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Machine Learning Regression Techniques to Predict Burned Area of Forest Fires

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Abstract: The study presents the implementation of machine learning regression techniques to predict burned areas of forest fires. The data set used in this paper is presented in UCI machine learning repository that consists of climatic conditions and physical factors of the Montesinhopark in Portugal. Linear regression, ridge regression and lasso regression algorithms are used in the process of prediction. Accuracy score, Mean Absolute Error (MAE), Median Absolute Error (MDAE) and Mean Squared Error (MSE) were calculated. The size of the data set is 517 entries and the number of features for each row is 13. In this study the three algorithms are applied using two versions. In the first version, all features of the data set were included and in the second version, 70% of the features were included. In both versions, the training set is 70% of the data set and the test set is 30% of the data set. The accuracy of linear regression algorithm is 100%, thus it gives more accuracy than ridge regression and lasso regression algorithms in both versions.

INTRODUCTION

One of the most extremely occurring disasters in recent times is forest fires (known as wildfires). Due to these wildfires a lot of acres of forest area are getting destroyed. One of the significant reasons that leads to the occurrence of forest fires is warming due to the increase in the average temperature of the Earth[1]. The other reasons are due to human negligence, during thunderstorms and lightning. Annually, the number of forest fires in Europe is between 50-70 thousand and causing damage in millions of areas[1]. An important example of forest fires had happened in Portugal in June 2017, about 65 people were killed, about 200 people were injured and about 458 homes were destroyed completely[2]. Between 2010 and 2016, about 40,000 forest fires happened in Spain, Greece, Italy, France and Portugal per year[3]. In North America, forest fires occur naturally and in the last century forest fires have increased, these fires are very dangerous as they affect humans who live in many regions of North America. In 2015, a huge forest fire happened in North America, this was the worst forest fire that happened as many forests were burned. In Russia, various parts of the country were affected by forest fires and fortunately, these fires occurred in regions that are unpopulated. Every year, millions of forest fires occur in these regions. In 2010, western Russia had a lot of dense forest fires. The largest rate of forest fires is due to human factors. In northern Russia the largest rate of forest fires is due to lightning. Several studies refer to the change in climate will cause more forest fires due to the dryness of the climate, this will lead to several forest fires in different areas[4]. Dynamic Integrated Model of Climate and the Economy

(DICE) indicates that the economy will lose about $23 trillion in the next 80 years due to the change in climate[5]. In Africa, South America, Southeast Asia and New Zealand, forest fires occur due to human factors like husbandry of animals and agriculture[6]. Nowadays, there are various technologies for fire modeling to predict the spread of fires such as physical models and mathematical models[7]. These models depend on data collection during forest fires, simulation and lab experiments in order to specify and predict the fire growth in many regions. Recently, simulation tools are used to predict forest fires but simulation tools faced some problems such as accuracy of input data and simulation tool execution time[6].

Data mining is one of the most significant approaches such as the forest fires can be predicated upon their occurrences[8, 9]. Data mining requires real and clean data for making a prediction. If the data set contains many unknown values, then these values must be ignored or imputed before using them in the modeling. The data set used in this study presented in the UCI machine learning repository is about the forest fires and used for regression. In this study, linear regression, ridge regression and lasso regression algorithms are used in the process of predicting the burned area of forest fires. The performance metrics used in this work are: accuracy score, MAE, MDAE and MSE. In this study, we found that the linear regression algorithm gives better results than ridge regression and lasso regression algorithms.

Literature review: Ozbayoglu *et al*.[10] estimated the burned areas in forest fires using estimation methods as the Multilayer Perceptron (MLP), Support Vector Machines (SVM), Radial Basis Function (RBF) networks and fuzzy logic. The results indicate that MLP gives more accurate results[11].

