ARTIFICIAL INTELLIGENCE OPTIMIZATION FOR FOREST FIRE RISK PREDICTING APPLIED TO GREEN ENVIRONMENT

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Abstract. This paper aims to contribute to the field of green environment and meteorological signal processing by exploring methods for analyzing and predicting environmental factors. The focus is on developing an intelligent approach for preventing and predicting wildfires that may arise due to changes in atmospheric temperature or other conditions. The proposed solution involves using machine learning and evolutionary deep learning to create a neural model that can interact with the Internet of Things (IoT) and respond in real-time to minimize potential damage. The experiments were carried out in the forests of Jandouba, Tunisia, using Python software. The results demonstrate that this approach offers significant advantages over the most ranked existing Canadian method (FWI) for fire weather index.
Keywords: *green environment, meteorological signals, fire risk prediction, evolutionary deep learning, self-organizing neural model, IOT technology*

Introduction

The world's natural balance relies on the wealth of forests and their environmental exchange, but the risk of fires is increasing due to climate change and human actions.

Ensuring a clean environment and mitigating the risks associated with fires have become crucial global priorities. A clean environment not only promotes the well-being of ecosystems and human health but also plays a vital role in reducing the occurrence and intensity of wildfires. As the frequency and severity of wildfires continue to escalate worldwide, the need for effective fire risk prediction and prevention strategies becomes ever more pressing (El Kamel, 2014; FAO, 2019).

To effectively predict fire risks, it is imperative to comprehend the multifaceted factors that contribute to their occurrence. Natural conditions such as weather patterns, fuel availability, and topography significantly influence fire behavior. Human activities, including land use changes, improper waste management, and arson, also play a pivotal role in fire incidents. Analyzing these factors and their interactions provides valuable insights for developing accurate fire risk prediction models (Justice, 2006; Masanobu, 2014).

Harnessing the power of data and machine learning algorithms empower us to develop robust fire risk prediction models. By analyzing historical fire data, weather patterns, fuel characteristics, and other relevant variables, predictive models can be trained to anticipate fire behavior and identify areas prone to ignition. Such data-driven approaches facilitate

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informed decision-making, allowing stakeholders to allocate resources efficiently and implement targeted prevention measures (Padilla, 2018).

Furthermore, the introduction of advanced technologies has revolutionized fire risk prediction and prevention efforts. Remote sensing, geographic information systems (GIS), and satellite imagery provide real-time data on vegetation health, fuel moisture, and landscape conditions (Hansen, 2013; Lizundia, 2020). These technologies enable the identification of high-risk areas, early detection of fire outbreaks, and prompt response, thereby minimizing the potential impact of wildfires. Integrating these tools into fire management strategies enhances our ability to proactively address fire risks.

This paper aims to analyze the key parameters that contribute to wildfires and develop an optimized intelligent model for predicting and preventing them in real-time. The model considers several input parameters such as Fine Fuels Moisture Content (FFMC), Duff Moisture Code (DMC), Drought Code (DC), Initial Spread Index (ISI), Build Up Index (BUI), temperature intensity, wind speed, region humidity and annual precipitation rate (Funk, 2015; Abatzoglou, 2018). The comparison of these parameter data with real experimental field data from Jandouba, Tunisia, is made while considering geographical variability and climatic overconstants. The results of this analysis will be used to train a machine learning algorithm to predict fire indicators for the coming years. If the predicted value exceeds a predetermined threshold, an intelligent control system based on embedded sensors and wireless interconnections will activate alarms and initiate possible interventions. The self-organizing neural model inside these embedded nodes performs noise filtering, hot zone classification, and fire point recognition. The proposed solution is evaluated against the Canadian model, and the obtained data is mapped as a real-time visualization and decision support tool. This paper is organized into five sections, including an introduction, materials and methods, results, discussion, and conclusion. Overall, this intelligent technological solution linked to the Internet of Things allows for an instantaneous response against natural disasters.

Materials and methods

Artificial intelligence has become a crucial tool in various fields, including agri-food and forestry sectors, where it is used to prevent fire risks. AI models are based on learning from past events, similar to how humans learn from experience. In the first stage, researchers provide the algorithm with a data history describing fire characteristics. In the second stage, the model learns, and in the third stage, it produces results.

Specifically, machine learning algorithms, has demonstrated remarkable potential in various domains, including fire risk prediction. By leveraging large datasets comprising historical fire incidents, weather patterns, vegetation indices, and topographical information, artificial intelligence (AI) optimization techniques can learn patterns and relationships to generate accurate predictions. This approach enables stakeholders to identify high-risk areas, allocate resources efficiently, and implement targeted prevention measures (Wagner, 1985; Risk, 2019).

Thanks to platforms like Google Earth Engine and Open Data Kit, accessing geospatial information has become more accessible. Google Earth Engine is a geospatial image data viewer with global and regional coverage, providing a panoramic view anywhere on Earth with relative measurements tracking changes over time. Open Data Kit is endorsed by global organizations like the Red Cross, the Carter Center, and Google, allowing for quick, accurate, offline, and large-scale data collection (Risk, 2019).

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A real example is presented on how artificial intelligence optimization can be applied to fire risk prediction based on meteorological signals:

a. Data Collection: Historical data related to fire incidents, meteorological signals, and associated features are gathered. This data may include variables such as temperature, relative humidity, wind speed and direction, precipitation, and atmospheric pressure. Additionally, relevant geographical information like vegetation type, land cover, and topography are included.

b. Preprocessing and Feature Engineering: Clean the collected data and perform necessary preprocessing steps, such as handling missing values and outliers. Extract additional features that could contribute to fire risk prediction, such as fuel moisture content, drought indices, and historical fire patterns.

c. Model Selection and Optimization: Choose an appropriate machine learning model for fire risk prediction, such as a random forest, gradient boosting, or deep learning models like convolutional neural networks (CNNs) or long short-term memory (LSTM) networks. These models are well-suited for handling complex relationships in the data. Apply AI optimization techniques, such as grid search or Bayesian optimization, to tune the hyperparameters of the chosen model. This optimization process aims to find the optimal combination of hyperparameters that maximizes the model's predictive performance (Karanam, 2020).

d. Training and Validation: Split the data into training and validation sets. Use the training set to train the optimized model, and the validation set to assess its performance. During training, the model learns the patterns and relationships between meteorological signals and fire incidents, enabling it to make accurate predictions.

e. Evaluation and Interpretation: Evaluate the trained model's performance by comparing its predictions with the actual fire incidents in the validation set. Common evaluation metrics for classification tasks include accuracy, precision, recall, and F1-score. Examine the model's ability to correctly identify fire-prone areas and its generalization capabilities. Interpret the model's learned features and their relative importance to gain insights into the meteorological signals that have the most significant impact on fire risk. This interpretation can provide valuable information for stakeholders and decision-makers.

f. Deployment and Monitoring: Once the model demonstrates satisfactory performance, deploy it in real-time fire risk prediction systems. Continuously monitor meteorological signals and feed them into the deployed model to generate up-to-date fire risk predictions. Combine these predictions with other relevant information, such as satellite imagery and on-ground observations, to provide comprehensive fire risk assessments. Regularly evaluate and update the model as new data becomes available to ensure its effectiveness and adaptability to changing environmental conditions.

