IIETA International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Mathematical Modelling of Engineering Problems
Vol. 13, No. 1, February, 2026, pp. 25-33
Journal homepage: http://iieta.org/journals/mmep

Using Classification Tree and Kernel Approaches for Classifying the Relative Humidity Dataset

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https://doi.org/10.18280/mmep.130103

Received: 28 October 2025
Revised: 18 December 2025
Accepted: 27 December 2025
Available online: 28 February 2026

Keywords:
kernel model, Classification Tree, classification, relative humidity, time series classification, autoregressive model

ABSTRACT

Studying the climatic status and meteorological effects is important to identify climatic effects on human life. In this study, the relative humidity variable is studied and classified based on its autoregressive variables through identifying the mathematical relationship among these variables by using Kernel and Classification Tree (CT) approaches, to improve the classification accuracy. Additionally, the study aims to evaluate and compare the classification accuracy of these two approaches for relative humidity time series during two seasons: hot and cold. Iraqi datasets taken from an agricultural meteorological station in Mosul city, Iraq, were used as a real case study. In these types of data, there are many obstacles, such as nonlinearity and uncertainty, which can cause inaccurate classifications. The results indicate a comparative advantage of the CT approach over the Kernel method in terms of classification accuracy for the relative humidity, while the results indicate that the Kernel method performs better in specific cases, particularly for the cold season with minimum relative humidity in the testing phase. Both CT and the Kernel method produce accurate results. In conclusion, CT and Kernel approaches can be used to classify relative humidity accurately.

1. INTRODUCTION

This study examined and discussed in detail the classification of one of the most important climate variables. The importance of prediction and classification lies in understanding the impact of these variables on humans, animals, plants, and other living organisms, and in planning for a future free from the negative effects of various climate variables and rich in their positive impacts.

Relative humidity data will be used and classified based on the principle of auto-regression, by analyzing the mathematical relationship between it and autoregressive variables using a specific Classification Tree (CT) model and kernel methods. Most weather and air pollutant data are non-linear.

Therefore, the use of some linear methods and models may lead to inaccurate results, because weather data is generally a type of time series that contains many seasonal and cyclical influences that may be negative causes of inconsistent and inaccurate classification results [1-6].

The study aimed to improve the classification accuracy, as well as to evaluate and compare the classification accuracy of these two approaches for seasonal relative humidity time series (hot and cold).

Cognitive analysis is an application of machine learning and an example of a decision tree. Decision trees are defined as a graph that shows possible actions based on the probability of events occurring. They are a classification model used in statistics, data mining, and machine learning. Decision trees are particularly important in analyzing decision problems involving a series of choices. In this study, we use the kernel method, specifically a Gaussian kernel classification model or a binary Gaussian kernel classification model. This is more practical with large datasets or long time series, but it can also be used with smaller, memory-fit datasets [7-9]. A time series is a set of successive observations generated according to a time variable. Based on the autocorrelation between observations, future time series observations can be classified [10]. An autoregressive model can be summarized as an expression of the current time series based on its past values. This study focuses on integrating the autoregressive model, a traditional model for relative humidity, with CT and kernel-based classifiers. This integration enables the models to handle the nonlinear boundaries and latent temporal dynamics of the datasets. A comparative study of CT and kernel-based autoregressive methods for classifying seasonal relative humidity has not been previously conducted.

This study primarily aims to employ methods that achieve the highest accuracy in classifying minimum and maximum relative humidity. A key objective is to utilize a method of dividing the data into two smaller parts to ensure homogeneity and obtain more precise results. This method is commonly known as chronological classification. The coherence index (CI) and kernel are also used to enhance the accuracy of the classification results, given their ability to efficiently handle non-linear and heterogeneous data, such as that presented in this study. To achieve high homogeneity in the studied data, which represents the minimum and maximum relative humidity, the data were divided into two parts according to atmospheric conditions (hot and cold seasons) in Nineveh Governorate. The first part (seasons) includes data from the hot months, while the second part includes data from the cold months. The data for the hot months includes May, June, July, August, and September, while the data for the cold months includes November, December, January, February, and March.

2. MATERIALS AND METHODS

2.1 Framework of study

The framework includes the following procedures:

a. Preparing homogeneous training and testing datasets.

b. Constructing the appropriate CT model based on autoregressive models.

c. Constructing the appropriate kernel model based on autoregressive models.

d. Calculating the accuracy measurements for CT and kernel classifications.

e. Comparing the accuracy of classification results to determine which model performed better.

