DeepFire

Deep Learning based Forest Fire Detection from UAV images

Class: SENG 499 (Summer 2020)
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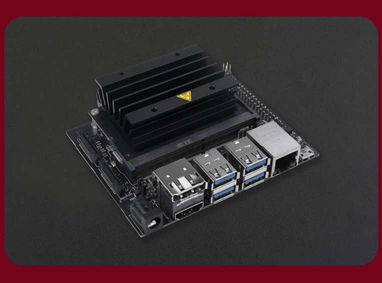
Problem and Project Goals

Each year Canada spends hundreds of millions of dollars on managing wildfires [1]. Climate change will increase the frequency and severity of these fires. To reduce associated costs, fires must be detected earlier.

[2]

The project objective is to create a machine learning (ML) model that detects wildfires and runs on an embedded system. There are two hard design requirements (DR): the model must have an accuracy of at least 90%, and the model must have an inference time of less than 1 second.

The Hardware



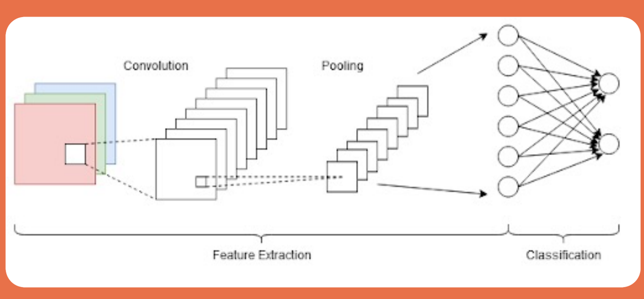
[3]

There are two critical requirements for the hardware. First, it must be able to support modern ML tooling. Second, it must have appropriate components to run ML models. The NVIDIA Jetson Nano was chosen as it has support for many modern ML frameworks (such as Tensorflow) and specialized CUDA cores to run ML models [3].

Wildfire Datasets

Data was drawn from a variety of sources to maximize the volume and ensure generalizability. Several public data repositories on GitHub were utilized, as well as a private database owned by Corsican University. This was supplemented by Google image search and drone video footage obtained from YouTube.

CNNs



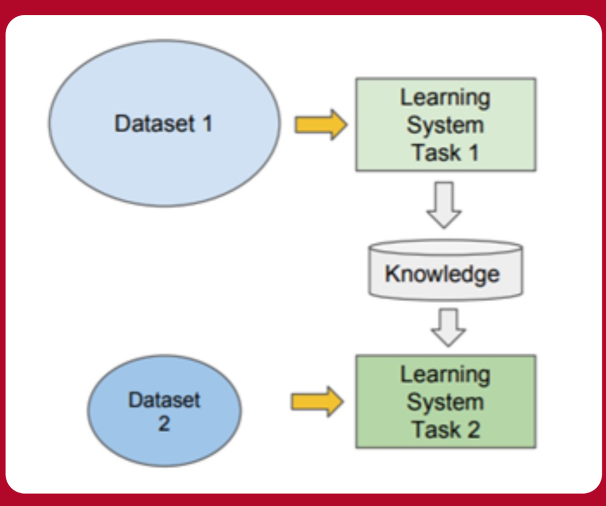
Convolutional neural networks (CNNs) are a subclass of neural network used for feature extraction from grid-like data such as images and time series [4]. Specifically, they contain at least one convolution layer where a small matrix (called a kernel) is convolved with the image to create several smaller feature maps. A CNN was chosen to construct the model based on the literature review.

Model Design

The team constructed a basic CNN with just a few feature extraction layers as a basis to compare to the rest of the models constructed. As expected, it's not very performant and has an accuracy of around 65%.

With the addition of transfer learning using ResNet50, and a single hidden layer with 60 nodes, the team constructed a model that is more accurate than the basic model. The ResNet50 based model has an accuracy of approximately 94% as shown in this section's figure.

