Automated Wildfire Prediction

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Abstract — While Hong Kong has experienced its fair share of natural disasters, wildfires are mainly overlooked. With its increasing temperature, Hong Kong’s tropical climate makes it more prone to wildfires. Between 2001 and 2021, Hong Kong lost 97 hectares of tree coverage due to fires. In 2018 alone, 47 hectares of tree coverage were lost to fires, making up 30% of all losses for this year [1]. This project aims to provide an efficient solution regarding the dangers of wildfires in Hong Kong. This project consists of a neural network to predict the percentage of wildfires happening and a user-friendly graphical user interface to allow easy access to preventative measures against wildfires. Hong Kong Observatory Open Data API [2] is used to collect real-time data and to provide an accurate percentage prediction for our users. This project offers a new option for overcoming wildfires and can be implemented to check the possibility of a wildfire. With this solution, organizations that utilize manual power to eradicate existing fires can provide immediate help and resources to areas with high percentages and prevent wildfires from taking place.

1. Introduction

Wildfires are a growing concern in Hong Kong, with increasing temperatures and changing climate conditions making the region more susceptible to these disastrous events. Using data to predict the probability of a wildfire, it aims to provide a new tool for addressing this critical environmental hazard in Hong Kong. Automated Wildfire Prediction leverages the power of artificial intelligence to predict and prevent wildfires. This software is built using Python and TensorFlow and utilizes data from the Hong Kong Observatory Open Data API [2] to gather information on temperature, relative humidity, wind speed, and rain. By analysing this and historical wildfire data, the neural network can identify patterns and trends that can help forecast the likelihood of future fires in each area. This project aims to provide a user-friendly solution that can be easily accessed by people on the ground, allowing them to take proactive measures to prevent fires from spreading and better allocate resources in the event of a fire.

1. Methodology

To predict the percentage chance of a wildfire occurring in Hong Kong, a supervised learning neural network is utilized. The Hong Kong Observatory Open Data API collects atmospheric data for a specific date and area, which is used as input for the model. The model is integrated into a graphical user interface to facilitate user interaction.

The model was trained and tested using a dataset provided by the UCI Machine Learning Repository [3], which contains multiple possible variables that affect the probability of a wildfire, including temperature, wind speed, rain, and relative humidity. This dataset was split into training and testing arrays, with the training set containing 75% of the data and the testing set comprising 25% of the data. The classes column of the dataset was then transformed into a binary array, with one representing the presence of a fire and zero representing the absence of a fire.

The model consists of five layers: an input layer, a dense layer, a dropout layer, another dense layer, and an output layer. The input layer defines the shape of the input data. The first dense layer uses 32 units, also known as the fully connected layer, has 32 units, and the rectifier activation function, with L1 kernel regularization to prevent overfitting is also utilized. The second dense layer has 16 units, representing the output vector's dimensionality, defining the output's size. The dropout layer randomly drops 20% of neurons during training to reduce overfitting. The output layer has one unit and uses the sigmoid activation function to produce a probability value between 0 and 1 for binary classification. In addition, the Adam optimizer is utilized with a learning rate of 0.001, where β1 and β2 are set to 0.9 and 0.999, and epsilon is set to 1e-07. The early stopping criteria is also then defined to monitor the validation loss and stop the training process after several epochs without improvement.

The GUI provides three options for data prediction:

* Manual input – The user is given the ability to manually input the weather conditions instead of relying on the Hong Kong Observatory Open Data API [2].
* Present data prediction – Present weather data for specific regions is accessed using the Hong Kong Observatory Open Data API [2].
* Future data prediction – Future weather data for the next 1-9 days is accessed using the Hong Kong Observatory Open Data API [2].

The user inputs are processed by the saved and loaded neural network, and the GUI outputs the resulting prediction percentage.

1. Data

The data for this project was obtained from the UCI Machine Learning Repository database [3] and encompasses four crucial variables that are used to predict the likelihood of wildfire ignition. The variables deemed crucial are the maximum temperature (in Celsius), relative humidity (in %), wind speed (in km/h), and rainfall size (in mm). The temperature data ranges from 22-42 degrees Celsius, while the relative humidity data ranges from 21-90%. The wind speed data ranges from 6-29 km/h, and the rainfall size data ranges from 0-16.8 mm.

IV.DISCUSSION

The current approach to address the threat of wildfires involves manual guards in high-risk areas, deployment of cameras with image recognition, and manual analysis of climate data to issue warnings [8] However, these solutions have limitations and only respond after the fires have already started affecting the environment and nearby communities. In comparison, the AWP offers a preventative approach by providing an early warning of the likelihood of a fire outbreak. The implementation of AWP has the potential to significantly improve the current methodologies in addressing the threat of wildfires.