2.2 Classification Trees methodology

This method is one of the fundamental tools of machine learning. It relies on the design of a decision tree, which is the basis of decision trees. The principle of this method is based on the premise that all elements of the studied population constitute a single group, and that it is necessary to classify it into two or more groups through the tree's branching points. These points are represented by logical terms as conditions for new branching, and then these groups are divided into two or more subgroups, and so on. The branching process continues until the final nodes (terminal nodes) are reached to improve the decision-making process. Each branching point produces two or more branches, and the process continues until the researcher determines the stopping order [8]. Decision trees are widely used in many diverse fields and were proposed by Breiman et al. [11]. The design of decision trees involves several stages [12-14]:

(1). The construction. This stage consists of several steps:

a. Determining the dependent variable.

b. Selecting the explanatory variables as autoregressive variables.

c. Choosing the root node to be suitable for the objective of the research.

d. Determine the logical rules for branching.

(2). The division or partitioning process.

(3). Operation stops.

(4). The pruning processes.

(5). Drawing the tree.

The CT test is designed using data characteristics taken from the sample items, which include observation of explanatory variables x and the corresponding observations of the target variable y, when x is a set of corresponding observations $x_{1i}x_{2i}\ldots x_{pi}$ for p variables, and $i = 1,2,3,\ldots,n$. Let $N_j(t)$ be the number of sample elements of the explanatory variable j where $\sum_{j=1}^{p} N_j(t) = N(t)$ which belongs to the region $R(t)$ which corresponding to the node t and to the group G_j together. The group G_j is over several groups that make up the target variable, the group y. The probabilities of belonging to the region $R(t)$ and distribution to the group G_j corresponding to the node t belongs to the sample n can be such as follows [15, 16]:

$$P(t) = \frac{N(t)}{n} \tag{1}$$

The probability that element i belongs to the area $R(t)$ corresponding to the node t and distribution to the group G_j may equal

$$P(G_j / i \in R(t)) = \frac{N_j(t)}{N(t)} \tag{2}$$

For the same assumption above, but when the element i belongs to the left or right nodes, respectively.

$$P[l(t)] = \frac{N[l(t)]}{n} \tag{3}$$

$$P[r(t)] = \frac{N[r(t)]}{n} \tag{4}$$

$$P_l = \frac{P[l(t)]}{P(t)} = \frac{N[l(t)]}{N(t)} \tag{5}$$

$$P_r = \frac{P[r(t)]}{P(t)} = \frac{N[r(t)]}{N(t)} \tag{6}$$

Therefore, the following rule can be deduced: Each element i is classified within the set G_k if its corresponding conditional probability is greater than the corresponding conditional probability of the other sets. This rule can be expressed as follows [13, 16]:

$$P(G_k / t) = \max_{j=1}^{g} P(G_j / t) \tag{7}$$

2.3 Gaussian kernel

Every classification method aims to accurately predict categories (classification). The kernel method, a machine learning technique, and classification algorithms based on the categorical regression model rely on initially separating data linearly. From Figure 1, for a linearly separable dataset, it is easy to see that all points above the line belong to the first category, while points below the line belong to the second category. However, it is impossible to have a dataset that is so simply and smoothly linearly separable. In most cases, data separation is difficult, and therefore, the kernel method, as a machine learning technique, provides simple classifiers that resemble the principle of logistic regression (LR).

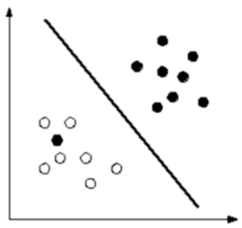


Figure 1. Two groups can be separated linearly

Linear classification in a kernel model may depend on the principle of one of learner and, Support Vector Machine (SVM) or LR, based on the following equation:

$$f(x)=T(x)\beta+b \tag{8}$$

where, x is a row vector observation from p explanatory variables, $T(\cdot)$ is a transformation of p explanatory variables x as a matrix, $T(x)$ maps x to a high-dimensional space, β is a vector of coefficients (regression parameters), and b is the scalar bias part which is equivalent to the error or the residuals statistically. In the basic concepts of SVM and LR models, the response (target) variable range is $y \in \{-1,1\}$ where +1 is for the positive class and –1 for otherwise, while the loss function for SVM is different from the LR model. The loss function for the SVM and the LR model, respectively, can be expressed as follows [17, 18]:

$$\ell\,[y, f(x)] = \max[0, 1-yf(x)] \tag{9}$$

$$\ell\,[y, f(x)] = \log\{1+\exp[-yf(x)]\} \tag{10}$$

In this study, the objective of the kernel algorithm is the binary classification of the target variable into +1 for the positive class and –1 for the negative class. As a machine learning method, a logistic kernel regression evaluation will be done to have a benchmark model. After that, the training process will start for a kernel classifier to see if it can obtain better classification results. The basic steps of the algorithm, before training and evaluating the model, especially in MATLAB programming, are as follows:

• Importing the datasets.
• Preparing the variables to be fitted with the model requirements.
• Kernel-based classification models can be theoretically related to SVM and LR.
• Evaluating the parameters of the model.
• Constructing a kernel classifier based on a previous specific model.
• Evaluating the parameters of the kernel classifier.

