WildfireNet: Predicting Wildfire Profiles (Student Abstract)

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Abstract

Forecasting an accurate wildfire profile is an essential tool for firefighters when planning an evacuation strategy. Therefore, we propose a WildfireNet that can predict the shape of the wildfire of the next day, when given historical wildfire profiles, elevation, and weather data. The motivation behind WildfireNet is to locate fires in a precise manner and be able to accurately predict upcoming fires. The model's architecture was built in the inspiration of U-Net, which is a Convolutional Neural Network (CNN) commonly used in a biomedical image segmentation. Intersection over Union (IoU) and recall were calculated to measure the performance of the model. The model achieved an IoU score of 0.997 in the test set. Since the objective of the model is to predict upcoming fires, pixels that were labeled as fire but not on the previous days were extracted to calculate recall. In the test set, WildfireNet scored a recall around 0.75 for fires that grew slowly. Overall, WildfireNet is a novel wildfire spread model and has the potential to be a tool to aid firefighters in their decision making.

Introduction

In recent years, wildfire has become an unavoidable natural disaster that continues to threaten fire-prone communities. Due to the climate change, global warming and consequent fuel drying, the frequency of devastating wildfires will increase (Halofsky, Peterson, and Harvey 2019). The consequences of massive wildfires are brutal. For instance, in 2003, wildfires that occurred in San Diego County, California, burned over 376,000 acres and 3,241 households, which sums up to $2.45 billion in terms of total economic costs (Diaz 2012). Traditional, physics, and empirically based wildfire spread models have been continuously studied to mitigate losses resulting from wildfire. However, these models often require extensive inputs, which are often difficult to obtain or even impossible to obtain. Thus, we present a novel deep learning method to determine dynamic wildfire profiles with the basic input data: historical wildfire profiles, weather, and elevation data.

Related Work

Modeling wildfire has been an active research topic. Reinforcement Learning was utilized to learn forest wildfire spread patterns from the satellite images and FireCast combined 2D Convolutional Neural Network (CNN) and data collection from geographic information system (GIS) to predict areas that are expected to burn during the next 24 hours (Radke, Hessler, and Ellsworth 2019). To our knowledge, WildfireNet is the first artificial intelligence model to use 3D CNN to predict the profiles of upcoming wildfires.

Model and Implementation

We decided to utilize the architecture of U-Net because 1) the model has a capacity to input an image and output a precisely segmented image, 2) it works well with a small dataset, 3) and it is capable of predicting a wildfire profile within a second.

WildfireNet Architecture

The U-Net model is adjusted so that it becomes more applicable to our study. Similar to the U-Net, WildfireNet is composed of the two major paths: contraction and expansion. A sigmoid activation function is used at the last layer to output a probabilistic distribution of fires. Binary classification is performed on each pixel of an image to determine whether there is a fire or not. Thus, binary cross-entropy is used as a loss function to train the model.

In contrast to the U-Net, WildfireNet consists of fully connected layers at the bottom of the architecture. After the last downsampling, the 3D image is flattened into 1D array and weather and elevation data are added. The model is further trained with fully connected layers to learn the effect of weather variables in its prediction. Furthermore, past wildfire profiles can play a dominant role in the future shape of the wildfire. Therefore, 3D CNN was used instead of 2D. In

3D CNN, the model further extracts features from both the temporal and spatial dimensions, whereas, in 2D CNN, the model only focuses on spatial features (Tran et al. 2015). In this study, 3 previous days of wildfire profiles are combined to convert input images from 2D to 3D. This allows the model to have a better sense on how historical fires are correlated to the fire on the next day.

Data

Dynamic wildfire perimeters were obtained from NIFC FTP Server. Elevation data were collected from the USGS national map. Weather data were retrieved from CEFA-WFAS FW13 Fire Weather Data File Interface.

Preliminary Results

The output of WildfireNet shows a probabilistic distribution of fires occurring at each pixel as shown in Figure 1. If the model is confident that there is a fire in a certain pixel, it will assign a high score. The model also projects how fire will spread in the future. For example, in Figure 1, the model predicts the fire will enlarge on the right side of the boundary, whereas, not so much on the left side. In fact, in the comparison between the current day to the next day, it shows that the actual fire of the next day didn't expand elsewhere except on to its right. Furthermore, in Figure 2, WildfireNet predicts the fire will continue to grow at the bottom most of the left fire body and the actual fire expanded at the predicted region. These results validate the model's capacity of predicting the growth pattern of wildfires.

Furthermore, the logistic regression model was used as a baseline model to compare the performance of the model.

Metrics

Intersection over Union (IoU) and recall were calculated to evaluate the model's performance in predicting the profile of the wildfire. WildfireNet achieved an IoU of 0.997 in the test set, while the baseline model scored 0.913. The result indicates that WildfireNet is excellent in precisely labeling each pixel with the presence of fire or not. Furthermore, to measure the model's performance in predicting the changes in wildfire profile, only the pixels that were labeled fire on the next day but not on the current day were evaluated. We defined such pixels as changed pixels. Thus, the recall score was formulated as the intersection between the predicted and the truth of the changed pixels divided by the area of the truth of the changed pixels. WildfireNet achieved 0.517 on recall and the baseline model scored 0.114. This implies that WildfireNet predicts correctly half of the time on how fires are growing in the actual fire. However, when inspecting each fire independently, WildfireNet scored a recall around 0.75 for fires that grew slowly. Overall, WildfireNet is a novel wildfire spread model and has the potential to be a tool to aid firefighters in their decision making.

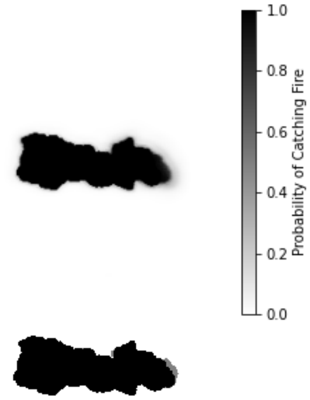

Figure 1. Top) WildfireNet predicts the fire will continue to expand at the right most of the boundary. Bottom) Comparison between the current day (solid black) and the next day (light gray).

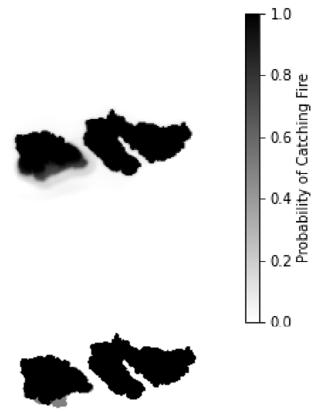

Figure 2. Top) WildfireNet predicts the fire will continue to expand at the bottom most of the left fire body. Bottom) Comparison between the current day (solid black) and the next day (light gray).

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