Salis used Federated, Available and Reliable Storage for an Incompletely Trusted Environment (FARSITE) simulator in order to predict forest fires spread in the Euro-Mediterranean countries. The outputs of FARSITE were obtained by two models, custom fuel model and standard fuel model. The experimental results showed that the accuracy of the custom fuel model was better than the standard fuel model.

Castelli *et al*.[12] developed an intelligent system called geometric semantic genetic programming in order to predict burned areas. The results obtained using that intelligent system were better than using the standard genetic programming.

Radke *et al*.[13] presented a novel system called Fire Cast to predict the spread of forest fires in the future[14]. FireCast is a system that combines Artificial Intelligence (AI) and Geographic Information Systems (GIS). Fire Cast obtained more accurate results when compared to other random prediction models.

Mote *et al*.[6] presented an intelligent system that depends on genetic programming in order to predict burned areas by using data like: temperature, wind, speed, slopes and relative humidity.

Zhu *et al*.[15] presented a machine learning algorithm based on Wireless Sensor Networks (WSN) in order to predict forest fires.

Deng *et al*.[16] proposed a fire prediction tool called Disjunctive Normal Form (DNF) Model in order to predict forest fires. The results obtained from the DNF Model were compared with other machine learning models as naive Bayes, decision tree, SVM, RBF and polynomial kernel functions. The DNF Model gave the highest average accuracy with 97.8% among the other machine learning models.

Sakr *et al*.[17] presented an algorithm that depends on SVM in order to predict forest fires. SVM used two class predictions of fire risk. The results demonstrated that the accuracy of SVM was approximately 96%.

Perez-Sanchez *et al*.[18] proposed the Artificial Neural Network (ANN) model in order to predict the size of burned areas of forest fires in Southern Spain. ANN was used in two stages: classifying forest fires size and evaluation of the burned surface areas. The results mentioned that the process of prediction was over 60%, prediction can reach more than a 70% in some central areas.

Dacre *et al*.[19] proposed a probabilistic model in order to predict forest fires. There were three steps to design the probabilistic model. In step 1, the probabilistic model of forest fires was built from data of weather forecast and historical satellite. In step 2, the prediction of forest fires was produced using the data of the weather forecast as an input in the model of forest fires. In step 3, the warnings of forest fires were transported on different levels based on the need of the user.

Coffield *et al*.[20] proposed machine learning models to predict the size of forest fires at the time of their inflammation.

Decision tree, random forests and MLP Models were used in the process of prediction. The decision tree model predicted that 40% of the inflammation led to the large amount of fires and this percent is about 75% of the total burned area. Random forests and MLP models were tested but they did not perform the accuracy as the decision tree model.

Stojanova *et al*.[21] proposed different machine learning models to predict forest fires in Slovenia. Logistic regression, decision tree, random forests, bagging and boosting of decision tree models were used to predict

forest fires in Slovenia. These models were applied on these three data sets: Kras region, Primorska region and continental Slovenia. From the experimental results, the bagging decision tree model obtained the best accuracy for all the data sets.

Boubeta *et al*.[22] proposed semiparametric models in order to predict forest fires. Two semiparametric models that depend on time series were used to predict the burned area every week per year. The experimental results obtained show that the first semiparametric model accuracy in results was better than the second semiparametric model where the errors were lower in the first semiparametric model.

Kansal *et al*.[23] proposed several machine learning models in order to predict forest fires. SVM, decision tree, regression, ANN etc. models were used for prediction of forest fires. The accuracy of regression was better when compared to the other machine learning models.

Al_Janabi proposed five machine learning models in order to predict forest fires, namely, MLP, RBF, SVM, Polynomial Neural Network (PNN) and Cascade Correlation Network (CCN). The Principal Component Analysis (PCA) Model was used to find the best patterns in the data set and the Particle Swarm Optimization (PSO) Model was used to make segmentation for the fire regions. The experimental results showed that the SVM model was more effective than other machine learning models.

