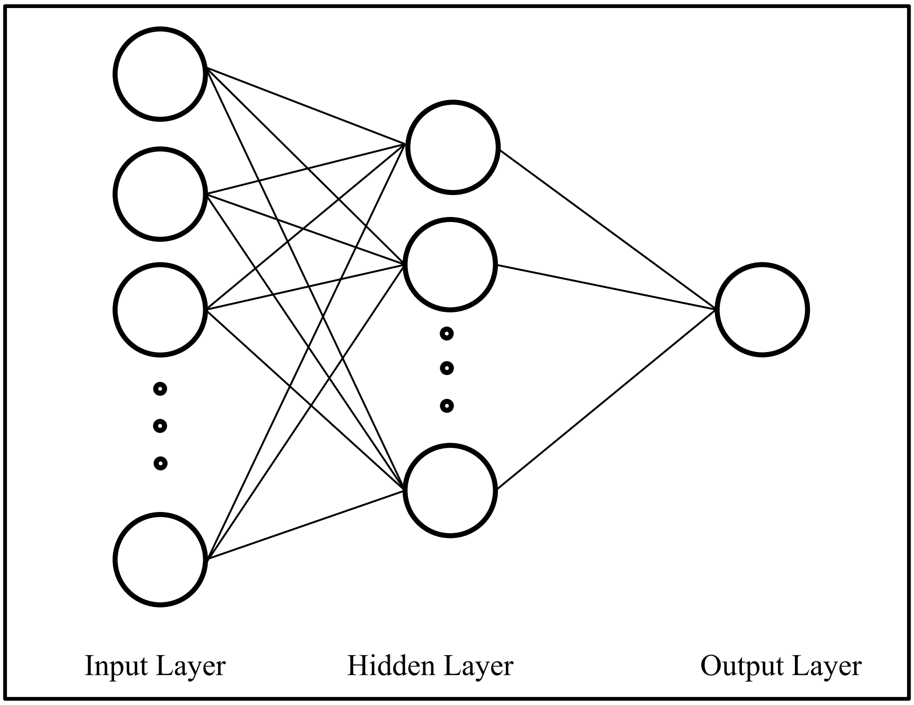

Fig. 2. General structure of multilayer perceptron neural network model.

artificial intelligence models (Fig. 1). Ten variables were used in the study: air temperature (T), relative humidity (RH), wind speed (W), needle moisture content (NMC), fine fuel moisture content (FFMC), ignition of fire line length (ILL), total fuel load (TFL), rate of fire spread (ROS), flame length (FL), and fire intensity (FI).

2.1. *Study area*

The study was carried out in an Anatolian black pine (*Pinus nigra* Arnold) forest located in the Kastamonu Forest District in northwestern Türkiye. This black pine species is the most widespread species in the area after Calabrian pine (*Pinus brutia* Ten.); it has economic and ecological value and is distributed in fire-prone areas in Türkiye (Kucuk 2000; GDF 2022).

The study area is located at 546819, 4577880 UTM, and its average elevation is 1200 m. The study area has a northwestern Black Sea climate characterized by short hot summers and long cold winters. During the summer season, the average temperature varies from 25 to 38 °C, and the fire season generally starts in late June and continues until mid-September. The stand age of the study area was 45 to 50 years, and the average stocking findings showed 560 stems ha^{-1} with an average tree diameter of 20 cm at breast height. The stand height was 16 m, and the mean stand crown closure was 75 %. Surface fuels consisted of a litter layer of dead needles, branches, and twigs on the forest floor.

2.2. *Measurements before the experimental fires*

A total of 33 small-scale burning plots were prepared on relatively flat surfaces in the thinned black pine stand. The fuel depth in the burning plots ranged between 20 and 45 cm. Three ignition line widths (1 m, 3 m, and 5 m) were used. Surface fuel load estimations were based on fuel samples randomly taken from areas immediately adjacent to and representative of each burning plot (Brown 1974; Kucuk et al. 2018). Each fuel component was weighed in the field and taken to the laboratory for the estimation of the surface fuel loading after oven-drying. Before the experimental fires, an automatic mobile weather station was established in the study area. During the experimental fires, the wind speed, air temperature, and relative humidity were recorded.