The Gaussian kernel maps nonlinear data into a higher-dimensional feature space in which linear separation may be achievable [9, 17].

2.4 Accuracy percentage and confusion matrix

The classification matrix, also referred to as a confusion chart, is a statistical indicator of the accuracy of classification. It classifies binary events using a confusion matrix that shows the actual observations versus the classified observations, such as in Table 1.

Table 1. The confusion matrix

Actual	Prediction	
	Negative	**Positive**
Negative	True Negative (TN)	False Positive (FP)
Positive	False Negative (FN)	True Positive (TP)

From the confusion matrix, the Accuracy Percentage (AP) measurement can be concluded and expressed as follows:

$$AP=\frac{TP+TN}{n}\times 100 \tag{11}$$

where, $n = TN + TP + FN + FP$ is the number of observations [19-23].

3. RESULTS AND DISCUSSION

3.1 Data used in the study

In this study, relative humidity data for maximum and minimum readings were analyzed. The data were collected from the Ministry of Agriculture/Agricultural Meteorology Center/Nineveh Governorate/Mosul Station. The datasets spanned from May 15, 2018, to July 19, 2020, comprising 797 daily observations.

To achieve greater consistency, the data were divided into two groups (seasons) according to the climatic characteristics of Mosul. The first group (season) includes observations from the months of November, December, January, February, and March, representing the cold season. The second group includes observations from the months of May, June, July, August, and September, representing the warm season. Data for April and October were excluded due to their moderate nature, which varies from year to year. By dividing the data into these two groups, the data becomes more consistent and homogeneous within each season, which may contribute to improving the accuracy of classifying relative humidity data.

For the purpose of using classification, nucleotide, and comparative classification methods, relative humidity, which is originally a quantitative variable, will be transformed into a binary variable. High relative humidity represents the positive characteristic and will be represented by the number +1, while low relative humidity represents the negative characteristic and will be represented by the number -1. To obtain the best binary data, certain measures of central tendency, such as the mean and median, were adopted, given the nature of the season, to transform the target variable into a binary variable. To establish binary classifications, continuous relative humidity values were divided into discrete values using defined thresholds based on internationally recognized climatic criteria, taking into account the descriptive statistical measures of the data. Specifically, for each condition (maximum and minimum relative humidity) and for each season (hot and cold), a threshold specific to each season was determined by combining the international reference criteria for relative humidity classification with measures of central tendency (mean and median) of the corresponding training dataset. The thresholds were calculated using only the training data to avoid information leakage.

The data must be further divided into two sets: a training set and a test set. The benefit of using the test set is to verify the accuracy of the model's classification performance, as the model is built using the training set and its performance is tested using the test set. Therefore, the summer and winter data were divided into 70% for training and 30% for testing. Accordingly, the daily data for the summer, which includes 372 observations, was divided into 262 observations for the training period and 110 observations for the testing period. The winter data, which includes 303 observations, was divided into 212 observations for training and 91 observations for testing.

3.2 Classification Trees results

The decision tree method is one of the most important classification methods. It is a type of decision tree whose primary function is to classify data of a binary dependent variable (the target variable) based on the behavior of its explanatory variables, whether continuous or categorical. In this study, the decision tree method was used to improve the classification accuracy of both the minimum and maximum relative humidity in summer and winter compared to the kernel method, and to achieve high classification accuracy.

The decision tree method will be used to model the data for the dependent variable and its corresponding explanatory variables. The target variable is represented by the original variable, while there are three explanatory variables as the lags of the original series based on the autoregressive principle of time series. MATLAB was used to apply the decision tree classification by following the sequential steps of the applied algorithm as follows:

(1). Data preparation includes:

a. Dividing the data of the explanatory input variables and the intentional (Target) variable into two groups: the training data (the largest part) and the test data (the smaller part from the end of the series) for both the hot and cold seasons.

b. Entering the datasets into MATLAB to be used in classification using the CT model.

(2). Writing a program in MATLAB to apply the CT, which includes several commands.

The CT construction used the default and widely adopted option in MATLAB's "fitctree" function. After completing the classification process using the CT method for the training period 70% and the test 30% for the hot and cold seasons of the relative humidity variable in both maximum and minimum cases. The CT was implemented in MATLAB using the fitctree function under the Classification and Regression Trees framework. The default classification settings were adopted, where node splitting was based on the datasets. Tree growth was controlled using MATLAB's internal stopping rules, with a minimum leaf size of 1 observation, a minimum parent node size of 2 observations, and no explicit restriction on maximum tree depth (maximum number of splits equal to *n*–1, where *n* is the number of training observations). Cost–complexity pruning was enabled within the Classification and Regression Trees algorithm to control tree complexity and reduce overfitting, following MATLAB's default pruning strategy.