Shidik *et al*.[25] proposed Back Propagation Neural Network (BPNN) model to predict the size of forest fires. The Fuzzy C-Means (FCM) model was used to cluster the data set into groups. The clustered data are used as input data in the BPNN model. Other classification models such as naive Bayes, SVM, decision tree, K-Nearest Neighbor (KNN) were performed. The experimental results obtained from BPNN were more accurate than other classification models.

MATERIALS AND METHODS

Machine learning models play a significant role in the process of evaluation and prediction. Prediction can be done by using the available variables in the data set. Through the available variables in the data set, machine learning models can make predictions for the future[25]. Machine learning models such as linear regression, ridge regression and lasso regression are implemented in order to predict burned areas of forest fires.

Linear regression: Regression analysis is the process of statistical analysis in order to evaluate the relationship between various variables. Nowadays, regression analysis models are being widely used for prediction in the field of machine learning. The concept of regression analysis is to show how the dependent variable value varies when one independent variable value changes where the other variables are restricted[26]. Also, regression analysis is used to compute the dependent variable average value when the independent variables are restricted. There are three main processes for regression analysis: first, identify the strength of the predictors as the regression analysis might be used to identify the effect of the independent variable(s) on the dependent variable. Second, forecasting an effect as the regression analysis helps to realize the change that happened in the dependent variable with the change that happened in one or more independent variables. Third, trend forecasting as the regression analysis is used to predict trends and future values, also regression analysis is used to get the estimates of the points. In the area of regression analysis, a lot of techniques have been presented that can be divided into parametric method and non-parametric method. A parametric method takes all information about the data via its parameters. All information needed in order to predict a value of future data from the model is the parameters. For example, in linear regression with one variable, two parameters (intercept and coefficient) must be known in order to predict a new value. In non-parametric method, more information is available, so the ability of predicting new values is more flexible. The parameters in non-parametric method are called infinite in dimensions, so the data characteristics are better than parametric models. Linear regression model is one of the most significant predictive analysis models. Linear regression model is a statistical model that explains the relationship between one dependent variable (or outcome variable) and one or more independent variables (or predictor variables). The main idea of the regression is to check two significant things: first, the performance of the independent variables while predicting the dependent variable. Second, the independent variables are important for the dependent variable. If one independent variable has a linear relationship with one dependent variable, then the regression is called a simple linear regression. If two or more independent variables have a linear relationship with one dependent variable, then the regression is called a multiple linear regression. The aim of the linear regression is to plot a line that comes near to the data through finding the intercept and the slope that minimize the error of the regression. There are a lot of relationships in data that do not plot a straight line, so in this case nonlinear regression is used instead of linear regression. When training a simple linear regression model using a single variable, this may lead to under fitting (high bias error). When training a multiple linear regression model using more than one variable, this may lead to overfitting (high variance error). Hence, it is very significant to avoid the two effects while training a linear regression model.

To avoid these two effects, dimensionality reduction is used during training the data set. Dimensionality reduction is very significant during training the data set for the following reasons: first, preventing overfitting as some data sets are high-dimensional and have a lot of features which may lead to overfitting (high variance error). Second, simplicity as the model has a lot of features which can be hard to be explained mostly when the features of the model are correlated. Third, computational efficiency as the model uses dimensionality reduction during training the data set, hence the data set is computationally efficient, so, it is very significant to use the important variables that correlate with the target variable in order to build a linear regression model. Linear regression works very perfectly on real data. Through linear regression a lot of advantages can be done such as the model of linear regression in training is faster than a lot of predictive models[27]. Linear regression is used to calculate the relationship strength between the dependent variable and the independent variables in order to calculate which independent variables have no relationship with the dependent variable and also to specify which independent variables include redundant information about the dependent variable. Also, linear regression models are very easy in the process of the implementation and require limited space of memory[28]. In linear regression model, if there is one independent variable, then the regression function is a straight line, if there are two independent variables, then the regression function is plane and if there are independent variables, then the regression function is hyper-plane with-dimensional. If there is a fitting between the actual values and the predicted values, then the actual values will be similar to the predicted values. But if there is a difference between the actual values and the predicted values, this difference is called cost, loss or error. The regression function $\tilde{y}$ dependent on independent (predictor) variables x_1, x_2,..., x_n can be expressed as in Eq. 1:

