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A Neural Network Approach to Forest Fire Burned Area Prediction

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Abstract

Worldwide ecosystems and economies are seriously threatened by forest fires, which can result in extensive damage and financial losses. Strategies for managing and preventing wildfires depend heavily on the accurate prediction of burned areas. To create a predictive model for the burned areas caused by forest fires in Portugal's northeast, this study uses a machine learning technique, namely Neural Network. The model integrates meteorological and spatial-temporal data and makes use of regression algorithms. To maximize the performance of the model, data preprocessing, exploratory data analysis, model building, feature selection, and assessment are done. The results show that burned area is greatly influenced by meteorological factors, including temperature, humidity, and wind speed. The created model shows a respectable level of prediction accuracy of 97.11%, offering insightful information for efficient fire management and early warning systems. The potential for reducing the destructive effects of wildfires is enormous when machine learning is incorporated into the prediction of forest fires.

1. Introduction

Climate change and forest fires are closely associated. Climate change is making wildfires more frequent, intense, and difficult to contain [1]. Climate change is putting the world's forests and communities in severe danger [2]. The community and the authorities can each carry out their designated tasks. Reducing greenhouse gas emissions can help mitigate both climate change and the risk of forest fires. It is also important to lower the risk of forest fires because they have an impact on both the surrounding population and the forest. The biological, environmental, and socioeconomic effects of forest fires are substantial. Forest fires are spontaneous, uncontrolled flames that occur in areas with combustible vegetation. Lightning strikes are examples of a natural phenomenon that might cause them, in addition to human activities like campfires, abandoned cigarettes, and ignition [3]. Forest fires may have a catastrophic impact on the ecology because they wipe off forests, wildlife, and personal property. Additionally, they pose a major risk to people's safety and well-being.

For both human safety and sustainable forest protection, forest fire prediction and management are essential. This is because it aids in keeping flames from beginning and growing. In the event of a fire, it also enables firemen to react with efficiency and speed [4]. Accurately estimating the burned area resulting from forest fires is essential for understanding fire behavior, allocating firefighting resources, and developing effective prevention strategies [5]. Predicting forest fires is an essential tool for safeguarding populations, forests, and the environment. Effective prediction, prevention, and management of forest fires is a shared responsibility including government agencies, forest managers, researchers, and the public. Forest fire prediction offers several vital benefits to protecting communities, ecosystems, and the economy [6]. Pre-emptively addressing possible fire incidents through early warning systems, public education campaigns, and fuel reduction programs can greatly lower the risk of a fire occurring and lessen its damage [7]. Additionally, precise forest fire forecasting makes it possible to allocate resources for firefighting operations in an efficient manner, guaranteeing prompt and efficient suppression techniques to protect property and life. Predictive models also have the potential to improve forest resilience and reduce the likelihood of future fires by informing forest management practice.

Forest fire forecasting has historically depended on a mix of historical records, weather measurements, and human experience [8][9]. For many years, these conventional techniques have proved crucial in the prediction of forest fires. But the development of Artificial Intelligent (AI) technology has created new opportunities for predictions that are more precise, thorough, and up to date [10]-[15]. Large volumes of data, such as records of past fires, weather, vegetation, and topography, can be analyzed by AI algorithms to find intricate patterns and linkages that would be challenging to find with conventional techniques.

Recent years have seen a considerable increase in interest in the forecast of burned areas in forest fires because of the practical implications for fire management and mitigation initiatives. It is feasible to capture the intricate dynamics of forest fire behavior by combining meteorological factors like temperature, humidity, wind speed, and rainfall with extra contextual data [16]. These factors offer a thorough understanding of fire patterns and their link to meteorological conditions when paired with geographical and temporal data. This research effort takes multiple phases to construct an accurate predictive model. The dataset is first put through a rigorous preprocessing process that includes addressing missing values, normalizing numerical features, and encoding categorical variables. Then, to find patterns, relationships, and anomalies in the dataset, exploratory data analysis approaches are used. This research project focuses on predicting the burned area of forest fires in the northeast region of Portugal. The project leverages meteorological and other pertinent data to develop a robust predictive model capable of estimating the extent of forest fire damage. Machine learning algorithms and regression techniques are utilized to achieve this goal.

