Predicting Wildfires in Alberta, Canada Using Advanced Neural Networks: A Post-Implementation Report

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***Abstract*—Wildfires have become an increasingly complex problem, with damages estimated at $1 billion annually in the 2010s. The cost of wildfires does not only encompass the financial impact but also the massive carbon emissions and the incalculable toll on families who lose homes, pets, and loved ones. Research into using advanced data science techniques to predict wildfires has become more prevalent in recent years. The goal of this project was to develop a sophisticated neural network capable of predicting wildfires in Alberta, Canada, based on historical data and satellite imagery.**

I. Introduction

WILDFIRES have become an increasingly complex problem, with damages estimated at $1 billion annually in the 2010s. The cost of wildfires does not only encompass the financial impact but also the massive carbon emissions and the incalculable toll on families who lose homes, pets, and loved ones. Research into using advanced data science techniques to predict wildfires has become more prevalent in recent years. The goal of this project was to develop a sophisticated neural network capable of predicting wildfires in Alberta, Canada, based on historical data and satellite imagery.

II. Data

The Canadian National Fire Database served as the primary data source for this project. It contains ignition data for Canadian wildfires from 1930 onwards, including longitude and latitude for ignition points and polygon data for fire perimeters. The dataset has some inconsistencies and sporadic data, requiring careful consideration in selecting the years to include in the model. We have made use of data from 1980 onwards. The dataset was then cleaned to become a weekly time series. The target variable was the number of fires. However we ultimately predicted the natural logarithm of fires plus 1. The plus one allows us to avoid the natural logarithm of zero (which results in - infinity). For the multivariate estimator, the province was binned into 16 sections based on their latitude and longitude. These bins were predicted separately using the same model architecture (described below).

III. Models

We implemented three deep learning architectures: DeepAREstimator, multivariate DeepAREstimator, and Temporal Fusion Transformer. The success of the models was evaluated using various loss functions such as RMSE, wQL, MAPE, MASE, and WAPE metrics. The DeepAREstimator and multivariate DeepAREstimator models were optimized using the Optuna hyperparameter optimization framework, while the Temporal Fusion Transformer used predetermined hyperparameters. The models were optimized for 6 hours on the Google Colab Premium GPU. The DeepAR models have a single layer of 55 hidden units and uses an embedding dimension of 37. It is trained for 181 epochs with a learning rate of approx 0.09185 and a batch size of 767. Additionally, a context length of 61 is used to define the length of the input sequence and a dropout rate of close to 0.11223 is applied to the network to prevent overfitting. The Temporal Fusion Transformer uses a context length of 6 and a hidden dimension of 32, with 4 attention heads to capture complex temporal patterns.It is trained for 100 epochs with a learning rate of 0.001 and a batch size of 32. The model applies a dropout rate of 0.1 to prevent overfitting, and also includes weight decay regularization with a strength of 1e-4.

IV. Procedure

We trained a DeepAR time series forecasting model on wildfire ignition data. The dataset is first loaded and pre-processed, with 75% of the data used for training (1979-12-30 to 2013-07-14) and the remaining 25% (2013-07-14 to 2021-12-14) for testing. The DeepAR model is then optimized using the Optuna library, which searches for the best hyperparameters based on the root mean square error (RMSE) metric. Optuna uses Bayesian optimization and a Tree-structured Parzen Estimator (TPE) technique to construct a probabilistic objective function model and then samples hyperparameters from this model. After obtaining the optimal hyperparameters, the DeepAR model is re-trained using these values. Finally, the model's performance is evaluated on the test set, and various visualizations and metrics are generated to analyze the results. The same process is repeated using a dataset with binned ignition data to assess the model's performance further.

V. Goals Assessment

We met several of our measurable and quantifiable goals as described in the project proposal. Specifically, we achieved the following:

- Developed three high-performing models (DeepAREstimator, multivariate DeepAREstimator, and Temporal Fusion Transformer) as planned.

- Optimized models using Optuna, as per our top ambitious goal.
- The models showed strong performance producing RMSEs of 0.5, 1.5, and 0.8 for the multivariate DeepAREstimator, univariate DeepAREstimator, and the Temporal Fusion Transformer, respectively.
- Location-based forecasts were produced (and increased model performance), however, we did not accomplish the goal of a clear easy-to-interpret forecast for wildfire numbers in geographic bins.
- We were unable to integrate the data with the Google Earth API for localized fire predictions due to time constraints, which was a stretch goal in our initial proposal.

VI. Conclusion

In this post-implementation report, we have summarized the development and results of advanced neural network models for predicting wildfires in Alberta, Canada. The project successfully implemented and optimized three deep learning architectures: DeepAREstimator, multivariate DeepAREstimator, and Temporal Fusion Transformer. All three models demonstrated strong performance, with the multivariate DeepAREstimator having the lowest RMSE of 0.5, followed by the Temporal Fusion Transformer with an RMSE of 0.8, and the univariate DeepAREstimator with an RMSE of 1.5.

While we achieved many of the project goals, some limitations remain. The geographic bin-based forecast was not as easy to interpret as initially hoped, and we did not manage to integrate the data with the Google Earth API for localized fire predictions due to time constraints. Nevertheless, the successful development and optimization of the neural network models provide a solid foundation for future work. With further refinement and improvement, these models can contribute significantly to wildfire prediction and management in Alberta, Canada, and beyond.