The confusion diagrams in Table 2 are similar to the summer confusion matrices for the maximum and minimum relative humidity variables. The confusion diagrams in Table 3 are similar to the winter confusion matrices for the maximum and minimum relative humidity variables.

Table 2. The confusion charts of classification accuracy for the hot season when the training data is 70% using the Classification Tree (CT) method

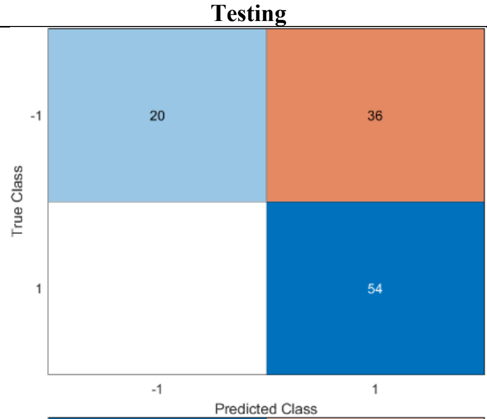
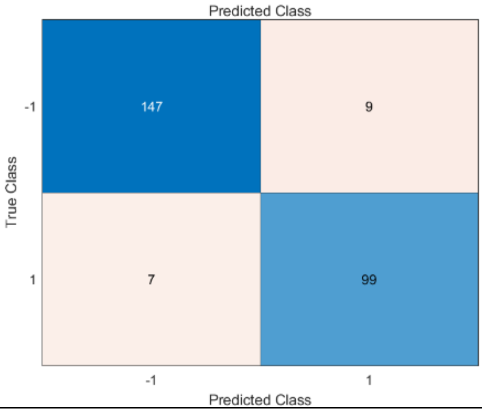
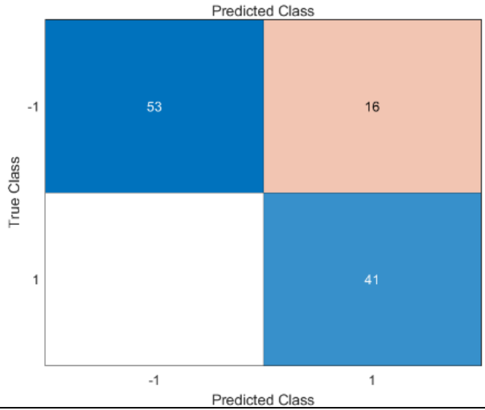
	Hot Season	
	Training	**Testing**
Maximum relative humidity		
Minimum relative humidity		

Table 3. The confusion charts of classification accuracy for cold season when the training data is 70% using the CT method

	Cold Season	
	Training	Testing
Maximum relative humidity		
Minimum relative humidity		

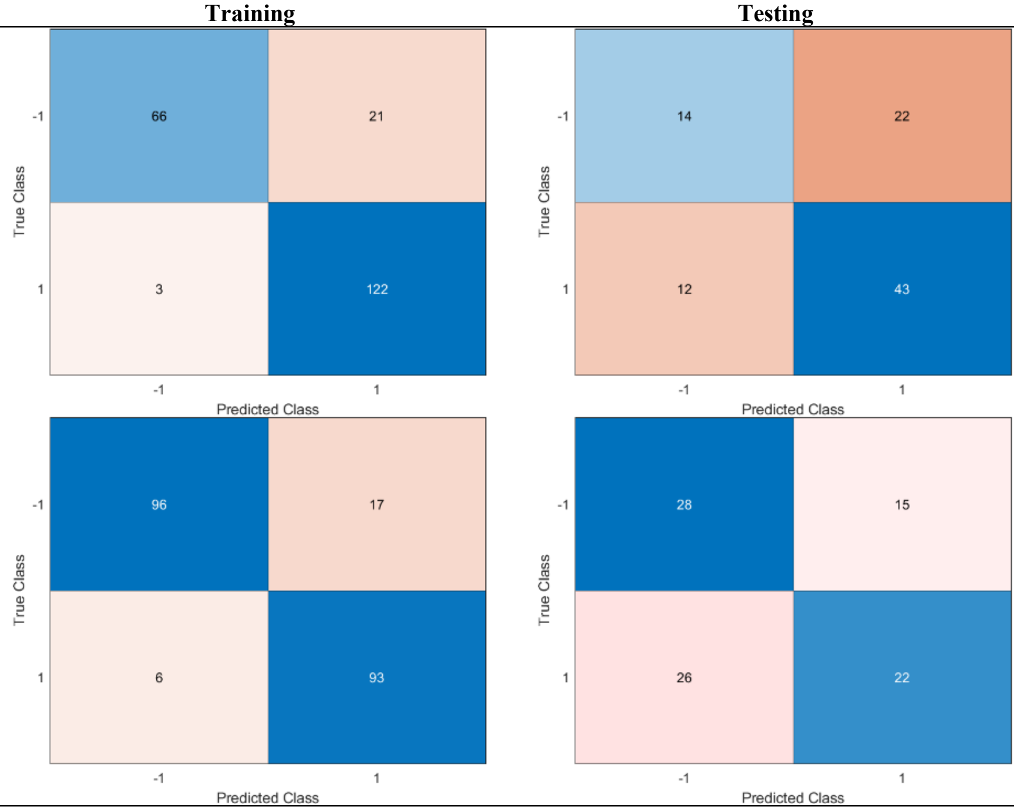


Table 4. The classification accuracy percentage for hot and cold seasons when the training data is 70%, using the method

