School of Civil & Mechanical Engineering

MXEN4000 - Mechatronic Engineering Research Project 1

Progress Report

AI-Driven Wildfire Risk Identification and Hazard Prediction

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Haloluwe Gedara Oneli Kithara Haloluwa
20937298

Supervisor: Dr. Hansani Weeratunge

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Abstract

This report outlines the initial progress report of the research focused on developing Machine Learning based models to predict the occurrence and severity of wildfires. The project focuses Montesinho Natural Park region located in Portugal due to the severe damaged caused by wildfires from 2000 to 2003 in Portugal specifically affecting this location. Therefore, historical record of prior wildfire instances from 2000 to 2003 of Montesinho Natural Park was utilised to train and develop the machine learning based model. The model is constructed by using the Canadian Fire Weather Index (FWI) system which consists of 6 core indices FFMC, DMC, DC, ISI, BUI and FWI to compute the wildfire prediction. Several non-linear ML algorithms including XGBoost regression and Mulit-Linear Perception was utilised to test and validate the accuracy and obtain the most suitable model. Additionally, the research focused on a background study of the reasons of wildfire occurrence, the development and the indices present in the Canadian Fire Weather Index (FWI) system and previously conducted research on wildfire prediction algorithms.

Introduction

Background

Wildfire also known as wildland fire or forest fire is an uncontrolled natural disaster which primarily occurs in dry grassland areas. These fires are considered destructive and dangerous, posing significant threat to inhabitants living in and around the forests and ecological systems including animal habitats, flora, and fauna[1]. Research has shown that widespread wildfires destroy hectares of terrestrial ecosystems annually which has led to extensive increase in ecological and economic costs. Beyond the immediate destruction, wildfires can damage the forest structure, soil fertility, and alter water cycles which significantly impact aquatic species and the overall health of the ecosystem[2].

Wildfires are induced by both natural causes, such as, lightning, extreme heat and drought which result in dry vegetation or fuel, and human activities, such as land mismanagement, unattended campfires, and negligence of the environment[1]. Wildfires are most common in United States, Canada, Russia, China, Australia, and the Mediterranean rim countries especially during summer[3].

Portugal has been the European country, which is most affected by wildfires, where an average of 93,731 hectares of land are burnt every year[4]. Research has been conducted on the percentage of the total burnt area due to wildfires between 1980 to 2003 and found that the total burnt areas in Portugal is 58% followed by 10% in France, 20% in Italy and 0% in Greece, which leaves Portugal at a high risk of wildfires[5].

This is due to Portugal's unique geography, since the country has a long coastline with rugged terrain and large forest areas, it is more prone to ignition and spread of wildfires. Additionally, Portugal experiences hot summers with little to no rain, resulting in dry vegetation which easily ignites[6]. According to the Forensic analysis the most affected regions are inlands in the North-eastern and Central Portugal[7]. In 2003, Portugal faced 4645 large spread wildfires and 16219 small fires, burning a total of 421,835 hectares of forest land and 44,876 agriculture areas. Montesinho, a Natural Park located in the municipalities of Vinhais and Bragança, North-eastern Portugal was also affected by the Wildfires during this period [5].

Montesinho Natural Park spans to approximately 75,000 hectares with of population of 9000 inhabitants and 92 villages. Its altitude varies between 1486m and 438m in the mountain range and the bed of the river respectively. Since it is situated in Terra Fria Transmontana climatic zone, the region experiences significant temperature fluctuations with the extreme temperatures recorded as -12° C in winter to 40° C in summer. The park is a habitat for diverse ecosystems and the vegetation in this region includes oak, chestnut, shrublands and alpine meadows. During the season of summer, the combination of high temperature and low humidity increases the flammability of vegetation. In particular, dry twigs from oak and chestnut vegetation act as fuel sources which ignite readily resulting in a wildfire[8][9].

Given the vulnerability of this region to wildfires, the ability to model and predict the likelihood and severity of the wildfire is necessary to aid in mitigating massive disruption of landscapes. Conversely, these models consist of several limitations specially in monitoring real-time wildfire behaviours due to the complexity of wildfire dynamics[10].

Literature Review

To address the increasing threat and environmental damage caused by wildfires across the world, researchers have explored diverse methodologies and artificial intelligence models in the recent years to predict the occurrence of wildfire by learning the complex relationships between climatic indexes, topographical and anthropogenic variables.