While AWP has demonstrated promising results, it is still possible to enhance its performance. Integrating diverse data sources, such as satellite imagery and remote sensing data, into the system could provide a more comprehensive understanding of the conditions in each area and thus further improve the model's performance. To achieve this, ongoing training and testing using real-world wildfire data are essential to refine the model and enhance its accuracy and reliability.

The Hong Kong government has implemented measures to address the issue of wildfires, including establishing the yellow and red fire warning system based on data analysis conducted by the Hong Kong Observatory [2]. However, these measures are reactive and only provide warnings once a fire has started. To enhance the approach to predicting and preventing wildfires in the region, the government could integrate our AWP into these existing initiatives. AWP offers a promising solution for reducing the threat of wildfires in Hong Kong. By providing an early warning of the likelihood of a fire, it has the potential to be a valuable tool for both government agencies and the public.

1. Data Analysis

A combination of natural and artificial factors can influence the likelihood of a wildfire igniting. Artificial causes of wildfires include the careless disposal of cigarettes, gas leaks, and unattended campfires, which are difficult to predict. Considering this uncertainty, this study focuses on natural factors, including wind speed, temperature, relative humidity, and rainfall, as predictors of wildfire occurrence. These meteorological variables play a crucial role in determining the fire risk and, thus, provide a reliable basis for wildfire predictions. The way these factors affect the likelihood of a wildfire igniting is further discussed in this section.

* 1. *The effects of wind speed against the likelihood of wildfires.*

Under the right circumstances, a spontaneous ignition can result in the rapid spread of high-intensity wildfires. Wind speed significantly impacts the rate and extent of wildfire spread, thereby determining the magnitude of the damage and the degree of difficulty in controlling the fire. High wind speeds can transport embers and flames over long distances, igniting new fires or accelerating existing ones. Moreover, the provision of oxygen by the winds reacts with the fuel of the fire, producing additional heat and enhancing the intensity of the fire. This can result in devastating fires threatening human life, property, and the natural environment.

[Chart

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Fig. 1 Maximum daily wind speed for fires in wildfire size Classes 1 through 5 for Oklahoma wildfires from 2000–2012  
Source: Accessed from [7]

* 1. *The effects of relative humidity against the likelihood of wildfires.*

Relative humidity plays a vital role in determining several aspects of a wildfire, including fuel moisture content, rate of spread, and fire intensity. Relative humidity is the ratio of the actual amount of moisture present in the air to the maximum amount of moisture that can exist at the same temperature and pressure [4]. A decrease in relative humidity is often associated with an increased likelihood of wildfires, as light fuels like grass and pine needles are more susceptible to ignition. This is because drier fuels ignite and burn more readily compared to fuels with higher moisture content.

* 1. *The effects of temperature against the likelihood of wildfires.*

Temperature plays a crucial role in the ignition of wildfires. Its impact on the environment's fuel dryness, evaporation rate, atmospheric stability, wind speed, and fire behaviour is a huge factor in predicting wildfires. As temperature increases, the fuel dryness level increases, making the fuels more susceptible to ignition and increasing the potential for spread. The elevated temperature can also lead to the evaporation of soil moisture, causing the available moisture in vegetation to decrease and result in drier fuels. Furthermore, elevated temperatures create thermals, which are columns of air temperature differences between the air at ground level and higher altitudes in the atmosphere [5]. These thermals are caused by the convection of warm air rising and less dense air taking its place, leading to an unstable atmosphere and optimal conditions for wildfire ignition.

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Fig. 2 Annual frequency of large western U.S. Forest wildfires (bars) and mean March through August temperature for the Western United States.

Source: Adapted from [6]

* 1. *The effects of rainfall on the likelihood of wildfires.*

Rainfall plays a crucial role in influencing wildfires through various mechanisms. One of the most significant effects of rainfall on wildfires is the moisture levels of fuels. Rainfall, like high humidity, can reduce the fire intensity and make it easier to control by increasing the moisture content of the fuels. This, in turn, decreases the fire's ability to spread and grow. Additionally, heavy rainfall can reduce the number of potential ignition sources, making it more challenging to initiate a fire. In regions with a dry climate, rain can also create ideal conditions for fire ignition by stimulating vegetation growth, leading to increased availability of fuels. Regarding fire behaviour, rainfall can also impact the speed of fire spread and its direction. Heavy rain can slow down the spread of fire, while light rain can create conditions where the fire can continue to burn gradually. Furthermore, the direction of rainfall can affect fire behaviour by determining the distribution of fuels and moisture levels across the landscape.

1. Conclusion

Automated Wildfire Predicion aims to develop a more efficient solution for predicting wildfires in Hong Kong by creating a neural network connected to a graphical user interface. The first draft of the project has been completed. In the future, optimization of the model and adaptation of the GUI will be undertaken to prevent and protect Hong Kong's forests.

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