Meteorological Variable	Hot Season		Cold Season	
	Training	Testing	Training	Testing
Maximum relative humidity	87.02%	67.27%	88.67%	62.64%
Minimum Relative humidity	93.89%	85.45%	89.15%	54.95%

In each confusion diagram above, the number in the top left represents the correct negative result (TN), the number in the top right the false negative result (FN), the number in the bottom left the false positive result (FP), and the number in the bottom right the correct positive result (TP), as previously shown in Table 1. From Tables 2 and 3 above, the accuracy percentages of the classification results were calculated and listed in Table 4 for summer and winter, for the highest and lowest relative humidity values.

It is evident from Tables 2, 3, and 4 above that the classification accuracy during the training period exceeded the accuracy of the test results. This is expected because the CT method was developed using training data representing 70% of the total data, while the validation was performed using test data representing 30% of the total data. Figure 2 illustrates and confirms the classification accuracy results in Tables 2, 3, and 4 above for the training and test data for summer and winter, for the highest and lowest relative humidity values, when the training data constituted 70% and the test data 30% for the CT method.

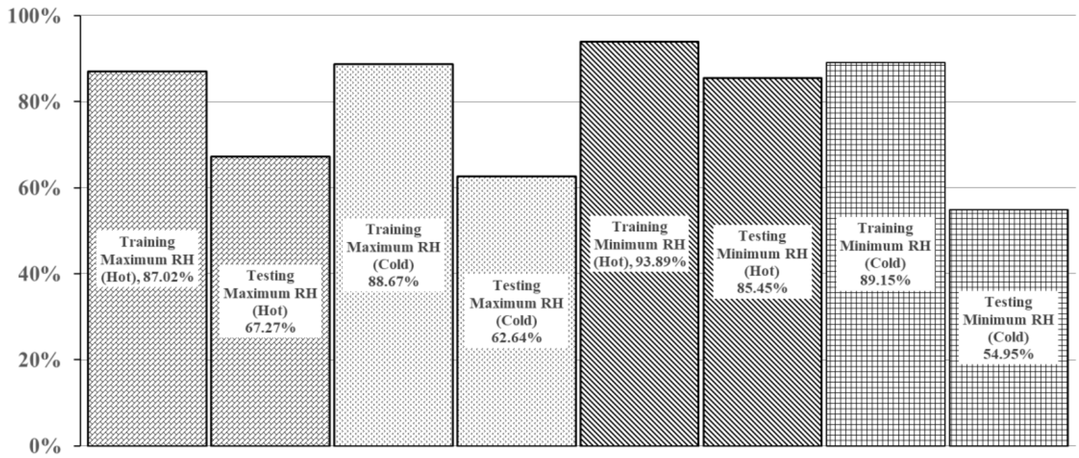


Figure 2. The classification accuracy for hot and cold seasons when the training data is 70% using the Classification Tree (CT) method

3.3 Kernel model

The Gaussian kernel classification model using auto-regression is a machine learning technique used in classification. Also referred to as cross-validation, it performs cross-validation on a binary classification model using a Gaussian kernel for nonlinear classification. This model is used to model large datasets containing massive training datasets and can also be applied to smaller datasets. In high-dimensional spaces, this model fits a linear model by minimizing the regularization objective function, which is equivalent to using the Gaussian kernel for the model in low-dimensional spaces. The linear classification model also includes SVM and LR regularization models, as discussed in the Methodology section.

The kernel method was used to improve the classification accuracy of both the minimum and maximum relative humidity in summer and winter compared to the conventional kernel method, achieving high classification accuracy. This method will be used to model the dependent variable and its explanatory variables. The target variable is represented by the parent variable, while the three explanatory variables are represented by the delay periods in the parent series, based on the principle of auto-regression of time series.

MATLAB was used to implement the kernel classification by following the sequential steps of the kernel algorithm as mentioned previously in the Methodology section, after enabling the cross-validation option and selecting K = 10 for the k-fold option. The number of folds to use in the cross-validation model can be specified as a positive integer value greater than 1. If it is specified k-Fold by k, the command will perform the following steps:

(1). The data is randomly divided into k sub-groups or sub-samples.

(2). For each sub-group, one of them will be used as a testing and validation dataset, and the remaining *k*-1 sub-groups will be used for the task of model training.

(3). The k sets used in the repeated training operations will be recombined and stored in a k by 1 vector.

