THE IMPACT OF IMAGE CLASSIFICATION USING A CONVOLUTIONAL NEURAL NETWORK ON WILDFIRE DETECTION

Introduction

In the current state of the world, wildfires are undoubtedly some of the biggest threats to the human population. Wildfires are unpredictable and uncontrolled and usually start in natural areas, such as forests, grasslands, or prairies. The environment suffers quite a great deal from the impact of wildfires. According to iii.org, in 2020 alone, over 10 million acres were burned down due to wildfires. Furthermore, these wildfires leave numerous people without a roof over their heads.

Research has been done on wildfires in the past. Research about wildfires has examined the effects of inhaling smoke from wildfires on individuals' health on a more general scale. Previous research has shown that once an individual inhales such smoke, it can lead to direct toxicity, oxidative stress, inflammatory reactions, immune dysregulation, genotoxicity, mutations, and much more (Lei et al., 2024). Similarly, other research has been conducted to find the impact of specific wildfire smoke on cardiovascular health. It was found that inhaled wildfire smoke with particular matter, the primary pollutant in wildfire smoke, can lead to many cardiovascular issues. These issues can primarily affect the elderly and pregnant women, young individuals, and the healthy, with symptoms like systemic inflammation and vascular activations (Chen, Samet, Bromberg, & Tong, 2021). These papers illustrate the destructiveness of wildfires on people. As stated before, the environment also gets damaged by wildfires. Research was done on the impact of wildfires on surface water quality. The study was specifically conducted to see the difference between pre-and post-wildfire water. They found that within a year, the pH of the

water changed, but it returned to normal after a year. The concentration of contaminants in the water also increased significantly after a wildfire. Total Suspended Solids also increased in waters with a flow of 10 m3 s−1, while higher flow decreased the total suspended solids, possibly by dilution. This research shows how the water could be affected by pollutants after wildfires, which can affect the environment and people's health (Raoelison et al., 2023). We can dramatically lower this number by effectively distinguishing real threats of wildfires and just a non-threatening fire.

Past studies have found the dangers of wildfires to people, their homes, and animals. Our research will include developing a machine learning model using neural networks that could accurately predict where wildfires could happen. More specifically, this machine learning model will be able to recognize wildfires before they truly develop fully; then, at such a small scale of a fire, we can quickly put it out. We would like to see if our convolution neural network model can detect wildfires. We hypothesized that if we changed certain factors for our CNN model, then the accuracy of our model to predict a wildfire from a picture would increase. This research could benefit anybody living in wildfire-prone areas, animals in those areas, and nature.

Methods

Libraries needed

For our project, we utilized the Scikit-learn library, which employed various machine learning tools, including utilities for preprocessing data, splitting datasets, and evaluating models. Using Scikit-learn, we loaded and prepared data, trained our model (a convolutional neural network model), made predictions, and evaluated our model's accuracy. Thus, we ensured that the data preparation and model training and evaluation were done efficiently.

We also used Pillow, a library specializing in image-processing tasks. With Pillow, important image manipulation features like cropping, rotating, and applying filters to images were possible. This was specifically helpful for our project as we dealt with many photos. Specifically, Pillow was used in our project to resample the picture. Resampling changes the image's size and, therefore, quality. This was helpful for our project, as the size of an image could correlate with the correctness of our model predictions.

Tensorflow was another library used that offered us all the tools to define, train, and deploy models. It was specifically helpful in making our convolution neural network. TensorFlow has been helpful in training neural networks in the past. Training and testing of the neural network have mostly been done using this library.

These libraries were imported at the start of our Python code. Without these libraries, essential steps could not be taken, and the creation of our CNN model was not possible.

Dataset used

We used "The Wildfire dataset" for our project because of its diversity, scale, and quality. The dataset spans 2,700 aerial and ground-based images collected from various online sites and databases such as Flickr and Unsplash, capturing a wide range of forest types and geographical accuracy. The dataset is organized into clear 'fire' and 'no-fire' categories to simplify processing and model training. Additionally, the high-resolution images ensure detailed data is inputted into our model.

Importing Images

Images from the wildfire dataset were stored in two files. The file containing the pictures of real wildfires was named “fire,” and the one without was named “no-fire.” These folders were inputted into our code by specifying their paths and assigning a numerical label. The pictures from the “fire” folder were assigned the label 0, while the pictures from the “no-fire” were assigned the label 1. Labeling the two files allows the model to map the input pictures to the correct output. This helps the model understand the difference between the two categories, allowing the model to predict whether a new image contains a wildfire. We could also rescale the photos to see if they affect our model's accuracy.