One approach focused on the spatial prediction of wildfire probabilities by utilising spatial data from the Hyrcanian ecoregion located. In this research four hybrid artificial intelligence models combining an adaptive neuro-fuzzy interference system (ANFIS) with metaheuristic optimisation algorithms including GA, PSO, SLA, and ICA were implemented by following the Step wise Weight Assessment (SWARA) methodology. It involved assignment of weights between variable classes and the fire occurrence to indicate the strength of the spatial relationship. The results showed that the hybrid models performed well in both training and validation while the single ANFIS model overfitted. The ANFIS-ICA hybrid model was able to achieve improved outcomes by 18% in comparison to traditional single models. Furthermore, the study highlighted several significant limitations in classical regression and bivariate models due to the model's assumption of linearity which results in low accuracy of the predicted outcomes. These findings emphasized that the incorporation of hybrid models enhances the accuracy of the final outcomes[2].

Similar to this research approach, another study was conducted by using hybrid models with Random forest for feature analysis and Gated Recurrent Units (GRUs) for temporal fire predictions. This study aimed to develop a sustainable AI-driven system named WiSEFire (Wildfire Surveillance and Estimation) which was utilised for real-time wildfire detection as well as prediction. The results showed that this system outperformed traditional ML algorithms showing reliable prediction even up to 30 hours[11].

Another study researched on the spatiotemporal heterogeneity in wildfire modelling of Montesinho Natural park located in Portugal. This research focused on classification algorithms including XGBoost, Random Forest, Support Vector Machine and Decision Tree by utilising the same dataset mentioned in this progress report. The methodology aimed to utilise the provided fire weather indices such as FFMC, DMC DC and ISI to explore the influence of spatiotemporal heterogeneity on fire occurrence. Among these models, the machine learning (ML) algorithms XGBoost classification has shown precise results with an accuracy of 0.8132. In addition, another approach utilised cognitive ai along with satellite imaging to achieve the accuracy of fire prediction in comparison to traditional methods[12].

The above sources focused on various aspects and more complex variables to predict wildfire occurrence. However, a similar approach and results can be obtained by focusing on the aspects of wildland fire risk assessment and prediction, based on the Canadian Forest Fire weather Index (FWI) system[13]. The Canadian Forest fire Weather Index (FWI) system is widely used for assessing fire risks. One study focused critically examining fire conditions during active fire spread areas in Canada. This research used statistical methods to compare fire weather data on spread vs non-spread days and correlation tests were performed between mean FWI systems indices and environmental variables[14].

Dimitrakopoulos et al. 2011 evaluated the Canadian FWI system in a dry Mediterranean environment (Crete, Greece). FWI values were calculated and used to analyse the correlations between FWI components and the fire activity. It was found that the existing FWI danger classes were inappropriate for the Mediterranean climate hence new danger classes were defined 0–38 Low, 39–48 Moderate, 49–59 High, >60 Extreme[15].

Ntinopoulos et al. 2022 found out that higher FWI values and a greater number of days exceeding high fire danger thresholds are in the drier and hotter regions. Furthermore, it was also found that FWI values were significantly impacted by precipitation[16].

Canadian Forest Fire Weather Index (FWI) system

The Canadian Forest Fire Weather Index (FWI) system is one of the most widely used approach to assess wildfire danger, likelihood, and severity. This system was developed by Natural Resources Canada and it estimates how meteorological variables such as weather conditions, affect the behaviour of wildfires or forest fires. The system composes of six core indices which provide numeric ratings of potential wildland fires.

Each component's numeric rating is vastly related to the daily observations of temperature, relative humidity, wind speed and 24-hour precipitation. The figure below illustrates the structure of the FWI system.