2.3. *Experimental fires and data*

Experimental surface fires were carried out in the fire season within a relatively narrow range of air temperature, relative humidity, wind speed, and fuel moisture content. Collection of the data on fire behavior started when the fire line had moved about 30 cm from the edge of the plot or when the fuel (from a drip torch) used to establish the fire line had lost its effect in the initial phase of fire spread. The rate of spread is expressed as the distance reached by the fire per unit time. Rates of spread were determined by recording the time the head fire front arrived at poles 1 m apart on each side of the burning plot. In the calculation of rate of spread, we used rate of fire spread formula in the literature (Kucuk et al. 2018). Fire behavior was monitored during each fire from the time the ignition line was fully established to the time the fire front reached the edge of the plots (Stocks et al. 2004; Sağlam et al. 2008a, b; Kucuk et al. 2012; Kucuk et al. 2018). Fire line intensity (*FLI*) is the proportional expression of the energy released per unit distance. FLI was calculated using Byram's equation (1959);

$FLI = H \times W \times ROS.$

Where,

FLI is the fire line intensity (kW/m),

H is heat yield of the fuel (kJ kg^{-1}),

W is the dry weight of the fuels consumed by the fire (kg m^{-2}) and.

ROS is the rate of spread of the flaming front (m/s).

In this study, an energy content of 18000 kJ kg^{-1} was used based on the relevant information (Alexander, 1982; Bilgili and Sağlam 2003).

2.4. *Artificial neural network models*

Artificial neural network models are information-processing technologies inspired by the workings of the human brain. They calculate predictive values through interconnected networks that imitate the working principles of neurons, which are the basic structures of the human nervous system. These artificial neurons, also known as artificial nerve cells or basic processing units, have five basic elements: input values, weights, sum functions, activation functions, and output values. Input values are the sample values introduced to the artificial neurons. Weights are the coefficient values that are multiplied by the variables

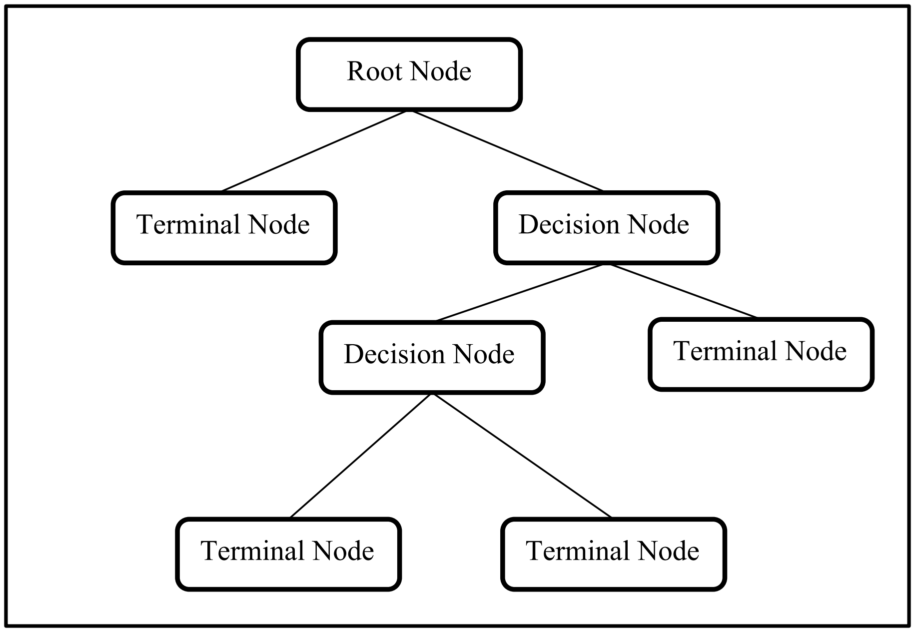

Fig. 3. Example of decision tree model.