In this study, the final classification model was a Gaussian kernel-based classifier applied directly to the autoregressive properties of relative humidity. The SVM and LR were not used as final classifiers; they were mentioned only to illustrate the general principles underlying kernel-based learning. The applied kernel model performs binary classification using a Gaussian kernel function without relying on a margin-based SVM or probabilistic LR optimization frameworks.

After completing the classification process using the kernel model for a 70% training period and a 30% testing period for the relative humidity variable in summer and winter, under both maximum and minimum relative humidity conditions, the confusion diagrams in Table 5 are similar to the confusion matrices for summer under both maximum and minimum relative humidity conditions. Similarly, the confusion diagrams in Table 6 are similar to the confusion matrices for winter under both maximum and minimum relative humidity conditions using the kernel model.

In each confusion diagram above, the number in the upper left represents a true negative result (TN), the number in the upper right represents a false negative result (FN), the number in the lower left represents a false positive result (FP), and the number in the lower right represents a true positive result (TP), as previously shown in Table 1. From Tables 5 and 6, the accuracy percentage of the classification results using the kernel model was calculated and listed in Table 7 for summer and winter under both maximum and minimum relative humidity conditions.

Table 5. The confusion charts of classification accuracy for the hot season, when the training data is 70%, using the kernel

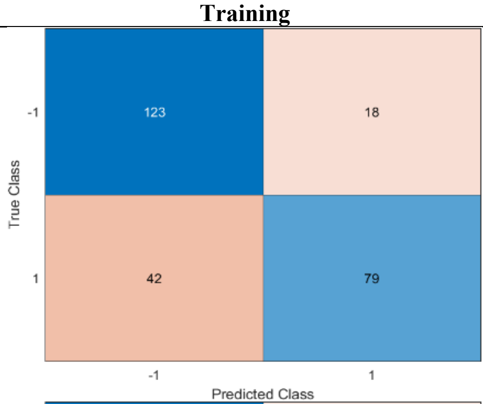
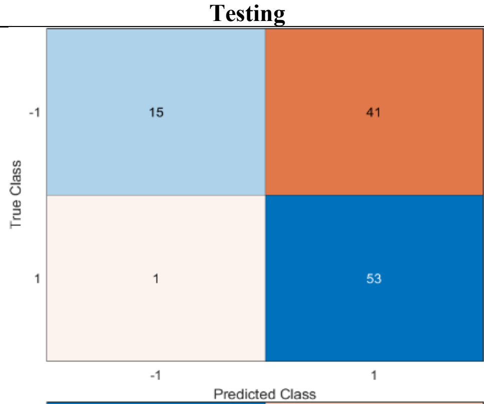
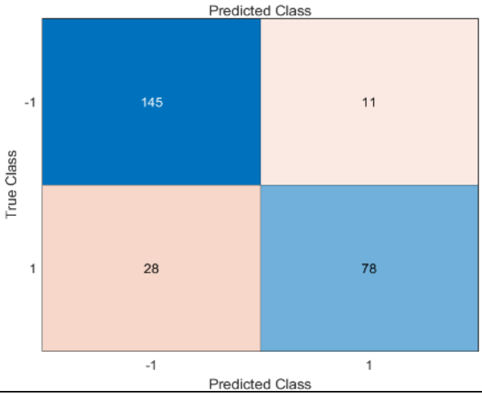
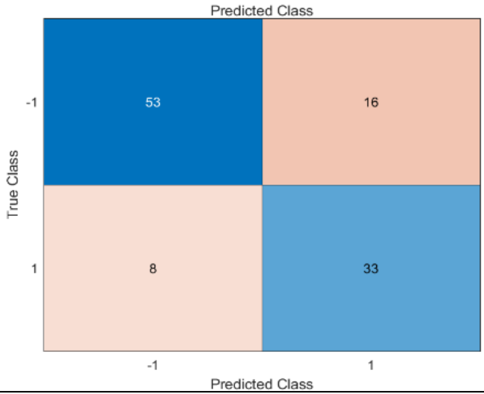
	Hot Season	
	Training	**Testing**
Maximum relative humidity		
Minimum relative humidity		

Table 6. The confusion charts of classification accuracy for the cold season when the training data is 70% using the kernel