$$\tilde{y} = w_0x_0 + w_1x_1 + ,..., w_n x_n + b \quad (1)$$

Equation 1 represents how the value of $\tilde{y}$ changes with the independent x_1, x_2, ,..., x_n. W_0, w_1,..., w_n are called feature weights (model coefficients) and is called a constant bias term (intercept).

An important concept in regression is Ordinary Least Squares (OLS) which is a statistical method that calculates the relationship between one dependent variable and one or more independent variables, the method calculates the relationship through minimizing the sum of the squares in the difference between the actual values and the predicted values of the dependent variable that represent a straight line. Also, OLS is easily applied to multivariate models that contain two or more independent variables. OLS finds and that minimizes the Residual Sum of Squares (RSS) over the training data between the actual values and the predicted values. RSS can be expressed as in Eq. 2:

$$RSS(w,b) = \sum_{i=1}^{N}(y_i - wx_i + b)^2 \quad (2)$$

Ridge regression: Ridge regression is used to analyze data that is multiple regression, these data contain multicollinearity (independent variables are highly correlated). Ridge regression is a technique in order to reduce the complexity of the model and to avoid overfitting. Prediction of new values done by ridge regression technique gives good results when there is a correlation between the predictor variables[29]. Ridge regression learns the parameters w, b through using the same criterion of the least squares with addition of adding a penalty term in order to make a big variation in the parameter of w. The penalty term is called regularization which restricts the model in order to prevent overfitting, and also regularization methods are used to control the coefficients of the regression, this will help to minimize the variance and reduce the sampling error[30]. Ridge regression uses L2 regularization which minimizes the sum of square of the coefficients[30]. L2 regularization has analytical solutions, thus L2 regularization is computational efficient. RSS for ridge regression can be expressed as in Eq. 3:

$$RSS(w,b) = \sum_{i=1}^{N}(y_i - (wx_i + b)^2 + \alpha\sum_{j=1}^{p} wj^2 \quad (3)$$

where, α is called a penalty term, the higher alpha refers to a simple model and more regularization. The penalty term α adjusts the parameters when the parameters take large values, then the optimization function is penalized. So, ridge regression minimizes the parameters in order to reduce the complexity of the model and multicollinearity.

Lasso regression: The word LASSO stands for (Least Absolute Shrinkage and Selection Operator). Lasso regression is another form of regularization that uses L1 regularization penalty for training[29]. L1 regularization minimizes the sum of the coefficients absolute values. RSS for lasso regression can be expressed as in Eq. 4:

$$RSS(w,b) = \sum_{i=1}^{N}(y_i - (wx_i + b)^2 + \alpha\sum_{j=1}^{p} |w| \quad (4)$$

where, α is called a penalty term that controls the amount of L1 regularization. When the value of α increases, the value of the bias will increase and the value of variance will decrease. L1 regularization penalty affects some

coefficients to be zero, this is called a sparse solution (feature selection)[30], hence, L1 regularization performs feature selection. When the value of increases, some of the coefficient values will be zero. So, lasso can give good results when there are few coefficients.

Data scaling: The method of data scaling is one of the most significant steps in machine learning during the process of preprocessing. This method is very effective in the process of normalizing the variables of the data[31]. In this study normalizer method is used to perform the normalizing process on the data, it normalizes the rows to unit norm. Each row with non-zero components is rescaled individually by its norm (L1, L2 or max). L1 norm is the sum of the absolute values of the row, L2 norm is the square root of the sum of the squared values of the row and max norm is the maximum values of the row.