By applying AI optimization techniques to meteorological signals, this example demonstrates how a data-driven approach can enhance fire risk prediction. The integration of advanced machine learning algorithms and meteorological data enables the identification of high-risk areas and provides valuable insights for effective fire prevention and management strategies. In this instance, we present as real example our involved model that deploys wireless sensor nodes across forested regions. These areas are divided based on feasible communication distances between the nodes. Each individual node embodies a minituarized embedded system, encompassing a climate signal-receiving sensor steered by a digital signal processor (DSP). The DSP is enabled by an evolutionary deep learning algorithm whose instructions have been fine-tuned for

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optimal performance. This algorithm serves as a dynamic recurrent neural self-organizing map (RSOM), taking Canadian system parameters as inputs. If the output of each node exceeds the setpoint of a nonlinear thresholding, an alert signal will be generated at the master node.

There are various worldwide systems for calculating fire intensities and risks, with the Canadian model being the most recognized, known as the Fire Weather Index (FWI). This model uses meteorological data inputs, including temperature, precipitation, relative humidity, and wind speed, and provides three primary fuel moisture indexes, two intermediate fire behavior indexes, and a final fire weather index. The output layer of this model consists of the fire spread rate (ISI) and the accumulation index (BUI), which provide information on the total fuel available for the spreading fire. The FWI represents the fire intensity in the study area (Har, 2019).

Mathematical models, such as the fine fuel moisture code (FFMC), are used to compute these system parameters. The FFMC measures the moisture content of fine-surfaced fuels and is used to predict fire occurrence. These systems' outputs help researchers and professionals in various countries like Alaska, some North American states, Mexico, New Zealand, France, Portugal, and Southeast Asia prevent and manage forest fires.

Certainly, the comparison between the Canadian approach and our new methodology shows that the Canadian one is essentially based on sampling and discontinuous measurements of atmospheric parameters on site following significant variations. It is based on long and unsimplified calculations. This model was able to achieve **92%** as detection rate of fire outbreak depending on the environmental conditions. While the new methodology takes into account the Canadian parameters, as inputs, with the continuous admission of the climatic signals through the sensors of each node. An internal comparative treatment is carried out. The population diversity of the compared internal signals offers an optimal global solution; the survival is assured to the best individual. In terms of output, this methodology can offer a fire outbreak detection rate up to **97%**.

The applied algorithm ensures the comparison between the various inputs such as: the Canadian model parameters, the continuous measurements of the climatic signals and the atmospheric data of past years. It involves Bayesian optimization techniques of regression, variance and of correlation, followed by a nonlinear thresholding, in order to define at the output, the prediction states of fire outbreak.

Knowing that we have considered the data sets of the past five years, when learning the system, because they represent the possible climatic variations which reflects the fire history of the country.

The *Figure 1* shows the Canadian model hierarchy.

The output layer of this model consists of the fire spread rate (ISI), and the accumulation index (BUI), which provide information on the total fuel available for the spreading fire. Finally, it offers, as a result, the fire weather index (FWI), which represents the fire intensity in the study area. The computing of these system parameters is based on mathematical models, namely:

The fine fuel moisture code (FFMC) expressed by Van Wagner and Pickett in 1985. It measures the moisture content of fine-surfaced fuels, and it is used to predict fire occurrence (Cortez, 2007; Syphard, 2008; Panagiota, 2013).

In the first step, we need to determine the previous (FFMC) labeled by ($FFMC_{t-1}$).

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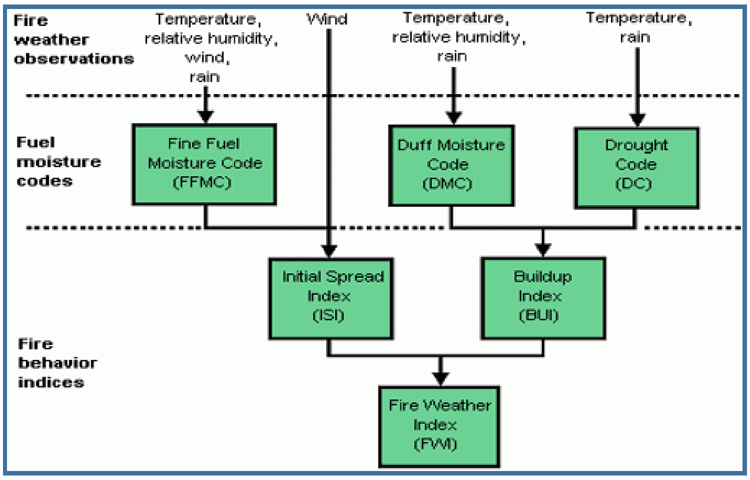

Figure 1. *Applied Hierarchy Canadian Model for Fire Prediction*

Next, we calculate the fine moisture content of the fuel, (mt−1) which is determineted by the below equation.

$$mt-1 = 147{,}2 \cdot \frac{101-FFMCt-1}{5+FFMCt-1} \qquad \text{(Eq.1)}$$

In a rain case, (i.e., when the precipitation P > 0.5), the daily fuel fine humidity is calculated as follow:

$$mrt = \begin{cases} mt-1+42.5\cdot Pf\cdot\left(e^{\frac{-100}{251-mt-1}}\right), & if\ mt-1 \leqslant 150 \\ mt-1+42.5\cdot Pf\cdot\left(e^{\frac{-100}{251-mt-1}}\right).\left(1-e^{\frac{-6{,}93}{Pf}}\right)+0.0015\cdot(mt-1+150)^2.Pf^{0{,}5}, & if\ mt-1>150 \end{cases} \qquad \text{(Eq.2)}$$

The effective rain (Pf) is measured in [mm] and calculated as follows:

$$Pf = P - 0.5, \quad \text{for } P>0.5 \qquad \text{(Eq.3)}$$

Then, the moisture content of the fine fuel for the drying phases (Ed) should be calculated as follows:

$$Ed = 0.942.H_{12}^{0.679} + 11\cdot e^{\frac{H12-100}{10}} + 0.18\cdot(21.1-T_{12})\cdot(1-e^{-0.115.H12}) \qquad \text{(Eq.4)}$$

Knowing that (H_{12}) is the relative air humidity in per cent [%], and (T_{12}) the air temperature in [°C] at noon (12 o'clock).