according to the importance and impact of the information entering the cells. The sum, or aggregation, function is created by adding together the information values weighted by the coefficients and turning them into a function. There are different approaches to constructing aggregation functions. The activation function determines the output to be produced in response to the information entering the artificial nerve cell. Activation functions are usually chosen to be nonlinear functions. There are several types of activation functions, such as the stepwise activation function, sigmoid activation function, piecewise linear activation function, Gaussian activation function, linear activation function, and hyperbolic tangent activation function. Finally, the output value is the result generated by the activation function. This value can be transmitted as a result, or the artificial neuron can process this result as an input to itself or to another artificial neuron. Although a neuron can have many inputs, it produces a single output. The first artificial neural network models were developed to provide solutions to linear relations problems. Examples of these models are simple single-layer perceptrons, simple perceptrons, and Adaline/Madaline units. Multilayer perceptron artificial neural networks have also been developed to examine nonlinear relationships in later stages. In addition, information about multilayer perceptron artificial neural networks is given (Sharma et al. 2012; Graupe 2013; Suzuki 2013; Da Silva et al. 2017; Walczak 2018; Alanis et al. 2019; Kubat 2021).

2.4.1. Multilayer perceptron neural network models

The multilayer perceptron neural network model is one of the models developed as an alternative to the simple perceptron models, which are insufficient in cases where the relationships between variables are not linear. A multilayer perceptron neural network model has three layers, the input layer, the hidden layer, and the output layer. No data processing takes place in the input layer. The basic processing units in this layer have only one input and one output. The output value is sent to all of the basic processing units in the next layer, the hidden layer. These units are responsible for processing the information coming from the input layer and sending it to the output layer. In multilayer perceptron neural networks, there can be more than one intermediate layer, and each layer can contain more than one processing unit. The processing units in the hidden layer are connected to all of the processing units in the output layer. In the output layer, the information coming from the hidden layer is processed and transmitted to the outside world. The number of processing units in the output layer can also be more than one. The general structure of the multilayer perceptron neural network model is shown in Fig. 2, (Sharma et al. 2012; Graupe 2013; Ramchoun et al. 2016; Park and Lek 2016; Sumsion et al. 2019; Amato et al. 2017).

The supervised learning approach is used in multilayer perceptron neural networks. In this approach, a sample data set containing both input values and output values is entered into the artificial neural network beforehand to generate predictive values based on these sample values. The multilayer perceptron neural network model (also called the error propagation model) makes estimations using the delta learning method, which has two stages: forward calculation and backward computation. The net input value is obtained by weighting and summing the data received from the input layer and reaching the processing unit in the forward calculation phase. The net input value is converted to an output value with the help of the activation function. Then this output value is sent to the processing unit in the next layer. These processes are repeated until the values obtained in the last output layer converge to the output values used in the training process. In the second stage, the aim is to reduce the errors in each iteration by distributing the weight values. The weight values randomly assigned to the system at the initial stage are updated in each iteration after the errors are distributed to the weights (Velo et al. 2014; Fernandes de Mello and Antonelli Ponti 2018; Zhou et al. 2016).

Artificial neural network models have some advantages and disadvantages over classical regression models. The most important advantage of artificial neural networks is that they store information on the entire network and the loss of a few pieces of information does not prevent the network from working. Also, neural networks can work with incomplete data and information. After the training phase, the network can produce output even with incomplete information. Artificial neural networks can produce output without being affected by an error in or corruption of one or more unit of data. The model has an error-free structure. Another advantage is that the network is trainable compared with other examples and can benefit from previous work. In addition, the network can learn from similar networks. Networks can work together to complement each other. They can perform multiple tasks simultaneously. Artificial neural networks can solve complex problems more successfully than linear approaches; do not need any assumptions or prerequisites in terms of data structure and model; have the ability to learn from data and make decisions; can reveal hidden