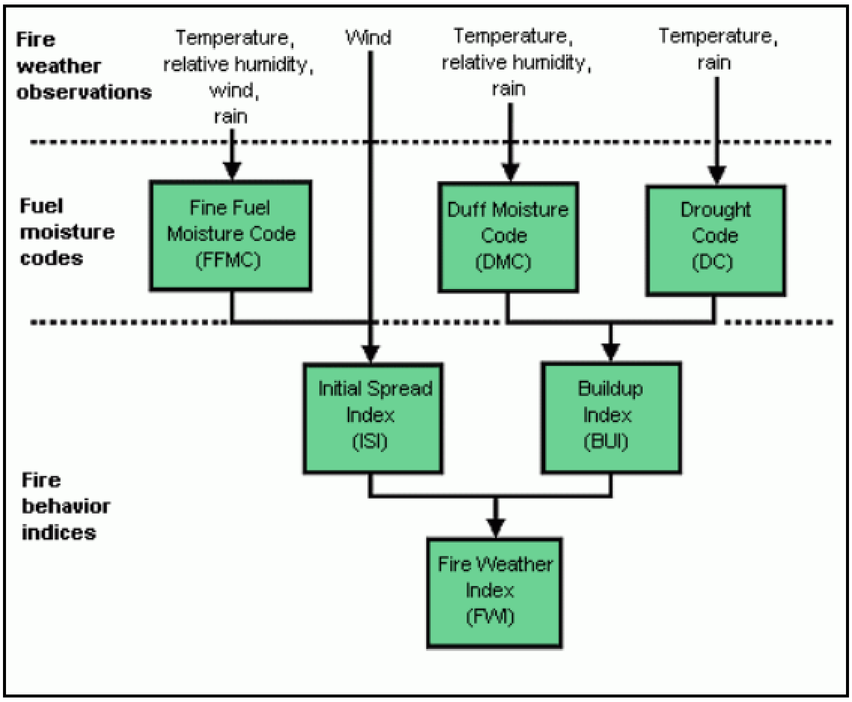

Figure 1-Canadian Fire Weather Index system (FWI)[17]

As illustrated in the above structure, three of indices, the Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC), Drought Code (DC), calculate the dryness of different forest layers such as the surface litter layers, intermediate organic layers and deeper compact organic layers while the rest of the indices, initial Spread Index (ISI), Build-up Index (BUI) and Fire Weather Index (FWI) estimate the rate of spread of the wildfire, the quantity of available fuel for combustion and the intensity of the wildfire. An additional component, the Daily Severity Rating (DSR) which is derived from FWI is utilised to provide the severity of the wildfire and the difficulty of suppression.

A further detailed explanation of the 6 core components are provided below.

1. Fine Fuel Moisture Code (FFMC)
    - The FFMC index represents the moisture content of litter and cured fuels such as leaves, twigs et cetera. It simply describes the flammability of the fine fuel.

2. Duff Moisture Code (DMC)
    - DMC index provides a numeric rating on the average moisture content of the loosely compact organic layers of intermediate depth. This component provides an indication of fuel consumption in moderate depth layers and average sized woody fuel material.

3. Drought Code (DC)
    - This component provides the average moisture content of deep compact organic layers and this index indicates the seasonal drought effects on forest fuels.

4. Initial Spread Index (ISI)
    - Initial Spread Index (ISI) measures the expected rate of wildfire spread. It is based on FFMC and the windspeed. Furthermore, it does not take the type of vegetation into account hence for the same ISI the rate at which the wildfire spread varies with the type of vegetation.

5. Build-up Index (BUI)
    - The Buildup Index (BUI) measure the total amount of fuel available for combustion. It is interrelated to DMC and DC.

6. Fire Weather Index (FWI)
    - The Fire Weather Index (FWI) is the numeric rating of the intensity of the wildfire. It is based on ISI and BUI and is widely used as the general index of fire danger.

The Fire Weather Index system provides a practical and informative approach by utilising simple weather data to determine wildfire behaviour. This methodology is applied beyond Canada, including the European countries such as Portugal. Hence, there is an increasing interest to improve this approach by combining new technologies such as machine learning models to accurately predict the potential occurrence, intensity and difficulty of suppression of the wildfire by considering its multifaceted nature using this simple yet effective approach[17].

Problem statement

As wildfire is a growing challenge as mentioned above, accurately predicting its occurrence and severity aids in minimizing environmental damage and harm to inhabitants in such regions. Wildfires are mainly known to occur in diverse landscapes such as Montesinho Natural Park in Portugal. Since it is a habitat for protected species the development of an accurate ML model has been considered crucial. Hence this study investigates ML algorithms in predicting the percentage likelihood of wildfire occurrence based on meteorological variables and the Canadian Forest Fire Weather Index (FWI) system, which is widely followed in Portugal. It focuses on the Montesinho Natural Park region and utilises historical records of wildfires during 2000 to 2003 provided by P. Cortez, Aníbal de Jesus Raimundo Morais[18].

Conversely, limited research had been conducted to systematically address how each of the fire weather indices predict wildfire occurrence and their importance. In addition to the above-mentioned statement, research on how to predict wildfire occurrence from only meteorological and topological data is also relatively limited. Therefore, this research objects to address this gap, by analysing and validating the fire weather indices.

Aims

The primary aim of this project was to develop a machine-learning based algorithm to estimate the likelihood and severity of wildfires within the Montesinho Natural Park region in Portugal. The project utilised a historical dataset of past wildfire records from 2000 to 2003 and the dataset consisted of tabular data including weather, climate, area affected and fire indices. Hence the project focused on calculating and analysing fire weather indices derived from the Canadian Fire Weather Index (FWI) system.

The plan of the project was structured into four sequential phases as outlined in the gantt chart provided below. Dark blue boxes indicate the planned path whereas light blue indicates the actual timeline.