If (Ed) is less than (mt−1), then the log drying rate (kd) should be calculated with the following equations (Stocks, 2011; Calda, 2020):

$$Ko = 0.424\cdot(1-(\frac{H12}{100})^{1.7}) + 0.0694\cdot U_{12}^{0.5}.(1-(\frac{H12}{100})^{8}) \qquad \text{(Eq.5)}$$

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$$\text{Kd} = \text{ko} \cdot 0.581 \cdot e^{0.0365.T12} \quad \text{(Eq.6)}$$

where (U_{12}) is the wind speed in [km/h] at noon.

Then, the fine moisture content of the fuel (m) can be calculated as follows:

$$\text{m} = \text{Ed} + (\text{mt} - 1 - \text{Ed}) \cdot 10^{-Kd} \quad \text{(Eq.7)}$$

If (Ed) is greater than (mt−1), then the fine equilibrium humidity of the fuel will be calculated for the wetting phases (Ew):

$$\text{Ew} = 0.618 \cdot H_{12}^{0.753} + 10 \cdot e^{\frac{H12-100}{10}} + 0.18 \cdot (21.1 - \text{T}_{12}) \cdot (1 - e^{-0.115.H12}) \quad \text{(Eq.8)}$$

If (Ew) is greater than (mt−1), then the log of the wetting rate (kw) must be calculated with the following equations:

$$\text{k1} = 0.424.(1-(\frac{100-H12}{100})^{1.7}) + 0.0694 \cdot U_{12}^{0.5}.(1-(\frac{100-H12}{100})^{8}) \quad \text{(Eq.9)}$$

$$\text{kw} = \text{k1} \cdot 0.581 \cdot e^{-0.0365 \cdot T12} \quad \text{(Eq.10)}$$

Then, the fine moisture content of the fuel at time ‘t’ (mt) can be calculated as follows:

$$\begin{gathered} \text{mt} = \text{Ew} - (\text{Ew} - \text{mt} - 1) \cdot 10^{-Kw} \\ \text{If Ew} \leqslant \text{mt} - 1 \leqslant \text{Ed, so, mt} = \text{mt} - 1 \end{gathered} \quad \text{(Eq.11)}$$

Finally, the FFMC is determinated by the following equation:

$$\text{FFMCt} = 59.5 \cdot \frac{250-mt}{147.2+mt} \quad \text{(Eq.12)}$$

Eventually, the duff moisture code (DMC) represents the moisture content of loosely compacted decomposing organic matter, which weighs approximately **5** (kg/m^2) when dry (Nhat, 2019).

In order to calculate the Canadian model parameters, a csv file should be created with 13 columns (Mahyat, 2019). They represent, respectively, the latitude and the longitude of the burned area, the day and month, the FFMC, the DMC, the DC, and the ISI from the FWI system, the temperature in Celsius degrees, the relative humidity in (%), the wind speed in (km/h), the precipitation in (mm/m^2), and the burnt area in (ha). The following *Figure 2* represents a file piece that we created using Python.

The X and Y variables indicate the geographic location of the fire. This study is conducted on the forest resources of the Jendouba region. The vegetation cover of this governorate, compared to other governorates, has been well preserved. Forests and woods spread over **118,470** (ha), covering **38.2%** of the land. The forests are of various species; these are cork oaks and, to a lesser extent, zen oaks. The cork oak covers the mountainous massifs of Khemir, thanks to the bioclimatic floors, which vary between humid and subhumid. Zen oak mainly occupies the mountain slopes in the delegations of Ain Draham, Tabarka, and Ghardimaou.

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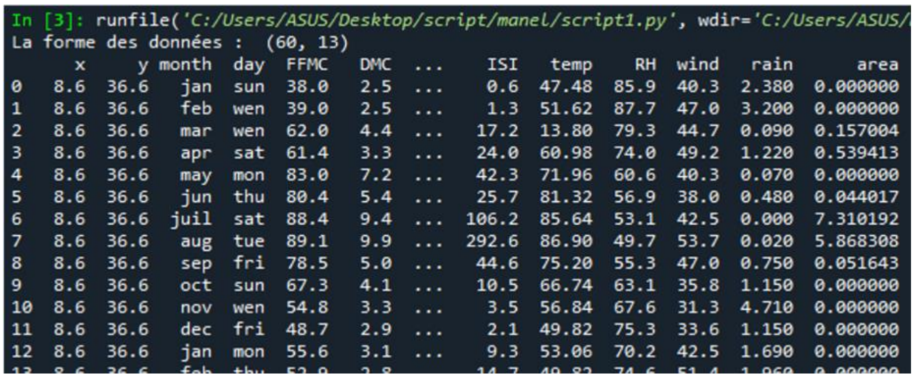

```
In [3]: runfile('C:/Users/ASUS/Desktop/script/manel/script1.py', wdir='C:/Users/ASUS/
La forme des données :  (60, 13)
      x     y month  day  FFMC   DMC  ...    ISI   temp    RH  wind   rain      area
0   8.6  36.6   jan  sun  38.0   2.5  ...    0.6  47.48  85.9  40.3  2.380  0.000000
1   8.6  36.6   feb  wen  39.0   2.5  ...    1.3  51.62  87.7  47.0  3.200  0.000000
2   8.6  36.6   mar  wen  62.0   4.4  ...   17.2  13.80  79.3  44.7  0.090  0.157004
3   8.6  36.6   apr  sat  61.4   3.3  ...   24.0  60.98  74.0  49.2  1.220  0.539413
4   8.6  36.6   may  mon  83.0   7.2  ...   42.3  71.96  60.6  40.3  0.070  0.000000
5   8.6  36.6   jun  thu  80.4   5.4  ...   25.7  81.32  56.9  38.0  0.480  0.044017
6   8.6  36.6  juil  sat  88.4   9.4  ...  106.2  85.64  53.1  42.5  0.000  7.310192
7   8.6  36.6   aug  tue  89.1   9.9  ...  292.6  86.90  49.7  53.7  0.020  5.868308
8   8.6  36.6   sep  fri  78.5   5.0  ...   44.6  75.20  55.3  47.0  0.750  0.051643
9   8.6  36.6   oct  sun  67.3   4.1  ...   10.5  66.74  63.1  35.8  1.150  0.000000
10  8.6  36.6   nov  wen  54.8   3.3  ...    3.5  56.84  67.6  31.3  4.710  0.000000
11  8.6  36.6   dec  fri  48.7   2.9  ...    2.1  49.82  75.3  33.6  1.150  0.000000
12  8.6  36.6   jan  mon  55.6   3.1  ...    9.3  53.06  70.2  42.5  1.690  0.000000
```