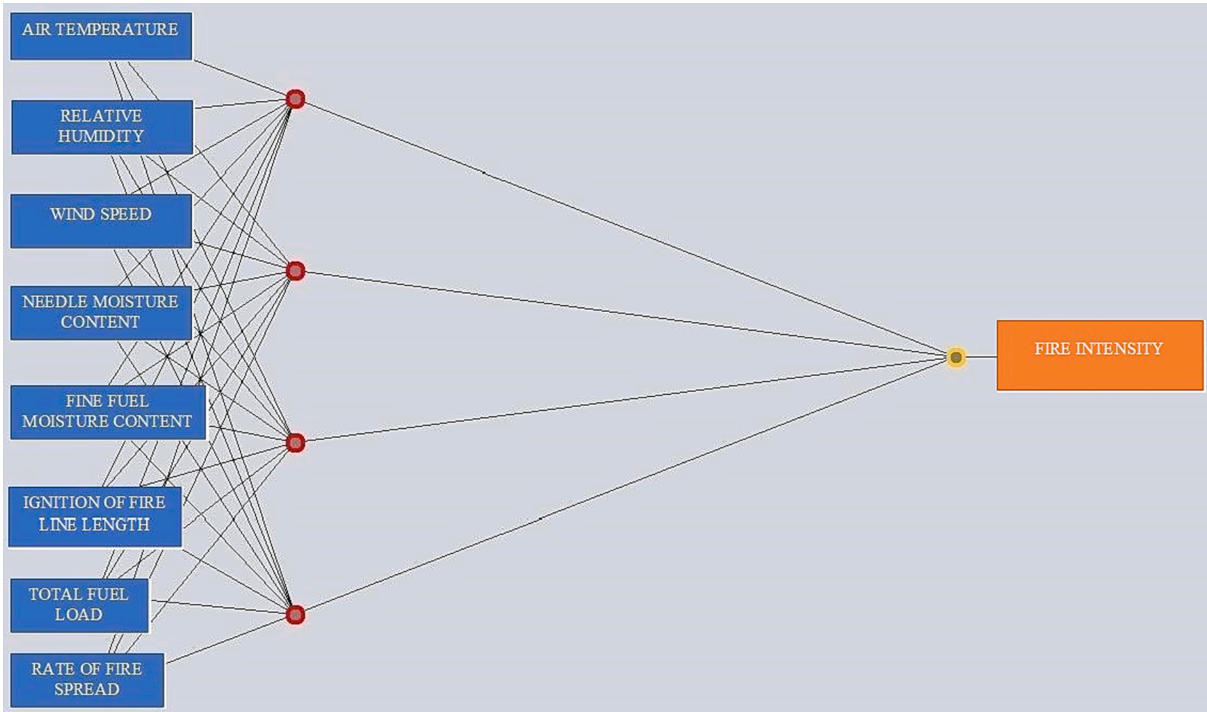

Fig. 4. Artificial neural network model for predicting fire intensity.

relationships in data; and are much more successful than other classical models at modeling data with a nonconstant variance.

There are also disadvantages to using artificial neural networks. For example, the performance capabilities of the networks are directly dependent on the power of the computer hardware being used. In addition, they may produce unexpected results because the how and causality are not considered during the creation of the network. There is no definite rule for their construction. A proper network structure may depend on experience and trial and error. Since artificial neural networks work with numerical values, some problems may be difficult to teach to the network if they must be changed to numerical values. This is a process that largely depends on the capabilities of the user or researcher. It cannot be guaranteed that the network obtained in the predetermined learning time will give the optimum result. One of the biggest disadvantages of artificial neural networks is that they do not give details of why and how the output prediction values they produce are found. This may pose a problem in explaining some analyses (Tu 1996; Livingstone et al. 1997; Dumitru and Maria 2013; Walczak 2018).

2.5. Decision tree models

Decision trees are nonparametric supervised learning methods that can perform both the regression and classification processes used in data analysis. Although artificial neural networks work in the form of an unknown closed box, decision trees are open. They create a prediction model structured like a tree, consisting of a root node (starting node) and decision nodes and leaf nodes that are added to the model according to the nature of the process. The nodes at which the branching ends are called terminal nodes. An example of a decision tree model is shown in Fig. 3.

