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Research Plan

Wildfire Prediction and Reduction for the West Coast of the USA using a Neural Network Approach

A. Rationale:

The first few months of 2019 alone have seen damages caused by 40,000 wildfires, destroying a total of 3.2 million acres of forests. The total recorded cost of these wildfires was over 18 million per state. They have caused 44 known deaths and displaced 170,000 people (Facts Statistics: Wildfires, 2019). Wildland forest fires are currently among one of the leading causes of carbon dioxide (CO_2) emissions into the Earth's atmosphere. In the month of June, wildfires in the Arctic emitted as much CO_2 as the entire country of Sweden did for the first six months of 2019 (Newburger, 2019). Many wildfires are only found hours, sometimes days, after they begin. This leads to a lack of control of their spread and major damage to wildlife and contributes to climate change. In recent years, a surge in wildfire cases led to the research for better methods of forecasting wildfire climate. The governments of Canada, United States, and other developed nations have created automated systems for the detection of wildfires. Among these are NASA's Moderate Resolution Imaging Spectroradiometer (MODIS), the Raytheon Company's Visible Infrared Radiometer Suite (VIIRS) and Canada's Forest Fire Weather Index (FWI).

Both the MODIS and VIIRS systems are based on data from one sensor, which cannot be verified, and are taken only once per day, which means the fire state is unknown for 23 hours. Additionally, the data is recorded over 375 -750m spaces in the VIIRS system and the 1km space in the MODIS system. These ranges limit the precision of the systems to changes in fire danger in smaller intervals. The FWI system has ambiguous outputs, making it difficult for humans to use it to make predictions. Additionally, all of these techniques suffer from data inaccuracies caused by wireless propagation effects.

Wireless signals, such as sensor data, propagate from a transmitter to a receiver along a channel, a multiplexed medium over which the wave travels. An example is a radio channel or a wire. As the signal propagates, the signal is amplified, reflected, and distorted (Koks & Challa, 2003). In many cases, loss or distortion of data ("noise") can lead to uncertain results or misleading information. To decrease errors and promote accurate information, methods such as data fusion and probabilistic data filtering are used (Koh, 1995). In the past, data fusion has been attempted using Bayesian, Kalman, and Dempster-Shafer methods. Bayesian systems assign true-false values to parameters that describe the system but are often inefficient. Kalman systems use a similar idea but do so with respect to past information (Sasiadek & Hartana, 2000). These are not useful because they all depend on extra information that may not necessarily be available in weather data or analyze data in a way that is inapplicable to weather data. Given the usefulness of data fusion, the use of a Neural Network with data fusion features is a good candidate for wildfire applications. Feed Forward Neural Networks (FFNN) are commonly used in machine learning because they perform better than Convolutional Neural Networks (CNNs) and Artificial Neural Networks (ANNs) in numerical classification tasks (Paik & Katsaggelos, 1992).

B. Hypothesis(es), Research Question(s), Engineering Goal(s), and Expected Outcomes:

The purpose of this study is to develop a robust machine learning model that can predict if a wildfire is occurring, or is going to occur in the future, using a large area, satellite-based, early warning sensor network system to determine the severity and solutions to those wildfires.

Expected Outcomes: Since the universal approximation function argues that any classification task is possible, it seems possible to make a neural network to classify weather data. However, making it efficient and able to apply solutions may be affected by its classification accuracy. Different methods may need to applied to find the best efficiency-accuracy balance in the network.

C. Procedures, Risk and Safety

Research will be conducted at the New York Institute of Technology, under the supervision of Dr, Batu Krishna Chalise.

Procedures:

Data and Networks:

A feed forward neural network (FFNN) will be developed using Matlab's "nntool." This network will be trained using climate and weather data from Mateoblue and Wildfire Today. Data will then be tagged into classes for neural network training. The parameters and types of data used to train the neural network will be chosen based on available data and which data is most used in decisions.

The structure of the network will be developed using a function that evaluates the performance at different combinations of layers and layer sizes. As the best performances are evaluated smaller ranges for possible combinations are found, efficient and proficient networks will be created.

Outputs of the performance testing, such as the receiver operating characteristic (ROC), confusion matrix, and performance indicators will be used to decide between different size combinations.

A solutions system will be developed using the same procedure to decide which solution, of multiple possible solutions, to take for a particular fire. These solutions will also be dependent on a regressive task that uses information such as the spread of the fire to evaluate the fire threat.

Forest design:

A sensor/drone/tower system will be designed that uses low cost sensors and relays to send data and make decisions. The size of the sensor networks and the types of sensors will be developed based on the efficiency of the neural network and in order to maintain costs that are less than the costs of wildfires.

D. Bibliography

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NO ADDENDUMS EXIST