Figure 2. *Visualization of calculating results on the interface (editor) of Spyder-Python*

The total area burned in 2017 reached **17,000** (ha). This area represents **4.10** times the average value recorded in 2013, which represents **4,196** (ha). Note that with **1.2** million (ha) of Tunisian forests, the burned area exceeds **2.2%** of the total area. See *Figure 3*.

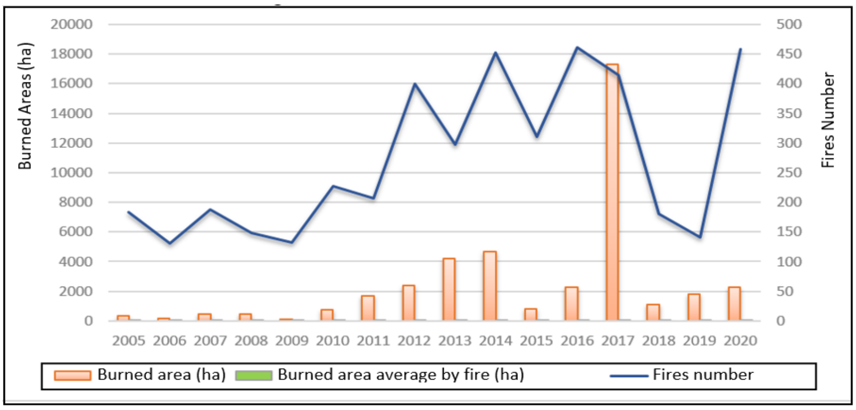

Figure 3. *Evolution of fires in number and area between 2005 and 2020*

The results shown in *Figure 3* illustrate the report of fire outbreaks on the Tunisia territory during the last 15 years period. They show an increase in the number of fires since 2005, with peaks of significant singularity recorded in 2016. The pace of the peaks is followed by a fall in 2018 and 2019. This decrease is also accompanied by a reduction in the surface area burned; less than **2000** (ha). Regarding the evolution diagram of burned areas, there is an irregular variation with the presence of significant peaks in 2017, also followed by a decrease in areas threatened by fires.

Our strategy in fire risk prediction is applied to the Jendouba region, which has the richest forests in Tunisian territory. The following *Figure 4* highlights the proposed methodology diagram.

This work primarily consists of predicting forest fire risk areas. Our approach is based on forecasting climate data over a two-year horizon in order to assess forest fire risks. This approach is based on the hybridization of the Canadian model FWI with an evolutionary optimized artificial intelligence one.

The study is carried out in three stages. The first step consists in the collection and analysis of data such as meteorological, quantitative, and qualitative fire data. A statistical

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study of correlation is applied in order to determine the meeting points between these parameters. During the second stage, we integrate the various classification tools referring to machine learning models in order to predict climatic data such as temperatures, precipitation, wind speed, relative humidity, and the number of fires.

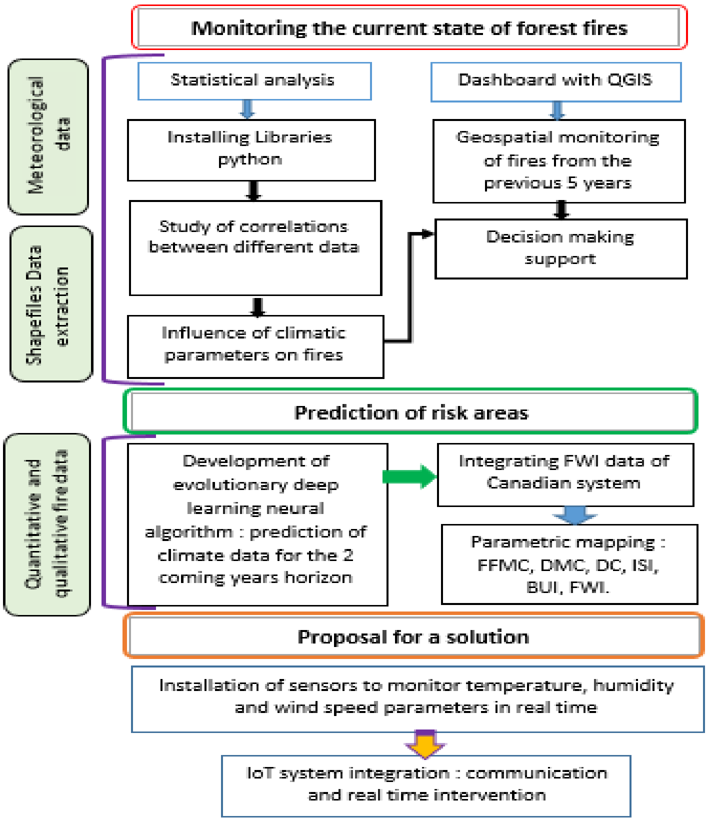

Figure 4. *Diagram of the Adopted Fire Prediction Methodology*

In the third step, we move on to calculating the Canadian Forest Fire Index (FWI) with future climate data (example, for next year). The prediction result obtained must be broadcast through the Internet of Things via the LoRa-WAN protocol, allowing a reaction against these disasters in real time.