In the decision tree model, learning is performed by dividing the data set into sections. The basic principle in the process of creating a decision tree is to ask questions about the data and to create decision rules by collecting the answers in line with the answers received. Questions are asked starting from the root node and continue until the terminal nodes that do not have branches are reached. The criteria used for branching in the decision tree are different for the regression and classification models. In decision tree models created for the regression process, a variable and a value that will divide this variable into two different groups are selected. This process is repeated for each variable and for each possible value to find out which variable and which value give the best result. The results are scored by taking the weighted average of the mean squares of error of both groups formed. The highest score indicates which variable and which value best discriminate among the groups.

Decision tree models have some unique advantages. For example, they are quite easy to understand and interpret in terms of the characteristics of their appearance. They can be used for both classification and regression. Decision tree models are some of the most practical methods for revealing the most significant variables and the relationship between two or more variables. Apart from these, they do not need any distribution-based assumptions, because they are nonparametric methods. They can work with both numerical and categorical data. In addition to requiring less preliminary preparation of data, they are also much less affected by outliers or missing values. They can also easily represent nonlinear relationships.

The most important disadvantage of decision tree models is that they may produce overestimations. There is also no guarantee that the obtained model is the optimal model. They cannot provide an information flow from other models. They are heavily affected by an increase in variance in the data. In addition, when working with continuous variables, they lose information during the categorization phase (Quinlan 1990; Rokach and Maimon 2005; Esmeir and Markovitch 2007; Kingsford and Salzberg 2008; De Ville 2013; Kotsiantis 2013; Breiman 2017).

2.6. Model fit and comparison of fire behavior models

For the artificial neural network model to examine fire behavior, the multilayered sensor function in the Weka (2021) program was used. After trying many network structure combinations, models with the best correlation and low error values were adopted. 64 % of the data set was reserved as training data and 34 % as test data. In this study, artificial neural networks model structure was customized as a solution to the overfitting problem, and the multilayer perceptron type artificial intelligence model was used based on 30 % learning rate and 20 %

Table 1
Results of fit for the artificial neural network model for predicting fire intensity.

Correlation coefficient	R^2	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)	Relative Absolute Error (%) (RAE)	Root Relative Squared Error (%) (RRSE)	Total Number of Instances
0.995	0.99	245.568	289.996	13.3	13.6	11

Table 2
Variables affecting fire severity according to artificial neural network model.

Independent variables	Weights
Wind speed	1995.028
Rate of fire spread	1337.682
Total fuel load	195.640
Air temperature	−144.161
Ignition of fire line length	−338.307
Needle moisture content	−384.758
Fine fuel moisture content	−385.732
Relative humidity	−557.832

momentum value.

Five hundred iterations were carried out during the training period. Two separate artificial neural networks were developed for the prediction of fire intensity and rate of fire spread. In the built decision tree models, the random tree function included in the Weka (2021) program was used. The independent variables for the prediction of fire behavior with the decision tree were air temperature, relative humidity, wind speed, needle moisture content, fine fuel moisture content, ignition of fire line length, total fuel load, and rate of fire spread. Sixty-six percent of the data set was reserved as training data and 34 % as test data.

3. Results and discussion

3.1. Development of an artificial neural network model for predicting fire intensity

Estimating the fire intensity is extremely important for planning the size of a firefighting organization (Calkin et al. 2011; Mitsopoulos et al. 2017), the equipment to be used, and the appropriate responses to take (Thompson et al. 2016). In this study, the temperature, relative humidity, wind speed, needle moisture content, fine fuel moisture content, ignition line width, total fuel load, and rate of fire spread variables were the independent variables for predicting the fire intensity. The artificial neural network model for predicting fire intensity is shown in Fig. 4; it is a single-hidden-layer network containing four neurons.

The results of the fit of the artificial neural network model created for predicting fire intensity are given in Table 1.

When the model performance results given in Table 1 are examined, it is seen that the model has a very high correlation value of 0.995. Similarly, the relative absolute error value of 13.3 % turned out to be a rather small value. This showed that the model made predictions with a nearly perfect result. According to the study's artificial neural network model, the factors that most affected the fire intensity were, from most influential to least influential, the wind, rate of fire spread, and total fuel load (Table 2). In the fire intensity formula provided by Byram (1959), the rate of fire spread and the amount of combustible fuel consumed were the basic parameters. Although similar results were achieved with the artificial neural network model, the effects of many other parameters were also revealed. This result shows that other parameters are factors and that they affect each other.

