Pixel-wise Deep Sequence learning for wildfire spread prediction

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INTRODUCTION

ABSTRACT

In Canada, an average of $800 million was spent yearly on fire management in Canada. For better decision-making, improving the accuracy of wildfire growth prediction is one of the most challenging but needed tasks for wildfire management agencies.

In this study, we proposed to apply the deep sequence learning models to wildfire growth prediction, considering the similarity of the two tasks. We built a benchmark dataset for daily fire progression of 256 large fires in Alberta. We evaluated a Recurrent Neural Network called the Convolutional Long Short Term Memory (ConvLSTM) with three model architectures. Intersection over Union (IoU) is used to evaluate the predicted images relative to the ground truth

Our objective is to predict wildfire growth for the next day given the current day's fire perimeter as shown in Figure 1.

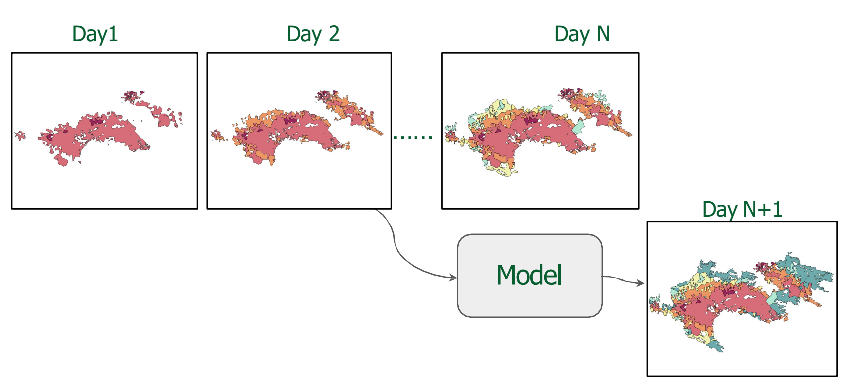

Figure 1. An example of input and output wildfire images

DATA PREPARATION

Currently, one of the biggest challenges in evaluating deep learning methods in wildfire growth prediction are the absence of dataset. In this study, we built a benchmark dataset by merging the MODIS hotspot [1] and wildfire final perimeters from the Canadian National Fire Database.

- 256 large fires (>500ha) in Alberta are used to build the A benchmark dataset as shown in Figure 2.
- The daily fire images is generated following steps in Figure 3.
- 6 feature variables are included in the ConvLSTM, including temperature, precipitation, wind speed, Fine Fuel Moisture Code, Duff Moisture Code, and Drought Code.