Our contribution aims to integrate, in the second processing stage, artificial intelligence by building a hybrid model capable of challenging human intelligence. This was done by developing a Python code that relied on rule engines capable of solving fairly complex problems, such as the prediction of areas and dates of fires based on a priori knowledge (knowledge basis) (Binh, 2020; Jaehyuk, 2023).

Furthermore, historical data is applied for the supervised learning of a neural classifier (machine learning). This task is often known as incident-predictive, as clarified in *Figure 5* below.

The deep learning (DL) is included within the machine learning neural system, which is also included in the artificial intelligence (AI) model. So, we offer the artificial intelligence neural system a pair (X, Y) containing a dependent variable column X to be predicted that is extracted from the climate dataset and a predicted outcome model Y. Therefore, we compare, on each evolutionary learning iteration, one element to predict

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(variable X) with predictors (variables Y) (Anh, 2022; Fouda, 2022). This element differs depending on the types of data to be predicted. That means:

If Y is qualitative, there is a classification problem.

If Y is quantitative, there is a regression problem.

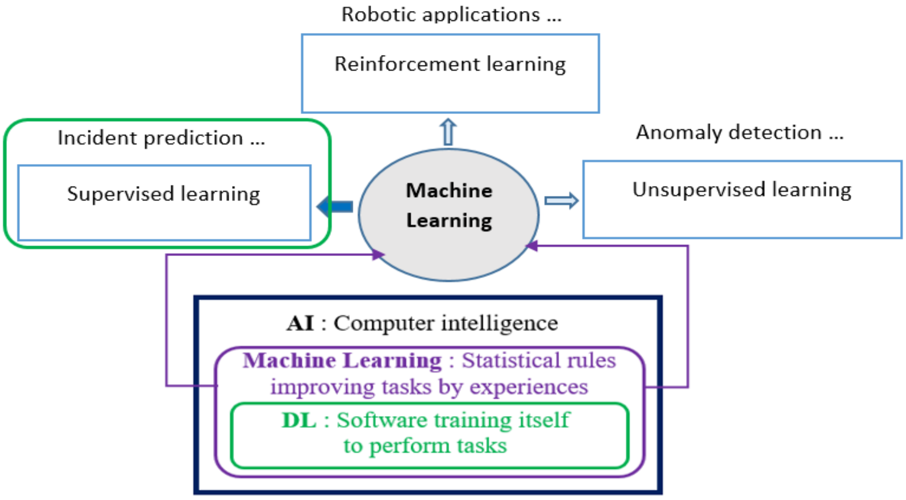

Figure 5. *Representative of the Incident Prediction Position*

The following *Figure 6* shows in which case classification or regression is applied.

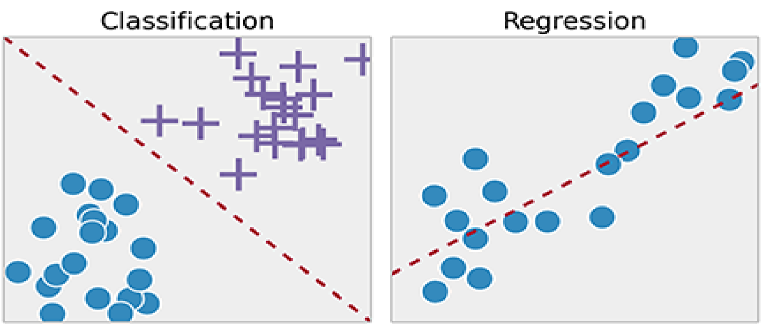

Figure 6. *Highlighting cases of classification and regression*

Subsequently, our model is subject to deep learning (DL) using more complex structure algorithms and a larger volume of data. These algorithms have a structure in evolutionary neural networks, such as the evolutionary recurrent self-organizing map (ERSOM), which allows them to adjust the predictions in an extremely precise way. The better the neural network is structured in terms of neurons number, topology, and learning, the better its predictions. The only challenge encountered in these research works is that this system requires a lot of computing power and a lot of data, so it is expensive. The performance and accuracy of this model are assessed by calculating the biases and variances.

The bias measures the difference between the predicted and the actual real values of the machine learning model. A model with a high bias results in poor predictive performance (Fouda, 2022; Kizilkaya, 2022).

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The variance measures the noise of the predictions. See the explanation in *Figure 7* below.

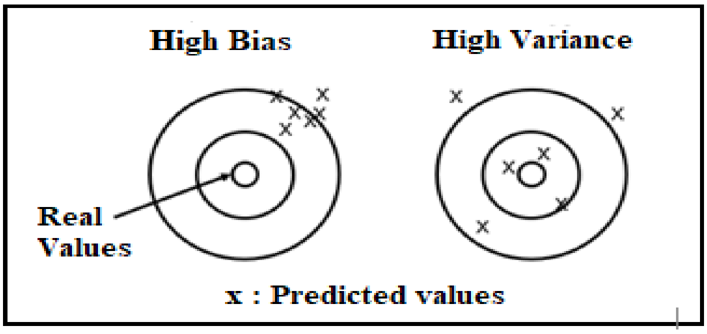

Figure 7. *Representative cases of Bias and Variance*

A successful model should have low bias and low variance. The bias will therefore be represented by one of the following quantities:

- Mean Squared Errors (MSE): the mean of the squared differences between actual values and predicted values.
- Root of the Mean Squared Errors (RMSE): square root of the MSE.
- Mean Absolute Percentage Error (MAPE): percentage of mean absolute errors.

The adopted strategy integrates artificial intelligence (AI) applications, using Internet of Things (IOT) tools for remote control and supervision of environmental parameter data in order to predict risk and intervene in real time. Indeed, the IoT implements two types of elements to interact with the physical world: sensors and actuators. Sensors collect information from the physical world and transmit it to the computer system. Actuators allow the computer system to act on the physical world by modifying its state.

Results

The Jendouba-Tunisia forest has a long history of fires. The climatic conditions of long, hot, and dry summers favor seasonal fires. Historical fire events are taken from the database available at the agricultural ministry. The obtained data over the past five years is used as training data for our prediction system. Current year data is used as validation data. The resulting model can support the determination of fire hazards. It is an estimate for better management of these risks and the planning of other mitigation measures. Nevertheless, simple linear regression is a statistical method that is used to quantify the relationship between a predictor variable and a response variable.