Transfer Learning

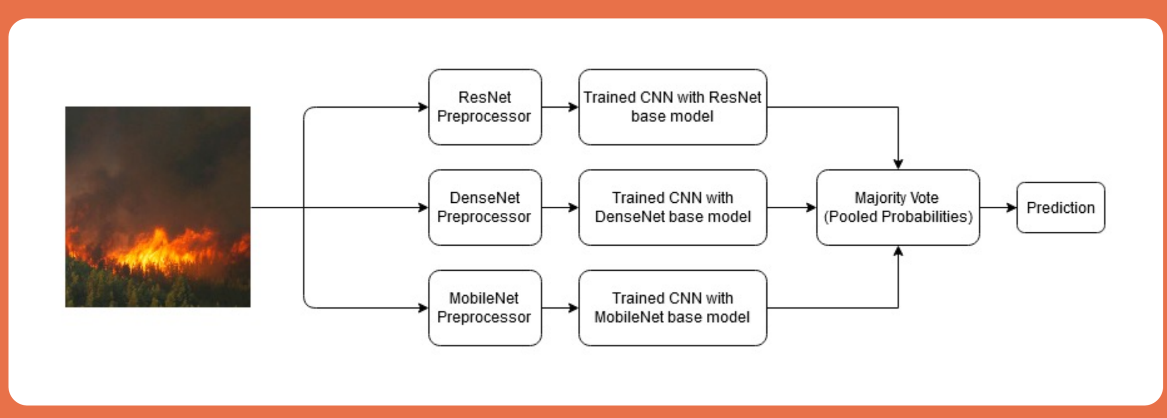


[5]

Transfer learning is the process of taking knowledge obtained from solving one problem and applying it to another. Considering the lack of forest fire photo data available, it was a vital technique for constructing an effective model. A number of base models were tested, ResNet50 was chosen due to its speed and accuracy.

Ensembles

Ensemble models combine the classifications of several different models into a new and potentially more accurate one. The team created several ensemble based models.



The first set of ensembles created combined two models: one that detected smoke, and another that detected fire. Due to a lack of data, the smoke model underperforms and makes any variation of the ensemble non-viable.

The second set of models created combines 3 models each with a different base model. Two variations were created: one that counts each classification in a majority vote, and another that takes the maximum value to ensure there are few false negatives. Each variation of the ensemble performs well, but has lower accuracies than single models with accuracies in the mid 80s.

Results

The following table summarizes the performance of each model the team created, as well as whether each model meets the original design requirements.

Model	Accuracy	Precision	Recall	Inference Time (s)	Inference Time DR Satisfied	Accuracy DR Satisfied
Simple Neural Net	0.6541	0.6348	0.73	0.1748	YES	NO
ResNet50	0.9348	0.9781	0.895	0.3858	YES	YES
DenseNet121	0.9424	0.9680	0.91	0.3984	YES	YES
MobileNet	0.8772	0.8663	0.875	0.2570	YES	NO
Ensemble (Pooling)	0.8571	0.9689	0.935	1.2447	NO	NO
Ensemble (Voting)	0.8571	0.9687	0.93	1.1520	NO	NO

Recomendation

The recommended model is the ResNet50 based CNN as it consistently ties for the highest accuracy, has the highest precision, and maintains a low inference time.

Classifications (with confidence percentages)[1]

References

[1] "Forest fires | Natural Resources Canada", Nrcan.gc.ca, 2020. [Online]. Available: https://www.nrcan.gc.ca/our-natural-resources/forests-forestry/wildland-fires-insects-disturban/forest-fires/13143. [Accessed: 30- Jul- 2020].

[2] "UAVs and Big Data Management - Raima Database Manager", Raima.com, 2020. [Online]. Available: https://raima.com/uavs-will-need-the-best-in-big-data-management/. [Accessed: 25- Jul- 2020].

[3] "NVIDIA Jetson Nano Developer Kit - DFRobot", Dfrobot.com, 2020. [Online]. Available: https://www.dfrobot.com/product-1909.html. [Accessed: 31- Jul- 2020].

[4] I. Goodfellow, Y. Bengio and A. Courville, Deep learning. MIT Press, 2016, p. Chapter 9.

[5] D. Sarkar, "A Comprehensive Hands-on Guide to Transfer Learning with Real-World Applications in Deep Learning", Medium, 2020. [Online]. Available: https://towardsdatascience.com/a-comprehensive-hands-on-guide-to-transfer- learning-with-real-world-applications-in-deep-learning-212bf3b2f27a. [Accessed: 31- Jul- 2020].

[6] D. Dorfer, K. Gorgichuk, J. Leahy, M. Fortier, G. Sato, "Deep Learning based Forest Fire Detection from UAV Images," Univ. Victoria, 2020

1. Dataset references are available in Table 4 of the Deepfire Report [6].

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