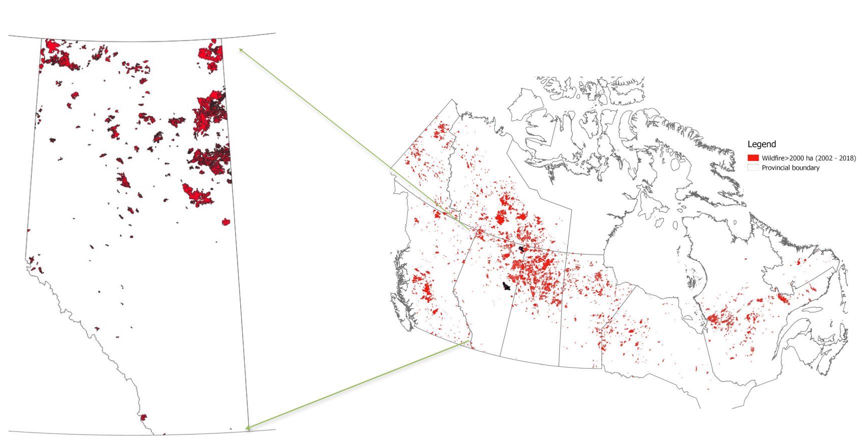

Figure 2. Visualization of the 256 wildfires in 2015

METHODS

GENERATE TRAINING FIRE IMAGE

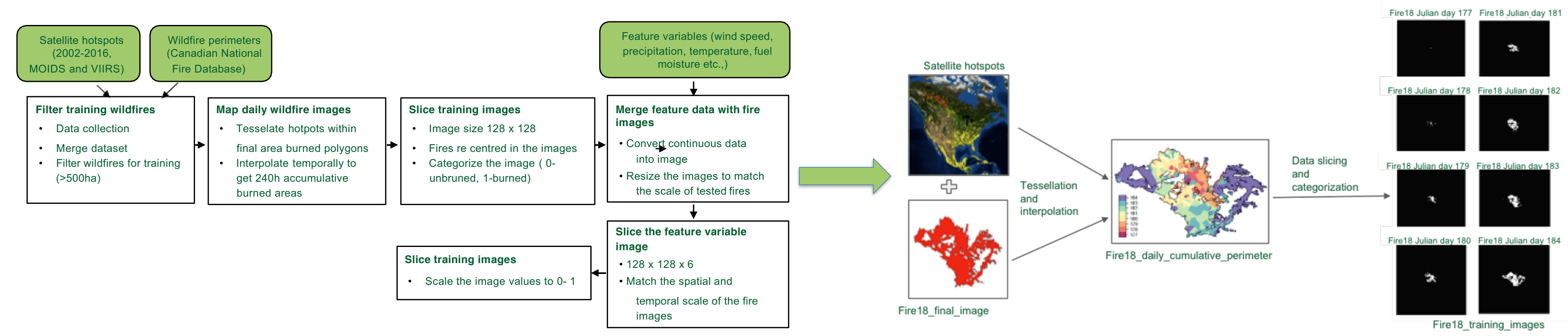

Figure 3. A high-level overview of the data processing flowchart (left) and an example of the daily fire images generating process

MODEL IMPLEMENTATION

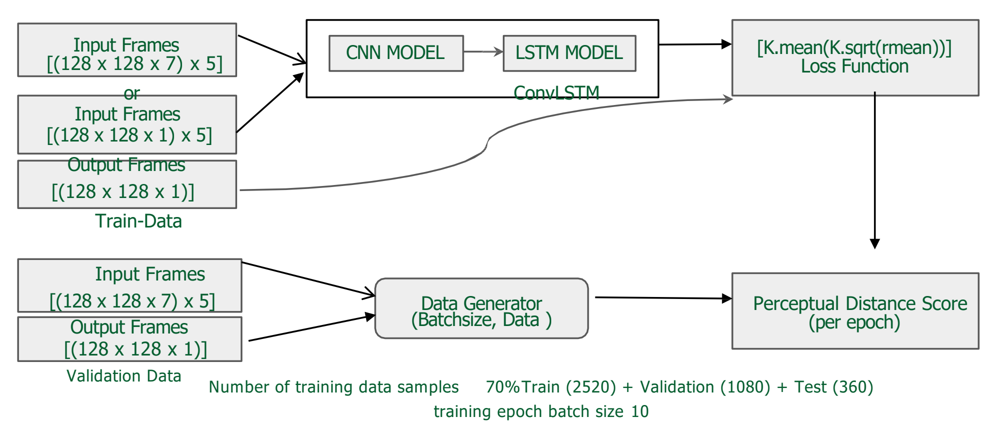

Figure 4. ConvLSTM model architecture.

The overall functionality of the ConvLSTM [3] is to produce the n+1th wildfire images, given a sequence of 5 images:

- Generator - This is used to convert the sequential fire evolution frames to an array of images of the specified batch size.
- ConvLSTM - This represents the part of the model in which we train the model to predict the next frame.
- Decoder – Having sequential behaviour same as generator but in reverse, this represents the part of the model where we reconstruct the image and compare it with the ground truth

MODEL EVALUATION

The ground truth images and predicted images are evaluated on a pixel basis. Among the various evaluation metrics, we selected Intersection over Union (IoU) to evaluate the predictions from the model to eliminated the effect of background pixel and evaluate models on the burned area. This is because a large portion of pixels in our training images were background pixel of value 0.