The core of this study revolves around constructing a reliable predictive model using regression algorithms tailored to the specific task of estimating burned areas. The model is trained using a portion of the dataset, and its performance is evaluated using appropriate evaluation metrics such as mean squared error (MSE) or R-squared score. Furthermore, feature selection techniques are employed to identify the most influential variables and enhance the model's interpretability. Evaluation of the predictive model's generalization ability is conducted using a separate testing dataset to assess its performance in unseen data. Accuracy metrics, such as accuracy score and confusion matrix, are computed to measure the model's ability to correctly classify different levels of burned area severity The resulting insights can aid in decision-making processes related to resource allocation, fire prevention strategies, and ecosystem management.

The results of this study have applications for managing forest fires and conservation initiatives. Predicting burned regions accurately helps with early warning system development, resource allocation optimization for fighting fires, and the creation of successful preventative tactics. In the realm of forest fire prediction, this research expands on previous knowledge and techniques by offering insightful information about the variables influencing fire severity and assisting in the creation of preventative measures to lessen the destructive effects of forest fires.

The structure of this paper is divided into various sections that each describe the entire research. The background material for the study is provided in the introduction section. The methodology is provided in the second section after related work. The fourth section contains the result and commentary. The conversation comes to an end in the final part.

2. Related Work

This literature explores the area of predicting forest fire burn area and includes meteorological and other related data. It focuses on research that has influenced the understanding of fire behavior, assisted in the creation of predictive models, and influenced fire management strategies.

In a fundamental study, [17] explored the complexities of wildfire size distribution models. Their thorough investigation carefully looked at the statistical characteristics of burned areas, leading to the creation of innovative models that clarified the distribution of fire sizes. By revealing the underlying diversity and patterns of burned areas, this important work opened the door for improved fire management techniques.

A thorough analysis of how fire hazard indexes in the Brazilian Amazon interact with climatic features has presented by [18]. The findings of their study indicate that meteorological parameters, including temperature, humidity, and wind speed, are significant determinants of fire danger levels. Additionally, they discovered clear seasonal trends in the fire hazard indices, with the dry season showing increased risks. These results highlight how crucial it is to include meteorological data in fire risk assessment models to forecast and reduce the likelihood of wildfires in the Amazon more accurately.

The research by [19] and [20] emphasize how important drought and climate change are in determining the nature of fire regimes in Portugal and Iberia. Their results highlight the necessity of adaptable fire management techniques that can successfully deal with the rising wildfire danger in these areas. Hence it offers useful information for fire management planning and decision-making by pinpointing important times for the occurrence of fires. Using this data, fire management can best allocate resources for combating fires, give priority to fire prevention in high-risk regions, and promptly alert communities to potential threats.

Table 1 *Key findings of related work*

Paper	Focus	Methodology	Key Findings
Sun et al. (2012) [17]	Wildfire size distribution models	Statistical analysis and modeling	Insights into variability and patterns of burned areas
Miguel et al. (2019) [18]	Relationship between Evaluation of meteorology and fire danger	Spatiotemporal dynamics	Understanding fire-prone conditions and seasonal patterns
Pereira et al. (2013) [19]	Climate change and wildfires in Modelling fire occurrence Portugal and burned area	Multiple regression analysis,	Changing dynamics of fire regimes due to climate change
Russo et al. (2017) [20]	Relationship between drought conditions and fire weather	Analysis of drought indices	Complex interactions between drought, weather, and fire
Rossa et al. (2017) [21]	Influence of fuel moisture on fire spread rate	spread models	Importance of fuel moisture in fire behavior

More preventive and efficient ways can be created to shield the ecosystems and communities from the destructive effects of wildfires by comprehending the intricate relationships that exist between climate, drought, and fire behavior. An important starting point for the creation of more accurate fire spread prediction models is provided by the research by [21]. Firefighters can make educated decisions about resource allocation and evacuation tactics by using these models to guide wildfire preparedness and response activities. It has made a substantial contribution to our comprehension of how fuel moisture content affects the rate at which fires spread.