Our algorithm is performed on Python using the machine learning library ‘Pandas’ to provide us with several high-level datasets and a wide variety of analysis tools. It allows for the translation of complex operations of grouping, combining data, and filtering functionalities of time series. Also, we used the SciPy library, which contains modules for optimization, linear algebra, integration, and statistics.

The datasets used in this work have been carefully chosen in order to meet certain basic requirements. The following *Table 1* represents the values of the machine learning input parameters based on the Canadian model characteristics in order to predict the FWI in coming years.

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Table 1. *Fire risk prediction for the year 2025, over Deep learning of Canadian System*

X	Y	ffmc	dmc	dc	isi	bui	fwi
8.7573829	36.9545614	91,1	11	21,9	16,7	10,9	15,8
8.9549877	36.703793	95,8	12,6	21,6	56,2	12,5	38,9
8.9532015	36.6048581	97,4	13,6	22	40,3	13,4	32,1
8.752647	36.6779725	96,5	13,1	21,9	39,1	12,9	31
9.1567713	36.814415	94,4	11,9	21,3	31	11,8	25,5
8.6879509	36.7774877	93,6	11,7	21,4	29,4	11,6	24,4
8.5895118	36.7626788	93,4	12	21,9	25,9	11,8	22,5
8.6957875	36.6556629	96,4	13,1	21,9	39	12,9	31
8.448252	36.450525	95,6	12,8	21,9	36,6	12,6	29,4
8.158144	36.496923	97,9	13,3	21,5	34,9	13,1	28,9
8.440355	36.759489	97,1	12,8	21,2	24,5	12,6	22,2
8.844103	36.977605	95,4	11,9	20,6	13,6	11,7	14

By interpolation of climatic tendencies of the past data and in agreement with the Bayesian statistical studies, we can draw the predictive outlines of fires for the next two years.

The fire risk result is shown in blue cases in the predict FWI column. The position of the risk area is indicated by the geographic lines X and Y. These data are also used to develop maps highlighting these results, which can also aid in decision-making. See *Figure 8* below.

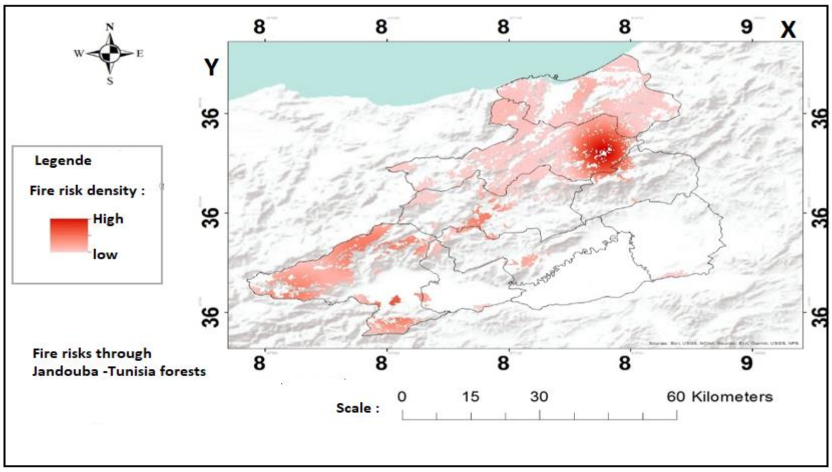

Figure 8. *Result of a fire density map through Jandouba delegations for the coming year 2025*

The red color represents the spreading of predicted fires over Jandouba delegations. Another database that contains new climate data variables has been created to analyze the variations and correlations between them. See *Table 2*.

This table is used to analyze the influence of climatic data on the fire's appearance. It can be noted from the following graph, *Figure 9*, that a sharp increase in the fires number starts at the beginning of the summer season. It is clear that the two months of July and August record the maximum number of fires during the five studied years.

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Table 2. *Jendouba weather data*

Monthly Rain (mm)	Max Wind Speed (m/s)	Average Monthly Temperature (°c)	Average Monthly Humidity (%)	Dates
60,6	18	8,6	85,9	01/01/Y_t
81,4	21	10,9	87,7	01/02/ Y_t
2,4	20	13,8	79,3	01/03/ Y_t
31,2	22	16,1	74	01/04/ Y_t
2	18	22,2	60,6	01/05/ Y_t
12,2	17	27,4	56,9	01/06/ Y_t
0	19	29,8	53,1	01/07/ Y_t
0,6	24	30,5	49,7	01/08/ Y_t
19,3	21	24	55,3	01/09/ Y_t
29,4	16	19,3	63,1	01/10/ Y_t
119,8	14	13,8	67,6	01/11/ Y_t
29,4	15	9,9	75,3	01/12/ Y_t

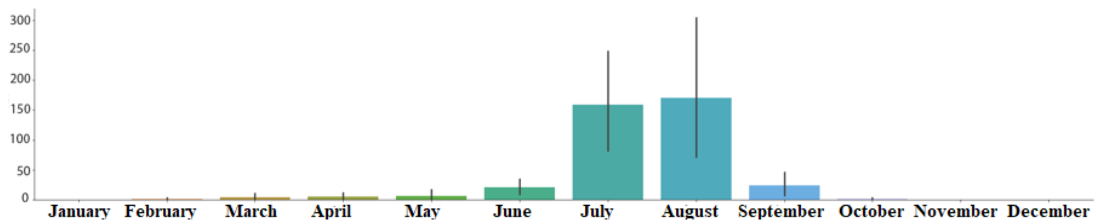

Figure 9. *Evolution of fires per month*

The analysis of collected data on forest fires over the previous five years has made it possible to determine that there is a significant geographical variation between the different delegations of Jendouba. We can analyze more deeply, taking into account the rainfall, humidity, wind, and monthly temperature with the highest damage category, in order to interpret whether these parameters are the basis of an accentuation of risks. See *Figure 10*.