RESULTS AND DISCUSSION

The implementation of the linear regression, ridge regression and lasso regression algorithms is done using Google Colab notebook. Google Colab notebook helps to write and execute Python in the browser where it is an open source and widely used for the implementation of machine learning algorithms such as regression, classification and clustering.

Implementation using all features: Linear regression, ridge regression and lasso regression machine learning algorithms are implemented on forest fires data set that is presented in UCI machine learning repository. Accuracy score, MAE, MDAE and MSE were calculated for these algorithms. The accuracy score on the training data set is 1, 0.98 and 0.88 onlinear regression, ridge regression and lasso regression, respectively. The accuracy score on the testing data set is 1, 0.95 and 0.81 on linear regression, ridge regression and lasso regression, respectively. MAE, MDAE and MSE on liner regression are 2.25e-16, 2.22e-16 and 6.46e-32, on ridge regression are 0.0044, 0.0027, and 4.58e-05 and on lasso regression are 0.0089, 0.0051 and 0.0002, respectively. So, from these results, linear regression gives better accuracy. Table 1-3 show these results. Figure 1 demonstrates a comparison of these algorithms in terms of accuracy score on training and testing data set using all features. Figure 2 demonstrates a comparison of these algorithms in terms ofMAE, MDAE and MSE using all features (Fig. 3).

Implementation using 70% of the features: The accuracy score on the training data set is 0.99, 0.76 and 0.84 on linear regression, ridge regression and lasso regression, respectively. The accuracy score on the testing data set is 0.99, 0.79 and 0.87 on linear regression, ridge regression and lasso regression, respectively. MAE,

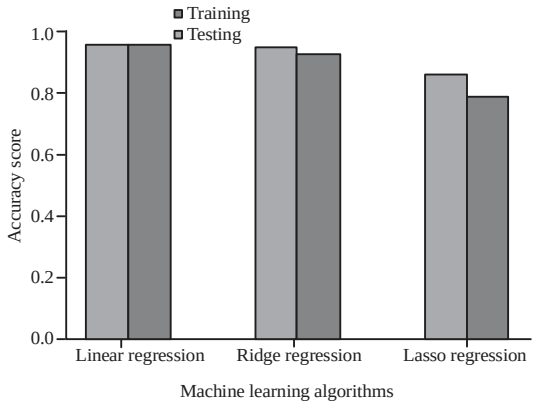

Fig. 1: Comparison of machine learning algorithms in terms of accuracy score on training and testing data set using all features

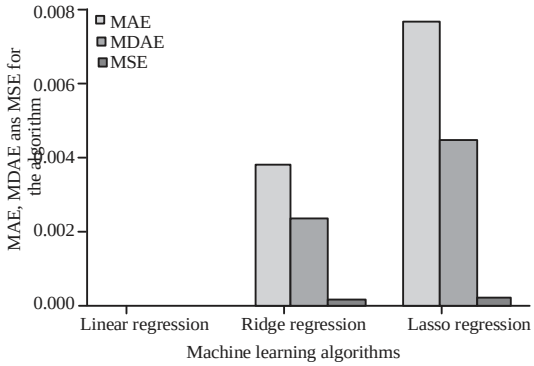

Fig. 2: Comparison of machine learning algorithms in terms of MAE, MDAE and MSE using all features

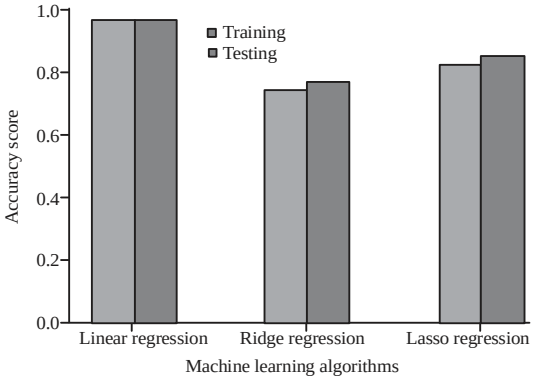

Fig. 3: Comparison of machine learning algorithms in terms of accuracy score on training and testing data set using 70% of the features