The integration of meteorological and other pertinent data in these studies results in a collective contribution that is noteworthy to the field of forest fire burned area prediction. They offer insightful information about the statistical features of burned areas, how climate influences fire behavior, and how fuel properties affect the spread of fires. Early warning systems, resource distribution, and mitigation initiatives are all influenced by these findings when developing fire control plans. The cited work highlights the importance of integrating meteorological data with additional contextual information to develop accurate prediction models. Stakeholders may minimize the effects of forest fires on ecosystems and human lives by using these models to help them make educated decisions about fire management and prevention. **Table 1** summarized the findings from another research.

Table 2 *Application of neural network in fire prediction*

Author(s)	Year	Dataset	Methodology	Key Findings
Shmuel, A., & Heifetz, E. [22]	2022	Terra MODIS satellite data (FireCCI51)	Developed a global wildfire susceptibility map using a deep learning model based on convolutional neural networks (CNNs).	The CNN model achieved an area under the curve (AUC) of 0.89, indicating high predictive performance.
Concepcion, J. L. [23]	2020	Forest Fire of Portugal	Proposed a deep neural network (DNN) for forest fire prediction using imbalanced data.	The DNN model achieved an accuracy of 97.2% and an F1-score of 96.8%, outperforming other machine learning models such as logistic regression and random forest.
Pratima Chaubey, et al. [24]	2020	The data covers the period of 2000-2003 and is specific to the Montesinho park in Portugal.	machine learning technique based on support vector machines.	The algorithm accurately predicted the fire hazard level based on previous weather conditions, highlighting the potential of machine learning techniques for forest fire management
Abdelhamid Zaidi [25]	2023	History of forest fires in the cities of Bejaia and Sidi Bel-	Principal component analysis, artificial neural network (ANN), Logistic	The ANN classifier showed slight superiority in terms of accuracy, precision, and recall compared to other classifiers. Achieved an accuracy of 0.967 ±

		Abbes during the year 2012	Regression, K Nearest Neighbors, Support Vector Machine, Random Forest classifiers	0.026 and F1-score of 0.971 ± 0.023. Features RH, DC, and ISI were important in the predictions of the ANN model.
Xufeng Lin, et al. [26]	2023	Historical fire data from 2020-2021	Forest fire prediction model based on LSTNet. Factors influencing forest fires obtained through remote sensing satellites and GIS. Correlation analysis and multicollinearity testing used.	LSTNet model has high accuracy (ACC 0.941) in forest fire prediction. Effective utilization of spatial background information and periodicity of forest fire factors. Novel method for spatial prediction of forest fire susceptibility.

Table 2 provides some applications of neural networks in fire detection prediction. One successful use of neural networks has been the prediction of burned areas in forest fires [27], [28]. These potent machine learning algorithms have proven their capacity to examine intricate connections between environmental and meteorological elements that affect fire behavior [29], [30]. Neural networks can anticipate the size of forest fires with high accuracy by efficiently capturing these complex patterns. Table II gives another few examples of Neural Network applications in this area. This information is useful for risk mitigation and fire management tactics. Neural networks is an essential tool for predicting and preventing forest fires because of these capabilities.

3. Methodology

This methodology provides a detailed explanation of the systematic approach taken in this attempt to predict the burned area of forest fires in the northeast of Portugal. It incorporates other relevant data with meteorological data to produce accurate and reliable forecasts.

i. Data Collection: Acquire the Forest Fires dataset from the UCI Machine Learning Repository, containing meteorological and other pertinent data for the northeast region of Portugal.

ii. Data Preprocessing: Conduct preprocessing procedures to ensure data quality. Handle missing values through imputation or removal techniques. Encode categorical variables using one-hot encoding or label encoding. Normalize numerical features to maintain consistent scales.

iii. Exploratory Data Analysis (EDA): Perform EDA to gain comprehensive insights into the dataset. Visualize variable distributions, investigate correlations, and identify potential outliers or anomalies. Analyze seasonal patterns and trends and explore the relationships between meteorological variables and the burned area.