RESULTS

ConvLSTM with real fire image

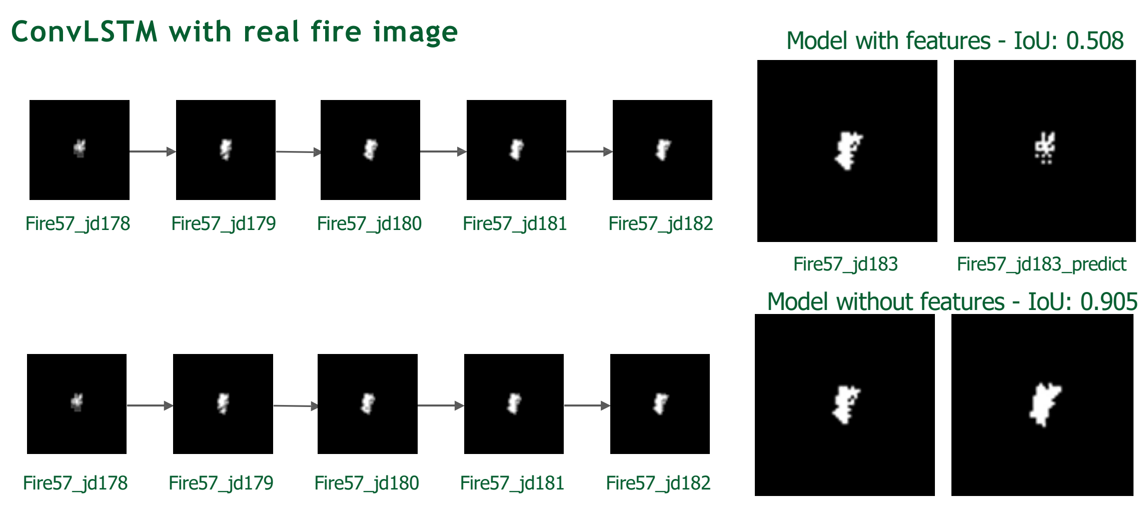

Figure 5. Input frames of fire 57 and ground truth result compared with predict from model with features (above) and without (below) features.

The predicted images from the basic model without any features produced the average IoU value of 0.754, whereas the model with features produced average IoU of 0.417.

The better performance of the model without features may because additional features increased the complexity of learning, so improving the model architecture and enlarging the number of training data-set might help the model with additional features to obtain better results.

ConvLSTM with simulated data

The simulated data was used to test if the ConvLSTM model works for wildfire growth prediction problem. The Conv2D predicted image had similar patterns compared to the ground truth, indicating the model framework is suited for wildfire growth prediction task.

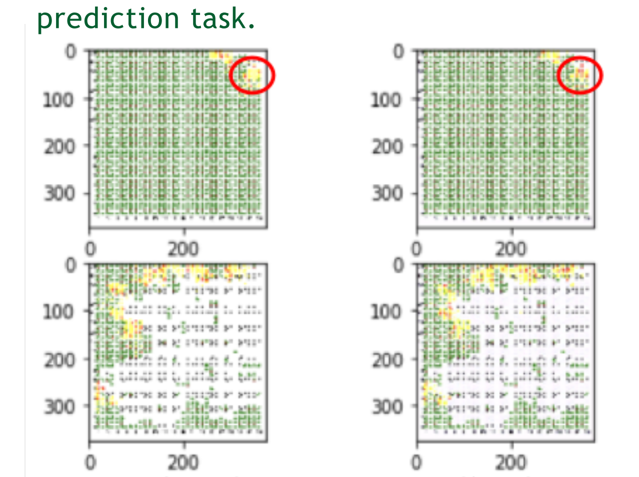

Figure 6. Ground truth and predicted images for ConvLSTM model with simulated data

SUMMARY

CONCLUSIONS

In this study, we evaluated three deep sequence learning models for wildfire spread prediction and we conclude our study as follows:

- Generated a benchmark dataset for deep sequence learning in wildfire growth prediction
- Evaluated three baseline models, including
  - ConvLSTM with simulated data
  - ConvLSTM with real fire images - no features
  - ConvLSTM with real fire images - 6 feature
- Results suggested models trained with real fire images outperformed models trained with simulated data, however, models without features is better than model with features
- Identified key challenges in using machine learning for wildfire growth prediction, including lack of data, size mismatch of wildfire and the extend of landscape, and imbalanced time interval for different fires,
- Overall, this study demonstrated the feasibility of using ML and image process techniques for wildfire growth prediction

FUTURE DIRECTIONS

- Improve the quality of the feature variables, especially the weather input. The feature variables may also be improved by normalizing with the global mean
- Improve the model capacity and replace the loss function (MSE) with pixel-wise entropy.
- Increase the number of wildfire used for the training (currently only 256 wildfires in Alberta, Canada)

ACKNOWLEDGEMENT

We thank for Dr. Lihang Ying's guidance and valuable feedback during the various stages of the project. We thank Piyush Jain (Natural Resources Canada) for helping generating the dialy wildfire growth progressions.

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The 2nd NOAA Workshop on Leveraging AI in Environmental Science
Presented on September 29th, 2020

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Canada Wildfire

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