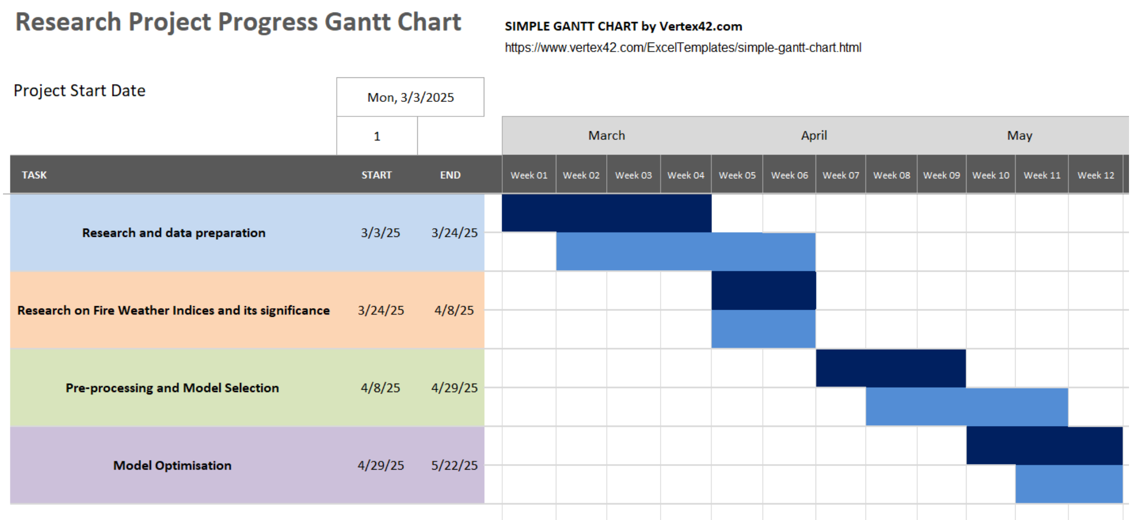

Figure 2 - Gantt chart

The above aims were mapped out across the semester in a way which balanced out the background and contextual research with the implementation and development of the final practical models. The key objectives of this semester are listed as follows:

1. Research and data preparation

    - The initial phase focused on finding datasets consisting of historical wildfire records followed by researching and gaining further knowledge on the most reliable dataset available. This included familiarising with the structure, features and parameters of the chosen dataset. In addition, research and analysis of prior work and literature relevant to wildfire prediction methods, occurrence of wildfire, particularly in the Mediterranean rim countries were conducted.

2. Research on Fire Weather Indices and its affect

    - This time period was dedicated to research and review the Fire Weather Index system followed in Portugal. Since Portugal followed the Canadian Forest Fire Weather Index (FWI) system research on each of the six core indices including FFMC, DMC, DC, ISI, BUI, and FWI and their connection to raw weather data was conducted.

3. Pre-processing and Model Selection

    - During this time period of the semester, the focus was on identifying and determining the most appropriate and accurate types of machine learning algorithms for this project. Hence linear algorithms were not taken into consideration since the relationship between weather data, indices and likelihood of wildfire is a nonlinear relationship. Thereby model such as XGBoost regression, Multi-linear perception and Neural Networks were implemented.

4. Model Optimisation

    - The final phase consisted on identifying the most accurate and reliable model out of the implemented models to perform further hyperparameter fine-tuning to optimise the accuracy of the model. Furthermore, feature importance analysis was conducted to determine which fire weather index and weather data significantly influence the likelihood and severity of wildfire.

Results and Discussion

This section of the progress report outlines the results and detailed explanation of the development of the ML models. The aim of the section is to present the best performing model to further fine tune and improve to support international datasets in the next semester. The experimental analysis was conducted using Python on Jupyter Notebook environment. The variables in the wildfire dataset is described as follows:

Table 1- Variables in the wildfire dataset[3]

	Abbreviation	Variables	Explanations
Location		X Y	X-axis spatial coordinates ($1 \le X \le 9$) Y-axis spatial coordinates ($1 \le Y \le 9$)
Time series		Month Day	Months of the year (from January to December) Days of the week (from Monday to Sunday)
FWI	FFMC	fine fuel moisture code	Water content of cured fine fuels (from 18.7 to 96.20), with a time period of 16 h
	DMC	duff moisture code	Water content of surface combustible material (from 1.1 to 291.3) in the upper layer of forest humus, with a time period of 12 days
	DC	drought code	Index of the effect of prolonged drought on forest combustibles (7.9–860.6), with a time period of 52 days
	ISI	initial spread index	The initial rate of fire spread (from 0 to 56.10)
Climatic conditions	temp RH	temperature relative humidity Wind Rain	Temperature (Celsius) (from 2.2 to 33.30) Relative humidity (%) (from 15.0 to 100) Wind speed (km/h) (from 0.40 to 9.40) Outdoor rainfall (mm/m^2) (from 0.0 to 6.40)
Burned area		Area	Total forest burned area (ha) (0.00~1090.84)