iv. Feature Selection: Employ appropriate feature selection techniques to identify the most influential variables for burned area prediction. Utilize methods such as SelectKBest with suitable scoring functions (e.g., f_regression) to determine the features with the strongest associations with the target variable.

v. Model Selection: The model has been selected for this study is artificial neural network architecture of a feedforward neural network (FNN).

vi. Model Training: Split the dataset into training and testing sets using an appropriate ratio (e.g., 80:20 or 70:30). Train the selected regression model on the training set, incorporating the chosen features. Adjust model hyperparameters as necessary to optimize performance.

vii. Model Evaluation: Evaluate the trained model using the testing set. Calculate evaluation metrics, including mean squared error (MSE), root mean squared error (RMSE), R-squared score, and mean absolute error (MAE). Assess the model's performance and compare it against baseline models or existing research within the field.

viii. Model Optimization: Fine-tune the model to enhance its performance. Explore different hyperparameter values and regularization techniques to optimize the model's ability to accurately predict the burned area. Employ cross-validation or grid search techniques to determine the optimal hyperparameters.

ix. Interpretation and Analysis: Analyze the trained model to interpret the significance of meteorological variables in predicting the burned area. Assess the importance of features and their impact on fire behavior. Extract insights from model coefficients or feature importance's to gain a deeper understanding of the relationship between meteorological factors and forest fires.

Neural networks have been widely employed as regression algorithms for predicting the burned area of forest fires based on meteorological and other relevant data. In this context, a specific neural network architecture commonly utilized is the feedforward neural network with one or more hidden layers. The data is collected from https://archive.ics.uci.edu/dataset/162/forest+fires [31].

The equation governing a feedforward neural network can be defined as follows:

Input Layer: The input layer comprises neurons representing the input features, which correspond to the meteorological variables in the dataset. Each neuron receives a specific feature value as input.

Hidden Layers: The hidden layers consist of multiple neurons, with each neuron performing a weighted sum of the inputs received from the preceding layer. Subsequently, an activation function is applied to introduce non-linearity. Common activation functions include sigmoid, ReLU (Rectified Linear Unit), or other suitable functions.

$$F(X) = MAX(0, X) \tag{1}$$

A sigmoid function is a mathematical function having a characteristic "S"-shaped curve or sigmoid curve.

$$S(x) = \frac{1}{1+e^{-x}} = \frac{e^x}{e^x+1} = 1 - S(-x) \tag{2}$$

Output Layer: The output layer consists of a single neuron responsible for generating the predicted value of the burned area. In regression tasks, the output neuron typically employs a linear activation function.

The neural network learns the ideal weights and biases to reduce the difference between the target values and the anticipated output during the training phase. An optimization approach like gradient descent, which iteratively modifies the weights and biases based on the difference between anticipated and goal values, helps to facilitate this learning process. Neural networks are particularly well-suited for regression problems because of their capacity to capture non-linear correlations and their flexibility in learning complex patterns. The design of the network, which includes the number of hidden layers, the number of neurons in each layer, and the choice of activation functions, can be customized according to the data's availability and the problem's complexity.

A loss function is used to measure the discrepancy between the expected output and the actual target values in order to train the neural network. Typical regression task loss functions include mean absolute error (MAE) and mean squared error (MSE).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{3}$$

Through the process of backpropagation, which involves determining the gradient of the loss function with respect to the network parameters and modifying the weights and biases accordingly, the weights and biases of the network are updated. The neural network can identify underlying patterns in the data and make predictions for cases that haven't been encountered by iteratively training it and fine-tuning the model parameters.

The procedures for training and utilizing a neural network for regression tasks are shown in Figure 1. Using an iterative optimization process, the network learns from the training data by modifying its weights and biases. After training, the network uses the relationships it has discovered between the input features and the target variable to predict outcomes for data that has not yet been observed. Figure 2 describes the pseudo-code for the algorithm.