3.2. Development of an artificial neural network model for predicting the fire spread rate

The temperature, relative humidity, wind speed, needle moisture content, fine fuel moisture content, ignition of fire line length, and total fuel load were considered to be independent variables in predicting the fire spread rate (Fig. 5).

The artificial neural network shown in Fig. 5 has two hidden layers. There are two neurons in the first hidden layer and five neurons in the second hidden layer. The results of the fit of the artificial neural network

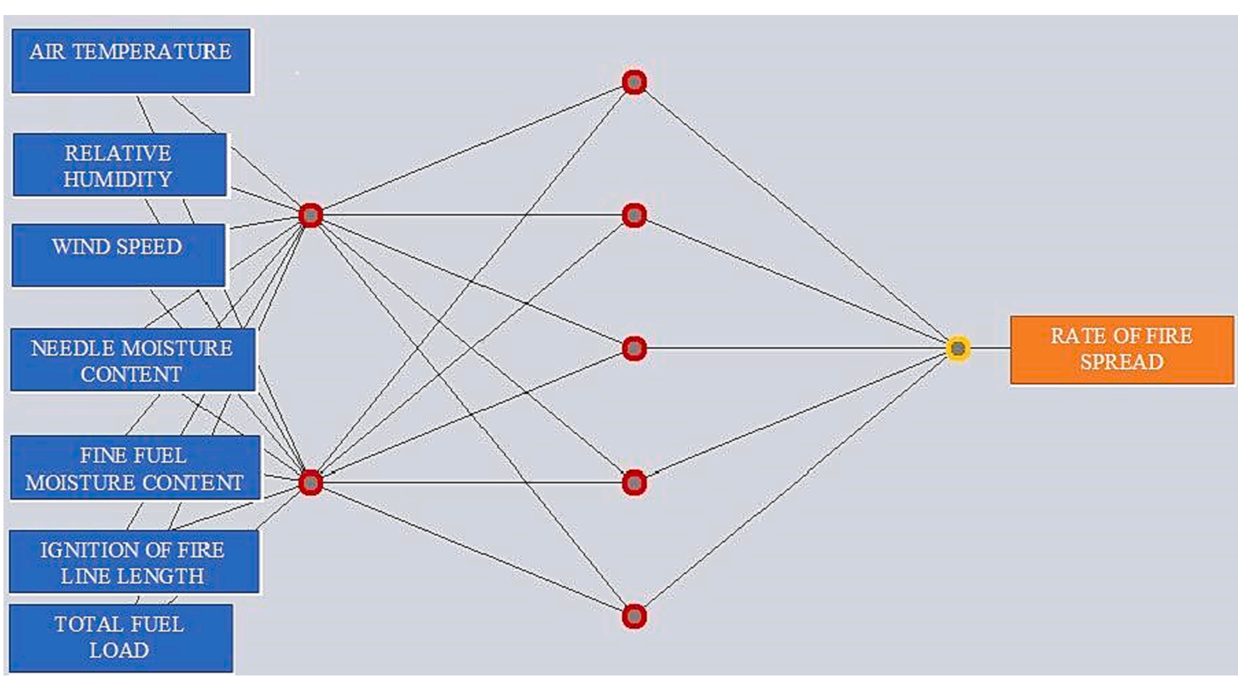

Fig. 5. Artificial neural network model for predicting the fire spread rate.

Table 3
Results of fit for the artificial neural network model for predicting the fire spread rate.

Correlation coefficient	R^2	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)	Relative Absolute Error (%) (RAE)	Root Relative Squared Error (%) (RRSE)	Total Number of Instances
0.906	0.82	0.443	0.591	33.321	39.803	11

Table 4
Factors affecting the rate of fire spread according to the artificial neural network model.