Data pre-processing and feature selection

Initially, the dataset underwent data pre-processing, in which missing values and duplicated rows were eliminated. Following that, data visualisation analysis was performed to gain insights into the distribution of wildfires monthly as well as across the 4 seasons. Thereby, to analyse the seasonal pattern, the monthly data were categorised into the 4-season based on the climatic characteristics of Portugal. The following figures depict the wildfire occurrences throughout the seasons and year.

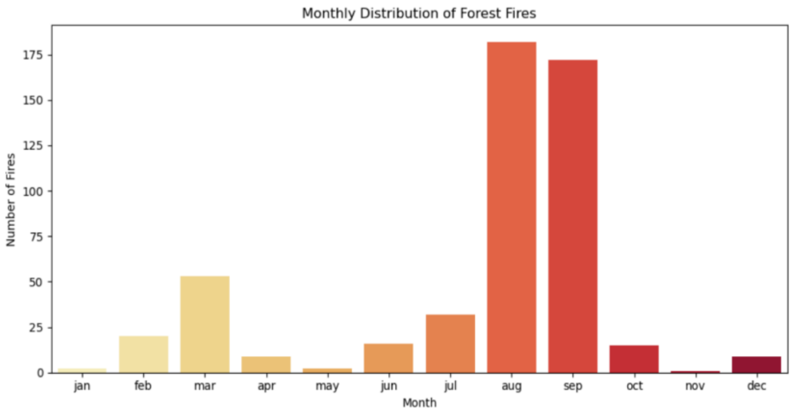

Figure 3- Monthly distribution of forest fires

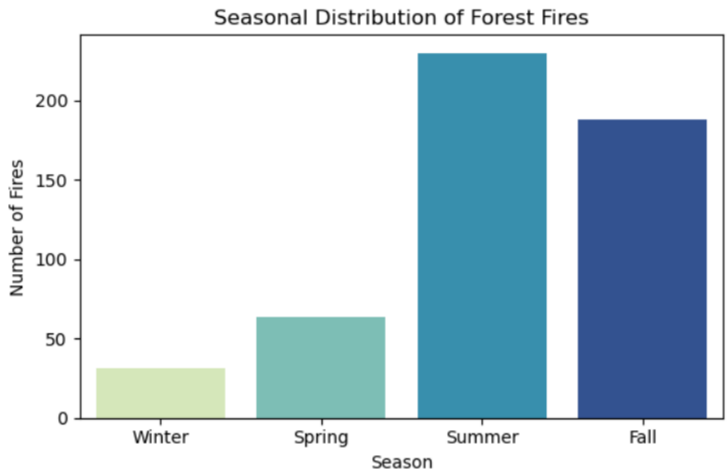

Figure 4 - Seasonal distribution of forest fires

To gain deeper understanding on the relationship between the features in the dataset the following correlation map was plotted. This visualisation aids in providing a clear overview of the correlations among the variables in temperature, relative humidity, wind speed, rainfall and the area burnt.

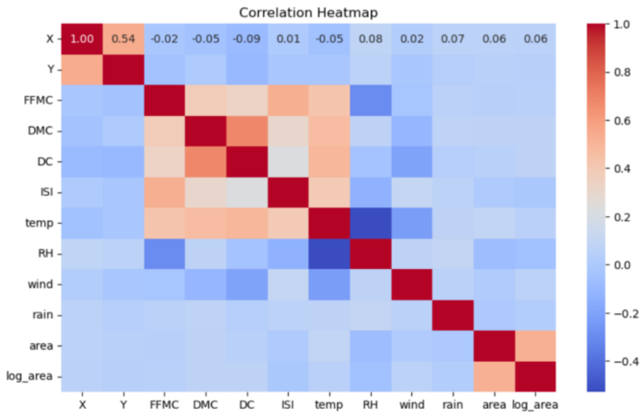

Figure 5- correlation HeatMap

As presented in table 1, the original dataset consists of 13 features, including spatial X, Y, temporal month, and meteorological temperature, relative humidity as well as fire indices, FFMC, DMC, DC and ISI. However, feature normalisation was performed to all attributes except for the categorical temporal and spatial data[3].