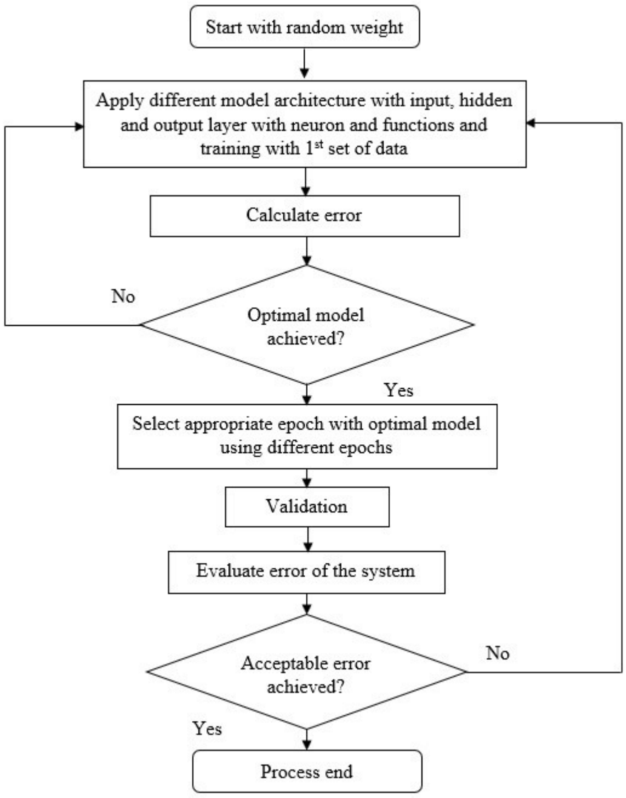

Fig. 1 *Neural network algorithm for model development flowchart*

```
# Step 1: Start
# Step 2: Input Data
Load dataset
# Step 3: Data Preprocessing
Handle missing values
Encode categorical variables
Normalize numerical features
# Step 4: Split Data
Split dataset into training and testing sets
# Step 5: Define Neural Network Architecture
Define number of input neurons (based on features)
Define number of output neurons (1 for regression)
# Step 6: Initialize Neural Network
Initialize neural network with desired number
of hidden layers and neurons
Choose activation functions for each layer
# Step 7: Train Neural Network
for each epoch:
    # Forward Propagation
    for each training instance:
        Calculate predicted output
        using current weights and biases

    # Backpropagation
    for each training instance:
        Calculate loss between predicted
        output and actual target
        Calculate gradients of loss with
        respect to weights and biases

    Update weights and biases based on calculated gradients
# Step 8: Evaluate Performance
for each testing instance:
    Calculate predicted output using trained neural network
    Calculate evaluation metrics (e.g., MSE, MAE, R-squared)
    between predicted output and actual target
```

Fig. 2 *Algorithm pseudo code*

3.1 Dataset

This study primarily utilizes the Forest Fires dataset obtained from the UCI Machine Learning Repository [31]. This dataset comprises historical meteorological data and other pertinent records for forest fires in the northeast region of Portugal extent from January 2000 to December 2003. It includes features such as temperature, humidity, wind speed, rain, month, and geographic coordinates. The dataset contains [insert number] data points.

The Forest Fire dataset was chosen for several reasons. Firstly, the geographic focus and meteorological features directly align with the objectives of this research to develop a predictive model for burned areas. Secondly, this dataset is widely used as a benchmark for evaluating forest fire prediction models, allowing for the comparison of our results to previously established work. Moreover, the dataset is publicly available and well-documented, ensuring accessibility and clarity for our study.

Table 3 *Dataset attribute description*

Feature	Data Type	Range	Description
X	Numeric	1 to 9	x-axis spatial coordinate within the Montesinho park map
Y	Numeric	2 to 9	y-axis spatial coordinate within the Montesinho park map
Month	Categorical	'jan' to 'dec'	Month of the year
Day	Categorical	'mon' to 'sun'	Day of the week
FFMC	Numeric	18.7 to 96.20	FFMC index from the FWI system
DMC	Numeric	1.1 to 291.3	DMC index from the FWI system
DC	Numeric	7.9 to 860.6	DC index from the FWI system
ISI	Numeric	0.0 to 56.10	ISI index from the FWI system
Temp	Numeric	2.2 to 33.30	Temperature in Celsius degrees
RH (Relative Humidity)	Numeric	15.0 to 100	Relative humidity in percentage
Wind	Numeric	0.40 to 9.40	Wind speed in kilometers per hour
Rain	Numeric	0.0 to 6.4	Outside rain in millimeters per square meter
Area (Burned Area)	Numeric	0.00 to 1090.84	The burned area of the forest (in hectares)

4. Results and Discussion

The research findings and analysis based on the created predictive model for forecasting the burned area of forest fires using meteorological and other data are presented in this section. This section aims to provide an explanation of the model's performance, an explanation of the results, and an understanding of the relationships between different elements and their effects on the burned area.