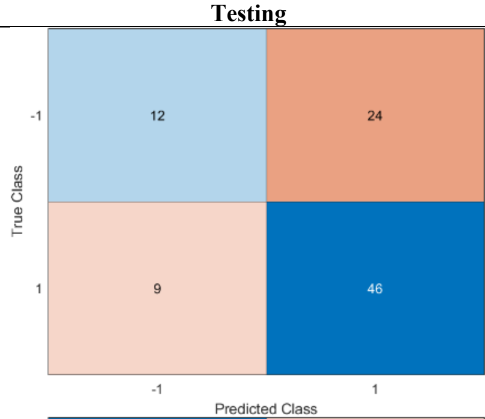
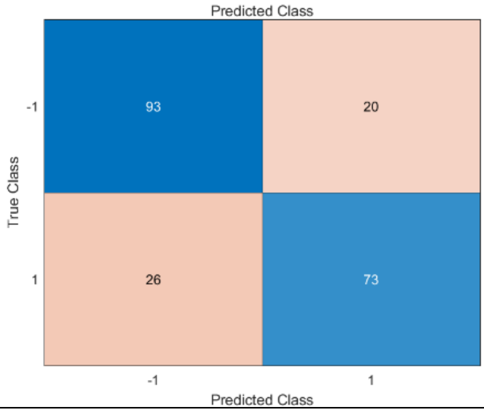
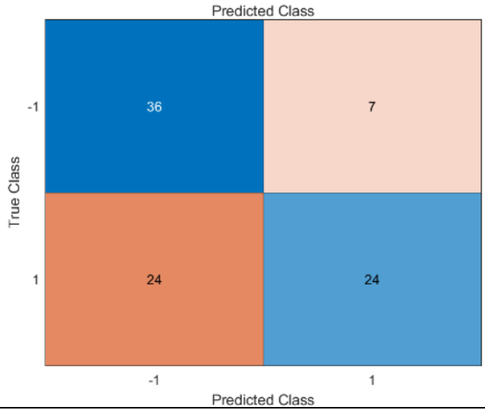
	Cold Season	
	Training	**Testing**
Maximum relative humidity		
Minimum relative humidity		

Table 7. The classification accuracy percentage for hot and cold seasons when the training data is 70% using the kernel

Meteorological Variable	Hot Season		Cold Season	
	Training	Testing	Training	Testing
Maximum relative humidity	77.10%	61.82%	78.30%	63.74%
Minimum relative humidity	85.11%	78.18%	78.30%	65.93%

Tables 5-7 show that the classification accuracy during the training period exceeded that of the test results. This is expected because the core model was created using training data representing 70% of the total data, while the validation was performed using test data representing 30%. Figure 3 illustrates and confirms the classification accuracy results in Tables 5-7 for the summer and winter training and test data for maximum and minimum relative humidity variables, when the training data comprised 70% and the test data 30% of the core model.

Figures 4 and 5 illustrate the comparisons between the proposed CT and Kernel methods for the classification accuracy results presented in Tables 2–7, as well as Figures 2 and 3 for the training and testing periods, respectively, for summer and winter, for the time series variables of maximum and minimum relative humidity.

Figures 4 and 5 also clearly show that the CT method outperforms the Kernel method in classification accuracy for both the training and testing periods, for summer and winter, for the time series variables of maximum and minimum relative humidity.

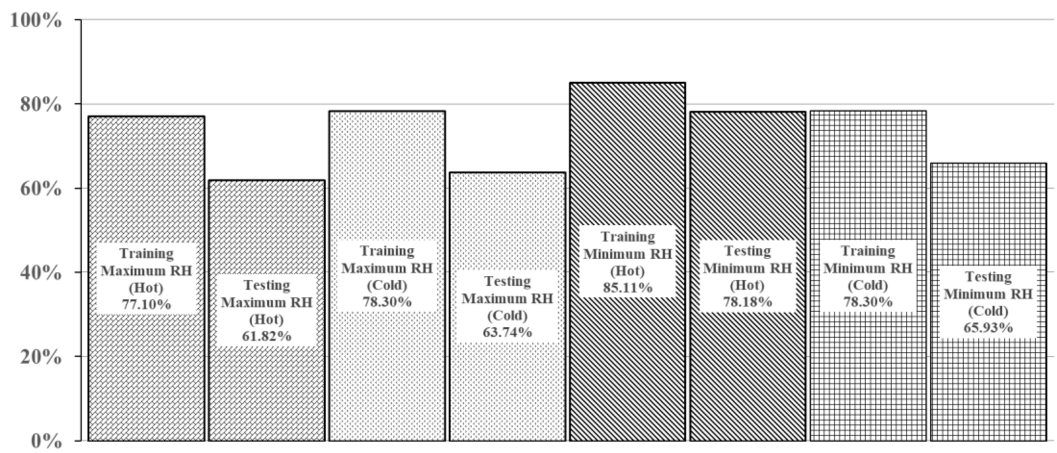


Figure 3. The classification accuracy for hot and cold seasons when the training data is 70% using the kernel