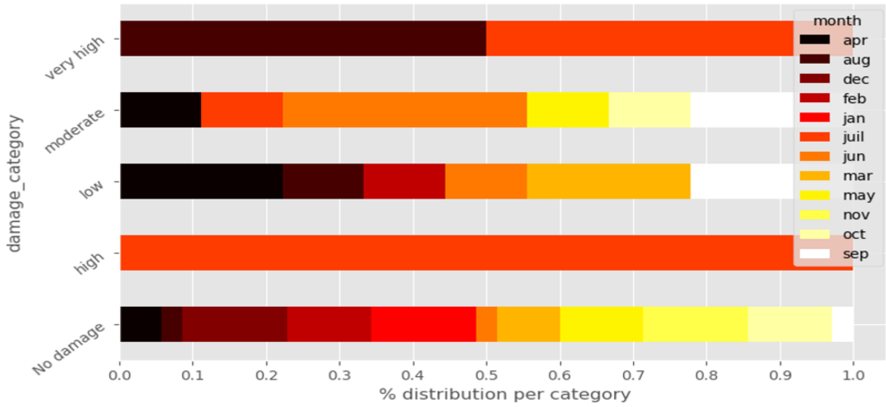

Figure 10. *Forest fire damage per month*

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The months of August and July present the most significant damage to our forest wealth compared to the months of October, November, December, January, and February. It can be deduced that temperature is a very important factor in the study of forest fires. The fires started in the cold period are much less numerous compared to the warm period. Since cold waves can prevent the first fire attack, we think about fires linked to natural causes. The fires in May may correspond to human intervention because the majority of the climatic data recorded show stability of the metrological parameters: a moderate wind speed and an average temperature.

Eventually, the analysis of the correlation between meteorological variables will be an important function, telling us about the common factor that contributes to fire outbreaks. We have correlable parameters where there is a correlation greater than **0.9** between the parameters that can be determined by drawing a straight line. In our study, we see that we have obtained a fairly strong correlation between temperature and relative humidity, with a correlation coefficient of **0.8475**, which is close to **1**. This implies that an intense temperature at the seaside will lead to vaporization which transforms into a moist cloud layer covering the ionospheric zone. It will compress the air in the studied region. So, it plays the same effect of a closed enclosure resulting in an increasing temperature. See *Figure 11*.

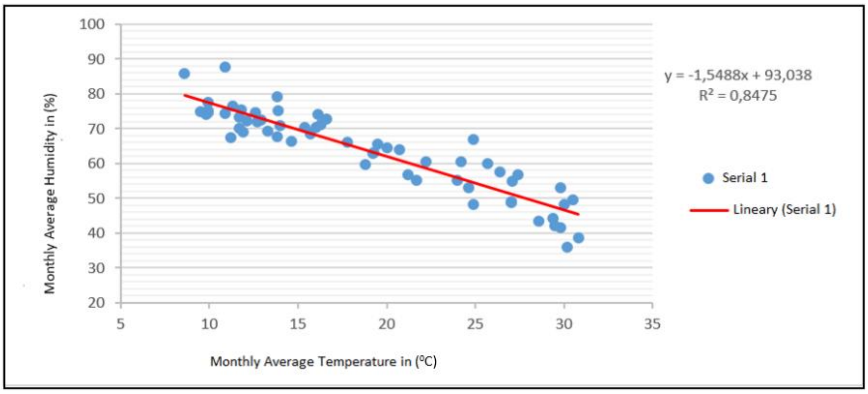

Figure 11. *Linear correlation between humidity and temperature*

The regression equation, in *Figure 11* above, explains the evolution of the monthly average temperature in (°C) according to the average monthly humidity in (%).

With a determination coefficient that is close to **1**. This result makes it possible to deduce that the temperature does not have a great influence on the humidity and that they are inversely proportional. Concerning the ratio between monthly rainfall and average humidity, it is also a weak correlation, having a coefficient of **0.3893**. The *Figure 12* below demonstrates the correlation between humidity and precipitation.

Similarly, the regression equation that explains the relationship between the evolution of monthly rainfall in mm and the monthly average humidity in (%), is presented in the figure above. With a coefficient of determination close to **0.4%**, this shows that no relationship exists between these two agents.

Because heat is an important factor in fire outbreaks, we use heat-map analysis in our research. This latter consists of a correlation matrix, which is basically a covariance matrix. It is also called an autocovariance matrix, or scatter and variance matrix. It is a

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matrix in which the i-j position defines the correlation between the i^{th} and the j^{th} parameter of the data set. See *Figure 13* below.

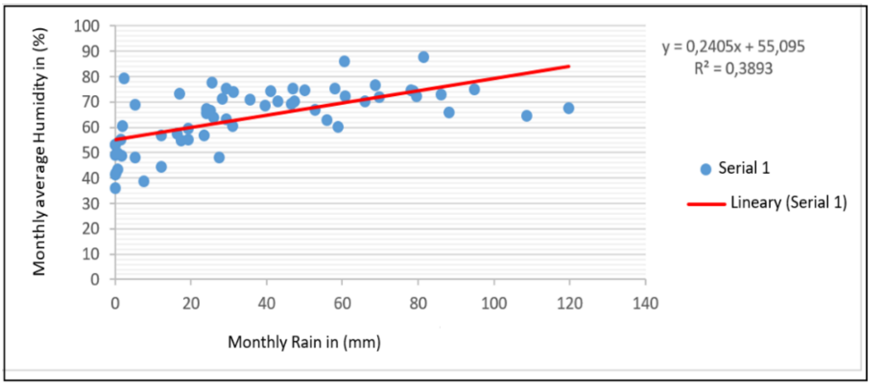

Figure 12. *Linear correlation between humidity and precipitation*

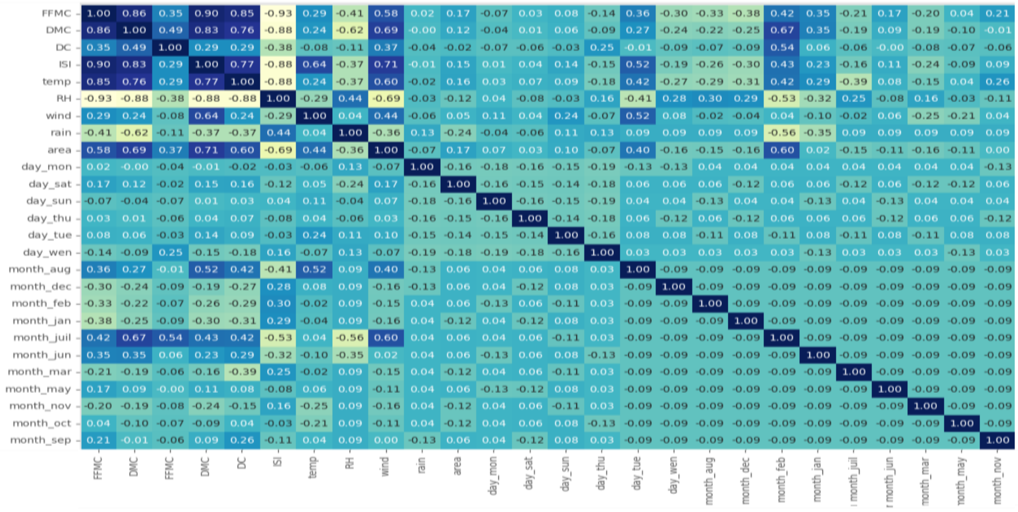

Figure 13. *Representative of Heat-map Correlation*

The heat map determines the correlation between the different climatic data of the studied region. We find that the correlation is maximum at the diagonal of the matrix.