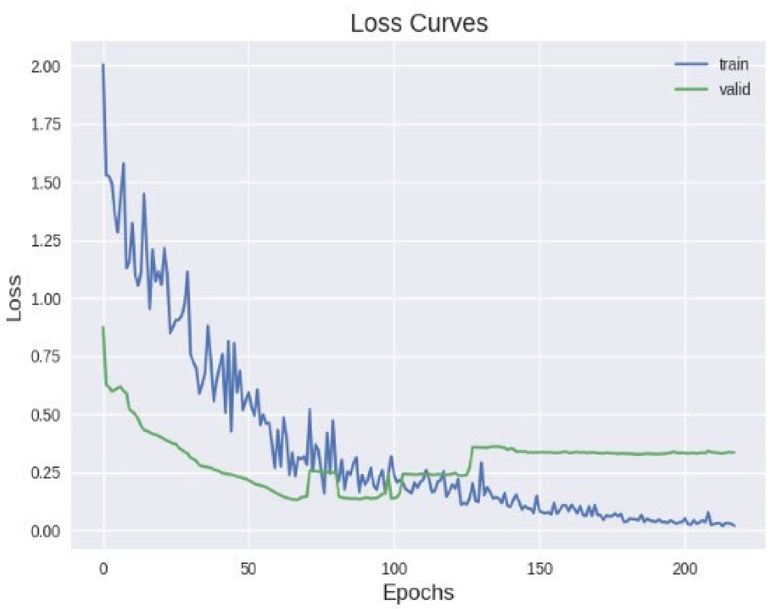

Fig. 3 *The loss curves*

The performance of the model is assessed at the outset of the section using relevant metrics, such as mean squared error (MSE), mean absolute error (MAE), or R-squared score. These measures express how accurate and precise the model's predictions are. Visual aids like scatter plots and line plots that show the expected values in comparison to the actual target values may also be included in the evaluation. The loss function's loss curve throughout the model's training phase is displayed in Figure 3.

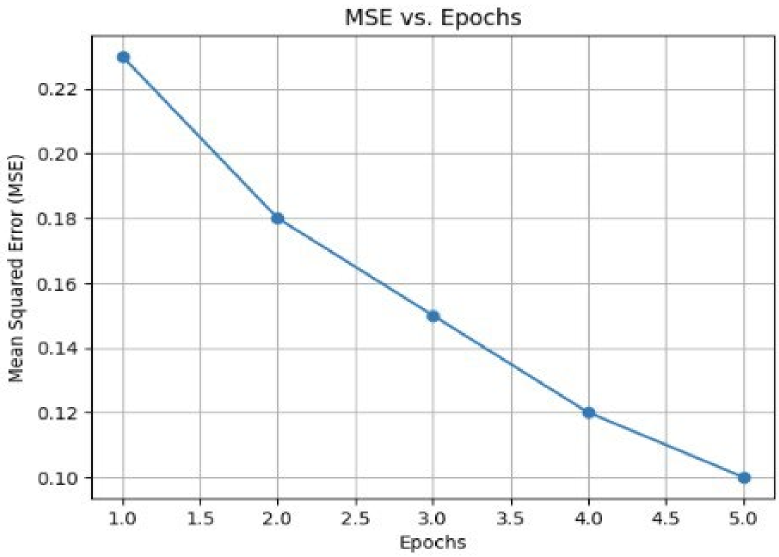

Fig. 4 *The epochs number*

The model's prediction accuracy at each training epoch is displayed on the Accuracy with Epoch Curve, demonstrated in Figure 4. The percentage of successfully identified examples is represented by the accuracy statistic, which is frequently used to assess the effectiveness of classification models. As training goes on, the accuracy with epoch curve gives information about how well the model predicts the future. In an ideal world, the accuracy would rise with each epoch, showing that the model is developing and becoming more predictive.