Z-score normalisation was performed via the StandardScaler() function from scikit-learn to ensure all features contribute equally to the training process. This approach transforms the mean and standard deviation of each feature to 0 and 1, respectively. The transformation is defined via the following formula:

$$Z = \frac{x - \mu}{\sigma} \tag{1}$$

Where,

- x – the original feature
- μ – mean of the feature

- σ – the standard deviation

The normalisation was implemented using a columnTransformer() which handles both numerical and categorical data simultaneously. Thereby, the numerical features were standardised, the categorical features were transformed via one-hot encoding. One-hot encoding instead of label encoding was used, even though the features were ordinal, because their numeric values 1,2,3 and 4 overlap across the categories and could be misinterpreted by the model. Therefore, Monday of January could be encoded as 1 thus causing confusion. This issue can be avoided by utilising one-hot encoding as this approach creates separate binary variables for each category thereby preventing the model from making incorrect assumptions.

Model development and training

The two models XGBRegressor and Multi-linear perception (MLP) were trained to determine the likelihood of fire occurrence and the severity of the fire. In order to achieve this, the FWI index and BUI index were calculated as follows

BUI index calculation:

For $DMC \leq 0.4 \times DC$:

$$BUI = 0.8 \times \frac{DMC \times DC}{DMC + 0.4 \cdot DC} \tag{2}$$

For $DMC > 0.4 \times DC$:

$$BUI = DMC - (1 - \frac{0.8 \times DC}{DMC + 0.4 \times DC}) \times (0.92 + (0.0114 \times DMC)^{1.7}) \text{ [19]} \tag{3}$$

The FWI index is derived by combining ISI and the BUI index, since ISI index is already available in the dataset, using the above calculation the BUI index was evaluated.

FWI, was initially expressed in D-scale ($f(D)$), which ranged from 0 to 16. This scale was then replaced to I-scale (Intensity scale)which was then improved by simplifying into B-scale (basic scale)by taking the square root which then leads to the final scale in use to date, S-scale (standard scale).

The calculation of the FWI index is as follows:

For $BUI \leq 80$

$$f(D) = 0.626 \times BUI^{0.809} + 2 \tag{4}$$

And for $BUI > 80$

FWI in Basic Scale is as follows:

$$B = 0.1 \times ISI \times f(D) \tag{5}$$

And FWI in Standard Scale – S-scale is as follows:

For $B > 1$

$$S = e^{2.72} \times (0.434 \times lnB)^{0.647} \quad (6)$$

For $B \leq 1$

$$S = B[19] \quad (7)$$

The calculated FWI was then added to the original dataset. Following that the model was then trained via a supervised learning approach. Subsequently, the FWI was then recalculated within the model and was validated via the test dataset to confirm the accuracy of the model.

The same procedure was followed to present the severity of the fire. This was obtained by calculating the DSR index as shown below

$$DSR = 0.0272\ (FWI)^{1.77} \quad [20]. \quad (8)$$

Model performance evaluation

Each of the models were assessed on the following evaluation metrics:

1. RMSE (Root Mean Squared Error)
2. R^2 Score
3. Mean Absolute Error (MAE)

The results for each model is as follows:

```
MLP RMSE: 5.16%
XGBoost RMSE: 0.00%
MLP R²: 0.923
XGBoost R²: 1.000
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Figure 6 - evaluation metric results

In accordance to this model it is visible that XGBoost has undergone overfitting and this is clearly visible in the following scatter plot diagrams of the actual vs prediction likelihood of wildfire.

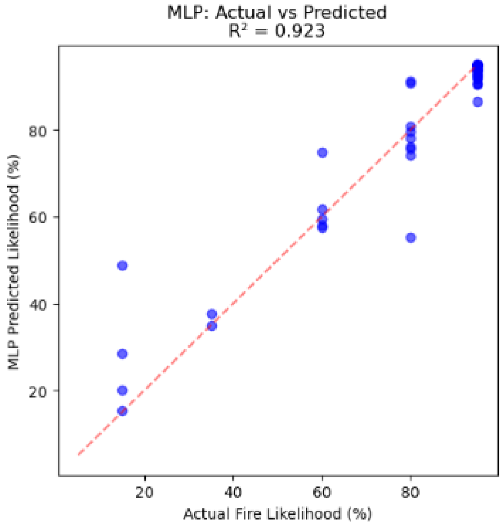

Figure 7 - MLP Actual Vs Predicted

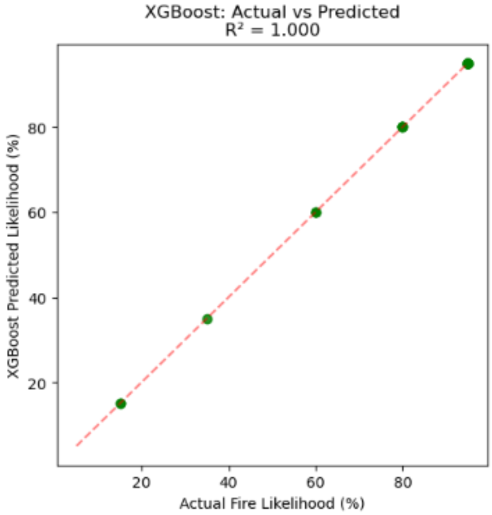

Figure 8- XGBoost Actual Vs Predicted

The XGBoost model showed high accuracy on the training data but performed much poorly on the testing data indicating overfitting. In contrast, the MLP model had a relatively low training accuracy during training but performed much better during testing. Therefore, the chosen model out of the two would be MLP.

Challenges faced and the corresponding mitigation strategies

Throughout the semester the following main challenges were encountered.

1. Limited availability of high quality and similar wildfire data

    - Reliable data for wildfire prediction for both tabular and image data was limited.

    - Therefore, to overcome this challenge, the publicly available data as used in the report was utilised to work on the preliminary model which would then be expanded in the next semester.

2. Modelling overfitting

    - The XGBoost model, which performed accurately in research journals showed signs of overfitting when implemented. Manual hyperparameter tuning and grid search was utilised to enhance the accuracy of the model and present overfitting, yet the model performed 100% accurate on training data with a RMSE of 0% but accuracy of only 57.6%.

    - To mitigate this problem, during the next semester cross validation strategies are planned to be implemented.

3. Computational complexity due to complex wildfire behaviour

    - Due to the complexity of the behaviour of wildfire, and consideration of several variables and fire weather indices, the overall model requires significant time due to the large number of resources.

    - Therefore, hyperparameter optimisation is considered to be difficult. However, this challenge can be mitigated by utilising proper feature engineering, feature importance and data pre-processing methods and strategies.

Future Work

During the time period of this semester, substantial progress was made in understanding wildfire, its causes and behavioural patterns with the focus of developing an accurate data-driven prediction model. An extensive research on prior work, research journals, articles and books related to this subject matter were reviewed and analysed. This foundation guided the selection of the most suitable and reliable machine learning based model as well as the parameters which significantly influence the likelihood of wildfires.

Since a wildfire prediction model is multidisciplinary, several factors, including spatial, climatic and environmental parameters affect its production and severity, therefore the model was decided to be evaluated via fire weather indices to simplify its complexity. Research was then conducted to identify the Fire Weather Index system followed by Portugal, and it was found to be the Canadian Forest Fire Weather Index (FWI) system founded by the National Resources Canada.

The dataset consisting of historical wildfire records of Montesinho Natural Park was thoroughly pre-processed and the key patterns of wildfire distributions monthly and seasonally were plotted to be assessed. During this stage, the preliminary training of the chosen model, XGBoost Regressor and Multi-layer perception (MLP) regressor, were conducted to predict the likelihood and severity of wildfire using FWI and DSR indices.

The next phase of the project will focus on refining the data-drvien algorithm's accuracy along with extending its reference to a global context by building on the foundation of this semester. The primary aim is to deepen the understanding of the correlation between the occurrence of wildfire and each of the six core fire weather indices. Therefore, a more statistical and detailed evaluation approach would be conducted focusing on designing, testing and developing an algorithm which adapts the Canadian Fire weather system to international datasets.

Since the fire indices rely on weather data, day length factor and type of vegetation, to enhance the accuracy of the system further, hybrid models for each of the above parameter would be implemented to obtain more precise wildfire prediction values and severity ratings.