Discussion

When the data points follow an approximately linear trend, the variables will be having an approximately linear relationship. In some cases, the data points approximate a straight line, but more often there is some variability in the points around the straight-line trend. A summary measure called correlation describes the strength of the linear association. This correlation summarizes the strength and direction of the linear (straight line) association between two quantitative variables. As denoted by (**r**), it takes values between **-1** and **+1**. A positive value for (**r**) indicates a positive association, and a negative value for (**r**) indicates a negative association.

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If (**r)** is closer to **1**, then more of the data points are closer to a straight line, and the linear association is stronger. More (**r**) is closer to **0**, the more the linear association is weakened.

In other circumstances, we can interpret that there is a strong correlation between the FFMC indices and the ISI indices, which are represented in dark blue with a correlation coefficient of **0.90**. On the other hand, there is a weak correlation between the other parameters.

The Jendouba regional analysis of the relations between the fires density, their size, the burnt surfaces, and the FWI system indices indicates a certain graphic correlation between the input variables and other cross correlations varying between **0.41** and **0.84**. However, if fire activity responds to variations in extreme weather conditions, the number and area of fires will be greatly increased in this region. These results show that climatic conditions are not totally independent. But we also observed fires due to entropic activities.

Furthermore, we present some assessment values related to the different experimentations in fire risk prediction using AI optimization techniques and meteorological signals. Comparing Different Machine Learning Models, we raised the following findings:

- Random Forest: Accuracy is **85%,** Precision is **83%**, Recall is 87%, F1-score is **85%**
- Support Vector Machines (SVM): Accuracy is **78%**, Precision is **76%**, Recall is **80%**, F1-score is **78%**
- Neural Networks: Accuracy is **81%**, Precision is **79%**, Recall is **83%**, F1-score is **81%**

The random forest model demonstrated the highest performance with the highest accuracy, precision, recall, and F1-score, indicating its effectiveness in predicting fire risk based on meteorological signals. However, this model remains complex and slower compared to neural model.

The experiment of Hyperparameter Optimization while using Bayesian Optimization gave as findings:

- Before Optimization: Accuracy is **75%**, Precision is **74%**, Recall is **76%**, F1-score is **75%**
- After Optimization: Accuracy is **82%**, Precision is **80%**, Recall is **84%**, F1-score is **82%**

The hyperparameter optimization using Bayesian optimization resulted in significant improvement in the deep learning model's performance. The optimized model achieved higher accuracy, precision, recall, and F1-score compared to the model with default hyperparameters. Therefore, the shorter the prediction period, from **20** to **30** days, the accuracy is enhanced and vice versa.

The experiment of Feature Importance Analysis offers:

- Temperature importance: **0.38** that means we have **38%**
- Wind Speed importance: **0.24**
- Relative Humidity importance: **0.19**

The feature importance analysis revealed that temperature had the highest importance value (**0.38**) in predicting fire risk, followed by wind speed (**0.24**) and relative humidity (**0.19**). These findings highlight the significant influence of these meteorological variables on fire incidents.

The experiment of Spatio-temporal Analysis allows:

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- Seasonal Variation: Peak fire activity observed during dry and hot seasons (e.g., summer) with a significant increase in fire incidents.
- Spatial Analysis: Identified high-risk areas with consistently high fire risk due to prevailing meteorological conditions such as low humidity and high wind speeds.

The spatio-temporal analysis revealed the seasonal trends and spatial patterns of fire risk based on meteorological signals. This information enables stakeholders to focus their resources and efforts on high-risk areas and during specific seasons to mitigate the risks associated with wildfires effectively.

These assessment values provide quantitative measures of model performance, feature importance, and spatial-temporal patterns, demonstrating the effectiveness and relevance of AI optimization techniques in fire risk prediction based on meteorological signals. They aid in evaluating the predictive accuracy, optimizing model configurations, and identifying critical meteorological variables and patterns that contribute to fire risk.

Compared to the different model contributions discussed above, our new applied methodology was able to guarantee much more enhanced results in terms of precision and in terms of prediction rate of fire outbreaks. It provides an accuracy, in time and space, of **90.5%** against **84.7%** established by the widely used Canadian model. Meanwhile, the prediction rate of fire outbreaks arises to **97%** against a rate of **92%** achieved by the Canadian model. This progress in the results is explained by the accuracy and diversity of our model inputs, the processing algorithm optimization, the efficiency, and reliability of the embedded nodes with wireless sensors, even under adverse environmental conditions.

Conclusions

This work deals with a precise analysis of climatic factors that can interact to cause fire risks in the Jandouba-Tunisia forests or other world’s region. This analysis is guided by application of artificial intelligence to Canadian system parameters to predict the locations and dates of risks. The results of this prediction allow us to intervene in real time by linking protection systems through the IoT.

Meteorological data covering the studied zone for the past five years has been exploited in order to predict its reciprocal for the next two years. It is to take into consideration that the meteorological forecasts can be effectively made for 20 to 30 days but the long-term prediction degrades accuracy.

The manipulation of an evolutionary deep learning neural system around the FWI Canadian system parameters allowed us to establish correlation and variance matrices, helping in the decision-making of the accurate prediction and the instantaneous intervention.

Creating a clean environment and accurately predicting fire risks are intertwined objectives critical to the well-being of both ecosystems and human populations. By adopting an integrated approach that combines proactive environmental management practices with advanced technologies and data-driven models, we can make significant strides towards preventing wildfires and safeguarding our planet.

Data availability statements. The data used to support the findings of this research are available from the corresponding author upon request.

Conflicts of interests. The authors declare no conflicts of interests in relation to this article.

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