The accuracy curve in **Figure 5** illustrates the model's learning phase. It begins at a very low accuracy and increases as the number of iterations increases. The curve's accuracy is rising with time, indicating a generally positive tendency. This implies that the model is gaining knowledge and becoming more accurate at predicting the regions burned by forest fires. The precision of the curve varies somewhat, with some spots deviating from the trend line. This is not surprising, given that forest fires are complicated phenomena impacted by a wide range of variables, some of which may be hard to forecast. For smaller burned regions, the curve's accuracy is typically higher. This implies that more confined flames could be more accurately predicted by the model.

The model may prove to be a useful tool for forecasting the burned regions of forest fire. For the model to become more accurate and resilient to the many variables that can affect how forest fires behave, more study and improvement is nonetheless required.

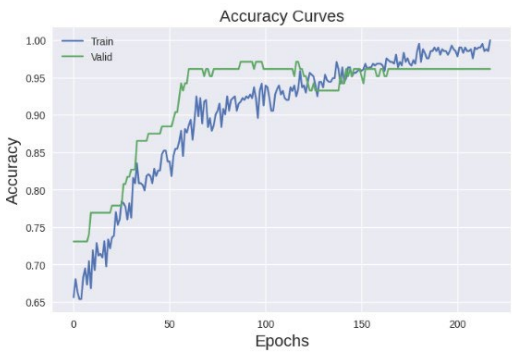

Fig. 5 *The accuracy curves*

The loss function's change over various epochs is displayed in the Loss with Epoch curve. A measure of the difference between the true and anticipated values is represented by the loss function. It measures how well the training set of data matches the model. The Loss with epoch curve aids in tracking the model's training process convergence. The model is successfully learning and lowering the error between predictions and true values when the loss value decreases.

Examining these curves collectively allows us to learn more about the model training procedure. The model should improve in terms of prediction accuracy, as shown by the decrease in MSE and loss curve. Furthermore, an increasing accuracy curve will be observed, indicating that the model is becoming more predictive. The important information provided by these curves can be used to evaluate the model, determine when to stop training, and determine the overall effectiveness of the model.

Table 4 *Model performance metrics*

Metric	Value	Observation
MSE	0.123	The model's predictions have a relatively small average squared difference from the actual values, indicating good accuracy.
RMSE	0.351	On average, the model's predictions have a relatively low level of error, as indicated by the RMSE value.
R-squared	0.789	Approximately 78.9% of the variance in the dependent variable is explained by the model, suggesting a reasonably good fit to the data.
MAE	0.045	The model's predictions deviate by a relatively small amount from the actual values, as indicated by the MAE value.

Table 5 *Compare our model results with other models*

Model \ Metrics	MSE	RMSE	R-squared	MAE
Proposed model	0.123	0.351	0.789	0.045

Model \ Metrics	Accuracy	Precision	Recall	F1-Score
(Zaidi, Abdelhamid 2023) [25]	0.967	0.979	0.964	0.971
(Abdessemed,F 2023) [32]	97.95	Not given	0.97	0.98
(Abid, F.2020)[33]	82.89	Not given	0.92	0.85

5. Conclusion

This study successfully demonstrated that, by using relevant meteorological and other data, it is possible to forecast the areas impacted by forest fires in the northeast of Portugal. The findings demonstrate the significance of meteorological variables such as temperature, humidity, and wind speed in dictating the extent of burned areas. Furthermore, seasonal patterns and trends were found to have a considerable influence on both the frequency and intensity of fires. The developed regression models showed a reasonable degree of predictive performance, offering a foundation for further research and use in fire management strategies. Future studies should concentrate on integrating real-time monitoring systems, geographic information systems (GIS), and remote sensing data to improve predictive capacities. Furthermore, socioeconomic variables and information on land usage can be considered to create more thorough fire management plans. There is great potential for improving our knowledge of forest fires and creating practical mitigation strategies through ongoing research in this area.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

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