However, one of the anticipated challenges would include the limited availability of historical records on wildfire similar to the current dataset. In addition, day length factors and vegetation classification may introduce complexity as it significantly varies from globally. Therefore, several assumptions and approximations would be necessary to be taken into account which could result in inconsistencies. Conversely, by fine-tuning the model appropriately minor inconsistencies could be eliminated and the aim of evolving the regional model to a globally adaptable and accurate wildfire system could be achieved.

References

[1] A. Malik *et al.*, ‘Data-driven wildfire risk prediction in northern california’, *Atmosphere (Basel)*, vol. 12, no. 1, pp. 1–2, Jan. 2021, doi: 10.3390/ATMOS12010109.

[2] A. Jaafari, E. K. Zenner, M. Panahi, and H. Shahabi, ‘Hybrid artificial intelligence models based on a neuro-fuzzy system and metaheuristic optimization algorithms for spatial prediction of wildfire probability’, *Agric For Meteorol*, vol. 266–267, pp. 198–207, Mar. 2019, doi: 10.1016/j.agrformet.2018.12.015.

[3] H. Dong, H. Wu, P. Sun, and Y. Ding, ‘Wildfire Prediction Model Based on Spatial and Temporal Characteristics: A Case Study of a Wildfire in Portugal’s Montesinho Natural Park’, *Sustainability (Switzerland)*, vol. 14, no. 16, Aug. 2022, doi: 10.3390/su141610107.

[4] ‘Area burned by wildfires in Portugal from 2009 to 2024’, Land burned by forest fires in Portugal 2009-2024.

[5] P. B. A. C. A. C. J. K. G. L. Jesús San-Miguel-Ayanz, ‘Forest Fires in Europe ’, Italy, 2004.

[6] Staff Writer, ‘Navigating the Danger Zones: A Detailed Map of Fire-Prone Areas in Portugal’.

[7] ‘Portugal heatwave, 2022 - Forensic analysis’, United Nations Office for Disaster Risk Reduction (UNDRR).

[8] ‘Montesinho Natural Park’.

[9] H. Dong, H. Wu, P. Sun, and Y. Ding, ‘Wildfire Prediction Model Based on Spatial and Temporal Characteristics: A Case Study of a Wildfire in Portugal’s Montesinho Natural Park’, *Sustainability (Switzerland)*, vol. 14, no. 16, Aug. 2022, doi: 10.3390/su141610107.

[10] Y. O. Sayad, H. Mousannif, and H. Al Moatassime, ‘Predictive modeling of wildfires: A new dataset and machine learning approach’, *Fire Saf J*, vol. 104, pp. 130–146, Feb. 2019, doi: 10.1016/j.firesaf.2019.01.006.

[11] T. S. R. Raj, J. R. F. Raj, R. S. Krishnan, G. Balamuralikrishnan, D. Vikkiramapandian, and J. N. Jothi, ‘Sustainable AI Systems for Monitoring and Predicting Wildfires in Vulnerable Forest Regions’, in *Proceedings of the International Conference on Multi-Agent Systems for Collaborative Intelligence, ICMSCI 2025*, Institute of Electrical and Electronics Engineers Inc., 2025, pp. 1129–1136. doi: 10.1109/ICMSCI62561.2025.10894262.

[12] M. Amir Hossain, T. Y. Rahman, M. A. Hossain, T. Yaseer, and R. " Cognitive, ‘Cognitive AI for Wildfire Management in Southern California: Challenges and Potentials’, *Journal of Science and Technology*, vol. 10, pp. 51–65, 2025, doi: 10.46243/jst.2025.v10.i02.pp51-65.

[13] A. Shmuel and E. Heifetz, ‘Developing novel machine-learning-based fire weather indices’, *Mach Learn Sci Technol*, vol. 4, no. 1, Mar. 2023, doi: 10.1088/2632-2153/acc008.

[14] X. Wang, J. Oliver, T. Swystun, C. C. Hanes, S. Erni, and M. D. Flannigan, ‘Critical fire weather conditions during active fire spread days in Canada’, *Science of the Total Environment*, vol. 869, Apr. 2023, doi: 10.1016/j.scitotenv.2023.161831.

[15] A. P. Dimitrakopoulos, A. M. Bemmerzouk, and I. D. Mitsopoulos, ‘Evaluation of the Canadian fire weather index system in an eastern Mediterranean environment’, *Meteorological Applications*, vol. 18, no. 1, pp. 83–93, 2011, doi: 10.1002/met.214.

[16] N. Ntinopoulos, M. Spiliotopoulos, L. Vasiliades, and N. Mylopoulos, 'Contribution to the Study of Forest Fires in Semi-Arid Regions with the Use of Canadian Fire Weather Index Application in Greece', *Climate*, vol. 10, no. 10, Oct. 2022, doi: 10.3390/cli10100143.

[17] Natural Resources Canada, 'Canadian Forest Fire Weather Index (FWI) System'. Accessed: May 05, 2025. [Online]. Available: Canadian Forest Fire Weather Index (FWI) System

[18] P. Cortez and A. Morais, 'A Data Mining Approach to Predict Forest Fires using Meteorological Data', 2007, [Online]. Available: http://www.dsi.uminho.pt/˜pcortez

[19] Van Wagner, 'Development and structure of the canadian forest fire weather index system', 1987.

[20] R. M. Durão, A. Soares, J. M. C. Pereira, J. A. Corte-Real, and M. F. E. S. Coelho, 'Bayesian Classification of a Meteorological Risk Index for Forest Fires: DSR', in *geoENV VI – Geostatistics for Environmental Applications*, Springer Netherlands, 2008, pp. 283–294. doi: 10.1007/978-1-4020-6448-7_24.