MDAE and MSE on liner regression are 0.0023, 0.0014 and 1.30e-05 on ridge regression are 0.0093, 0.0056 and 0.00037 and on lasso regression are 0.0083, 0.0050 and 0.00022, respectively. So, from these results, linear

Table 1: Accuracy score, MAE, MDAE and MSE on linear regression using all features

Accuracy score on training data set	Accuracy score on testing data set	MAE	MDAE	MSE
1	1	2.25e-16	2.22e-16	6.46e-32

Table 2: Accuracy score, MAE, MDAE and MSE on linear regression using all features

Accuracy score on training data set	Accuracy score on testing data set	MAE	MDAE	MSE
0.98	0.95	0.0044	0.0027	4.58e-05

Table 3: Accuracy score, MAE, MDAE and MSE on linear regression using all features

Accuracy score on training data set	Accuracy score on testing data set	MAE	MDAE	MSE
0.88	0.81	0.0089	0.0051	0.0002

Table 4: Accuracy score, MAE, MDAE and MSE on linear regression70% of the features

Accuracy score on training data set	Accuracy score on testing data set	MAE	MDAE	MSE
0.99	0.99	0.0023	0.0014	1.30e-05

Table 5: Accuracy score, MAE, MDAE and MSE on ridge regression using 70% of the features

Accuracy score on training data set	Accuracy score on testing data set	MAE	MDAE	MSE
0.76	0.79	0.0093	0.0056	0.00037

Table 6: Accuracy score, MAE, MDAE and MSE on lasso regression using 70% of the features

Accuracy score on training data set	Accuracy score on testing data set	MAE	MDAE	MSE
0.84	0.87	0.0083	0.0050	0.00022

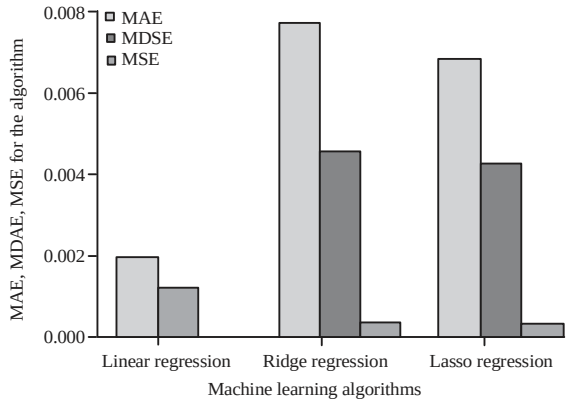

Fig. 4: Comparison of machine learning algorithms in terms of MAE, MDAE and MSE using 70% of the features

regression gives better accuracy. Tables 4-6 show these results. Figure 3 demonstrates a comparison of these algorithms in terms of accuracy score on training and testing data set using 70% of the features. Figure 4 demonstrates a comparison of these algorithms in terms of MAE, MDAE and MSE using 70% of the features.

CONCLUSION

In this research, the main idea is to perform three machine learning algorithms in order to predict forest fires. The data set is presented in the UCI machine learning repository. The size of the data set is 517 instances and a number of attributes are 13. Linear regression, ridge regression and lasso regression machine learning algorithms are implemented in order to perform the prediction process. The three algorithms are applied using two scenarios. In the first scenario, all attributes of the data set were included and in the second scenario, 70% of the attributes were included. The training set is 70% of the data set and the test set is 30% of the data set in the two scenarios. Accuracy score was calculated on both training and testing data set in training data set it was 1, 0.98 and 0.88 on linear regression, ridge regression and lasso regression, respectively in testing data set it was 1, 0.95 and 0.81 on linear regression, ridge regression and lasso regression, respectively. The experimental results demonstrated that linear regression algorithm presented the best result.

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