Independent variables	Weights
Wind speed	0.469
Air temperature	0.030
Total fuel load	−0.127
Fine fuel moisture content	−0.261
Needle moisture content	−0.265
Ignition of fire line length	−0.297
Relative humidity	−0.314

model for predicting the fire spread rate shown in Fig. 5 are given in Table 3. The factors affecting the rate of fire spread in the constructed artificial neural network model are given in Table 4 in decreasing order from most influential to least influential.

Data for experimental fires have shown the wind speed to be the environmental variable that leads to the most significant changes in the rate of fire spread. When the results given in Table 4 are examined, it is seen that the artificial neural network determined the most influential factor on the rate of fire spread to be wind speed. Wind is the most important factor increasing fire spread. The wind parameter, which is shown to be the most important independent variable in many models of rates of fire spread, was also the most important in our study (Nelson 2002; Cheney et al. 2012; Anderson et al. 2015; Cruz and Alexander, 2019). The second most important factor was the air temperature, and the third most important factor was the total fuel load. The least important factor was determined to be the relative humidity.

3.3. Development of a decision tree model for predicting fire intensity

The effect of the wind speed on the rate of fire spread is complex, and it depends on several factors such as fuel characteristics, wind speed profiles, and heat transfer from the fire. While creating the decision tree model for fire intensity prediction, the air temperature, relative humidity, wind speed, needle moisture content, fine fuel moisture content, ignition of fire line length, total fuel load, and rate of fire spread were used as the independent variables. The results of fit of the decision tree model created for predicting fire intensity are given in Table 5. The most influential factors for fire intensity are given in Table 6 and are listed from most influential to least influential.

According to the decision tree model created for predicting fire intensity, the most important factor was wind speed. The second most important factor was the rate of fire spread, and the third most important factor was the fine fuel moisture content. The least important factor was the total fuel load.

3.4. Development of a decision tree model for predicting the fire spread rate

When a decision tree model for predicting the fire spread rate was built, the independent variables chosen were the temperature, relative humidity, wind speed, needle moisture content, fine fuel moisture content, ignition of fire line length, and total fuel load. In studies similar to this study, the effectiveness of the same parameters was determined using classical methods (Kucuk et al. 2012; Kucuk et al. 2018; Sevinc et al. 2020; Cruz et al. 2022). The results of fit of the decision tree model created for predicting the rate of fire spread are given in Table 7. The factors that affected the rate of fire spread, from most influential to least influential, are given in Table 8.

According to the decision tree model created for predicting the rate of fire spread, the most important factor was the temperature, and the second and third most important factors were the wind speed and fine fuel moisture content, respectively. The least important factor was the total fuel load. Comparative predictions of fire behavior of all of the models created, from most influential to least influential, are given in Table 9.

The performances of the artificial neural network and decision tree models created separately for the prediction of fire intensity and rate of fire spread are compared in Table 10.

In regard to fire intensity, the correlation coefficients of both the artificial neural network and decision tree models were significantly high at 0.995 and 0.99, respectively. Both the artificial neural network model and the decision tree model performed better than the regression model, which had a comparatively low correlation coefficient of 0.844. The artificial neural network model performed better than the decision tree model or classical regression model. Its scores for the mean absolute error (MAE), root mean squared error (RMSE), relative absolute error (RAE), and root relative squared error (RRSE) were only approximately half of those scores for the decision tree model. Thus, briefly, the most successful model in predicting the fire intensity was the artificial neural network model, the second most successful was the decision tree model, and the least successful was the regression model.

When it came to predicting the rate of fire spread, the correlation coefficient of 0.906 of the artificial neural network model was higher than the correlation coefficients of the decision tree model (0.804) and the regression model (0.873). Although the MAE and RMSE values of the artificial neural network model were higher than those of the decision tree model, the RAE and RRSE values of the decision tree model were larger than those of the artificial neural network model. In this

Table 6
Factors affecting fire intensity according to the decision tree model.

Independent variables	Weights
Wind speed	1817.458
Rate of fire spread	1131.349
Fine fuel moisture content	43.691
Air temperature	40.895
Relative humidity	−68.900
Ignition of fire line length	−139.82
Needle moisture content	−350.633
Total fuel load	−782.927

Table 5
Results of fit for the decision tree model for predicting fire intensity.