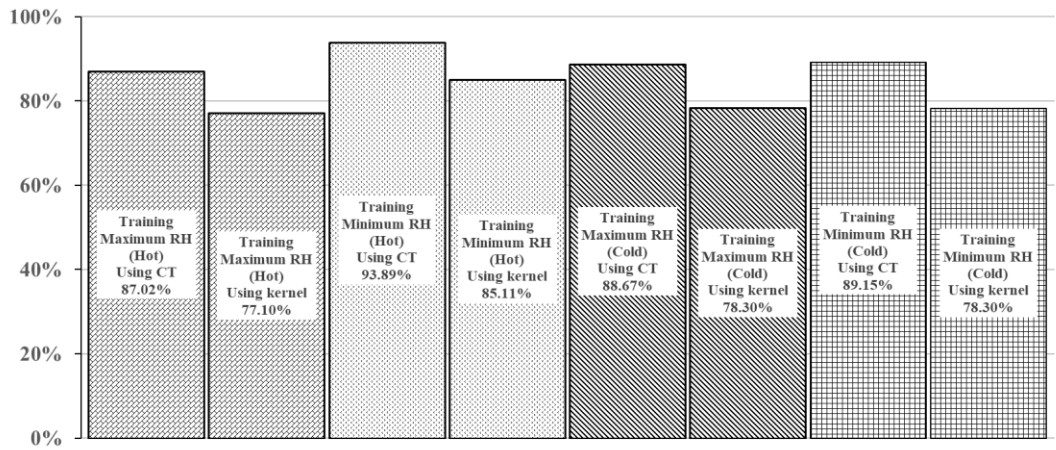


Figure 4. The classification accuracy of the two suggested methods, CT and kernel, for different datasets for the training period

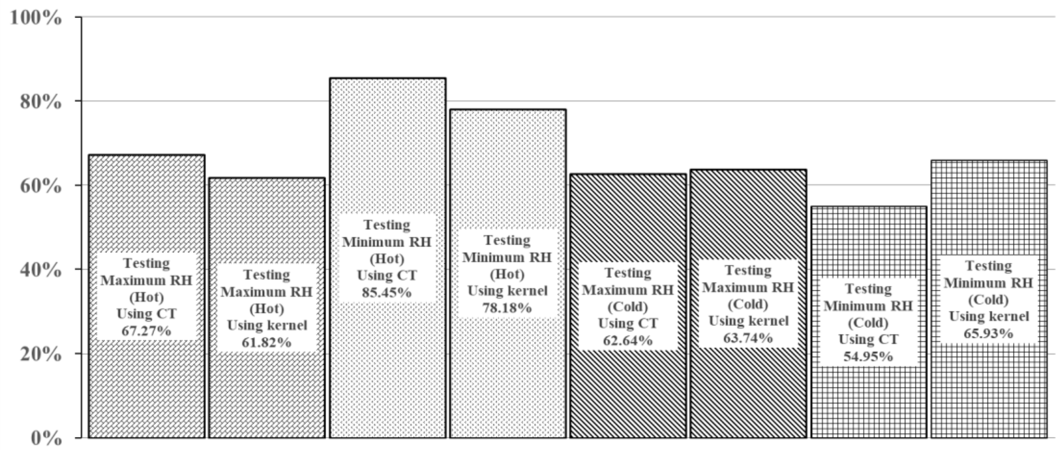


Figure 5. The classification accuracy of the two suggested methods, CT and kernel, for different datasets for the testing period

Figures 4 and 5 also illustrate the classification accuracy of both models (CT and Kernel) during the training and testing phases. As expected, consistently higher accuracy values are observed during training, due to model optimization using this data. The greater variability observed in the minimum relative humidity value during winter, particularly in the CT model, is attributed to the increased variability and decreased temporal stability of the minimum relative humidity value during the winter months. These conditions increase the sensitivity of tree-based models to local data patterns learned during training, which may not fully generalize to unseen observations. However, the overall trends in Figures 4 and 5 show relatively consistent performance between CT and kernel models, supporting the robustness of the comparative analysis.

4. CONCLUSIONS

In this study, the CT method and the Gaussian kernel model were proposed to improve the classification accuracy of relative humidity series at both the maximum and minimum levels. The dataset was divided into two seasons to achieve homogeneity and minimize the effects of seasonality and nonlinearity. The seasonal distribution of the data contributed to improved homogeneity, enabling the models to better capture the seasonal dynamics of relative humidity. The warm and cold seasons were adopted as the final datasets for analysis. From the results presented in the previous section, we conclude that the CT and kernel methods, as modern classification approaches, achieved good classification with improved results compared to other traditional techniques used in previous studies. The CT method can improve the classification accuracy of maximum and minimum relative humidity data across different seasons. The kernel can also be used to improve the classification accuracy for maximum and minimum relative humidity data, outperforming many classical methods. However, a significant decrease in test performance was observed in some cases, particularly for the minimum relative humidity during the cold season, indicating sensitivity to data variation when applied to limited seasonal samples.

ACKNOWLEDGMENT

The authors extend their sincere thanks to the University of Mosul/College of Computer Science and Mathematics and the University of Duhok/College of Administration and Economics for the facilities they provided, which contributed to improving the quality of this work.

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