Correlation coefficient	R^2	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)	Relative Absolute Error (%) (RAE)	Root Relative Squared Error (%) (RRSE)	Total Number of Instances
0.990	0.98	425.681	758.740	23.032	35.669	11

Table 7
Results of fit for the decision tree model for predicting the rate of fire spread.

Correlation coefficient	R^2	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)	Relative Absolute Error (%) (RAE)	Root Relative Squared Error (%) (RRSE)	Total Number of Instances
0.804	0.64	1.161	1.750	87.401	117.780	11

Table 8
Factors affecting the rate of fire spread according to the decision tree model.

Independent variables	Weights
Air temperature	0.249
Wind speed	0.201
Fine fuel moisture content	−0.059
Ignition of fire line length	−0.083
Relative humidity	−0.214
Needle moisture content	−0.294
Total fuel load	−0.306

comparison, it can still be suggested that the artificial neural network exhibited a slightly better prediction performance than the decision tree model. However, unlike in the previous case, the regression model performed better than the decision tree model in predicting the rate of fire spread.

4. Conclusions

In this study, predictions were made of the surface forest fire behavior based on the rate of fire spread and the fire intensity using two artificial intelligence methods, an artificial neural network and a decision tree. Additionally, the prediction performances of the two methods were compared with the performance of the conventional regression model. The artificial neural network performed better than the other models in predicting both the fire intensity and the fire spread rate. The decision tree model had a considerably more successful performance than the regression model in predicting the fire intensity. However, when it came to predicting the fire spread, the regression model performed slightly better than the decision tree model. Overall, the artificial neural network was the most powerful model in predicting the fire intensity and the fire spread rate, and this demonstrated that artificial intelligence models can be used quite successfully in predicting fire behavior. To expand on this study, other studies of the prediction of the fire intensity and fire spread rate can be performed with other artificial intelligence methods and using additional or different variables. This method can also be used for *Pinus brutia* in Mediterranean region.

CRediT authorship contribution statement

Omer Kucuk: Conceptualization, Methodology, Supervision, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Volkan Sevinc:** Methodology, Writing – review & editing,

Table 9
Comparative results of models for predicting fire behavior.

Fire Behavior Predicting					
Fire intensity			**Rate of fire spread**		
Artificial neural network model	**Decision tree model**	**Regression model**	**Artificial neural network model**	**Decision tree model**	**Regression model**
Wind speed	Wind speed	Wind speed	Wind speed	Air temperature	Wind speed
Rate of fire spread	Rate of fire spread	Total fuel load	Air temperature	Wind speed	Ignition of fire line length
Total fuel load	Fine fuel moisture content	Ignition of fire line length	Total fuel load	Fine fuel moisture content	Needle moisture content
Air temperature	Air temperature		Fine fuel moisture content	Ignition of fire line length	
Ignition of fire line length	Relative humidity		Needle moisture content	Relative humidity	
Needle moisture content	Ignition of fire line length		Ignition of fire line length	Needle moisture content	
Fine fuel moisture content	Needle moisture content		Relative humidity	Total fuel load	
Relative humidity	Total fuel load				

Table 10
Comparison of the performances of the artificial neural network models and decision tree models for predicting the fire intensity and rate of fire spread.

The Performance Results of the Models						
	Fire intensity			**Rate of fire spread**		
Measures	**Artificial neural network model**	**Decision tree model**	**Regression model**	**Artificial neural network model**	**Decision tree model**	**Regression Model**
Correlation coefficient	0.995	0.990	0.844	0.906	0.804	0.873
R^2	0.99	0.98	0.94	0.82	0.64	0.83
Mean Absolute Error (MAE)	245.568	425.681	542.125	0.443	1.161	0.552
Root Mean Squared Error (RMSE)	289.996	758.740		0.591	1.750	
Relative Absolute Error (%) (RAE)	13.3	23.032		33.321	87.401	
Root Relative Squared Error (%) (RRSE)	13.6	35.669		39.803	117.780	
Total Number of Instances	11	11		11	11	

Formal analysis, Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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