Splitting the data into training and testing sets.

After importing the images, a very important step was to split the data into training and testing sets. Splitting data into training and testing sets is incredibly important for evaluating our model's performance. The training set is used to teach the model to identify the patterns to classify. The testing set acts as the unseen data to see the model's ability to classify the new images correctly. This can also help identify overfitting, where a model performs well on the training data but not on the new data.

Our Convolutional neural network

The model used in our code was a Convolutional Neural Network (CNN). The CNN model is an artificial intelligence model specializing in processing data with a grid-like topology, such as images. The model is frequently used for tasks like image recognition, object detection, and natural language processing. To achieve this, CNN models employ a range of convolutional layers, pooling layers, and fully connected layers. The primary function of the convolutional

layers is to apply filters to the input of the image to extract its features. In our code, 32 features are detected by a 3x3 filter slid across the image. The output of this is the production of 32 feature maps, slightly smaller than the inputs of the image due to the 3x3 filters. This is what the first convolutional layer does. A pooling layer is then used to reduce the spatial dimensions of the feature maps. The spatial dimensions are the height and width of a feature map. The output of the pooling layer is that the width and height of the feature map are reduced by half while maintaining the depth of 32. A second convolution layer is used. For the second convolution layer, 64 different features are detected instead of 32. The size of the filters remains 3x3. The output produces 64 feature maps based on the reduced size input from the previous pooling layer. These 64 different features are many high-level features than those seen in the first pooling. Another pooling layer is used. The spatial dimensions are further reduced with the use of this pooling layer. The final feature maps are therefore created. The feature maps are three dimensional (3D). The maps need to be flattened to make the 3D feature maps into a 1D vector. Our CNN contained 128 neurons in each layer. After all of this, the output layer for classification is produced. The model is then compiled. The weights associated with each input are optimized during training. The accuracy is also tracked during the training. After the model was compiled, it was ready for training. While training the model, epochs and batch size are the two factors that can change the accuracy of our model predictions. The epochs are the number of times the model will iterate over the entire training dataset for a certain number of times. The batch size is the number of samples the dataset will be divided into. The model updates weights after processing each batch. The weights are then used later when the model is tested on new images, which it needs to classify correctly.

Testing Our CNN Model

After being trained, our CNN model is tested on a new data set it has never seen before. The accurate labels are also stored, so the model can check its accuracy. The model processes the input through its already trained layer to make predictions. The predicted output from the model is compared with the accurate labels. The accuracy is then calculated by the percent of classifications our model detected correctly. To further evaluate the performance of our model, we adjusted various factors in our code during training and testing, including the number of epochs, number of photos, and size of the photos.

Results

Table 1: The average accuracy of each epoch, depending on how many photos were in the training and testing data.

	Epoch = 5	Epoch = 10	Epoch = 15	Epoch = 20	Epoch = 25
10 photos	50.00%	50.00%	50.00%	50.00%	50.00%
50 photos	65.00%	60.00%	65.00%	65.00%	70.00%
100 photos	65.00%	67.50%	67.50%	62.50%	67.50%
500 photos	70.50%	71.50%	72.50%	72.00%	73.50%
700 photos	73.50%	72.43%	73.57%	72.36%	74.62%

Table 2: Highest accuracy of a certain amount of epoch, on detecting a fire or not, using 700 photos for the training and testing data. The epoch where the highest accuracy was recorded is

noted. If the model reached 100% multiple times, the epoch, where 100% was first reached, is recorded.

	Epoch = 5	Epoch = 10	Epoch = 15	Epoch = 20	Epoch = 25
700 photos	90.29% (epoch=5)	97.63% (epoch=9)	100.00% (epoch=15)	100.00% (epoch=19)	100.00 (epoch 17)

Table 3: The accuracy of our model based on the size the images are rescaled to. The epoch is set to 10, and 700 photos are being used for the training and testing set.

	10x10	50x50	100x100	250x250
Trial 1	71.43%	72.50%	70.29%	72.50%
Trial 2	73.21%	71.36%	76.07%	68.57%
Trial 3	70.71%	71.43%	73.93%	68.21%
Average	71.78%	71.76%	73.43%	69.76%

Discussion

The findings of our study demonstrate the potential of CNNs in wildfire detection, as evidenced by different levels of accuracy based on changing factors like dataset size, epochs, and image resolution. By optimizing these variables, our CNN model was able to predict wildfires with high accuracy. Finding these factors that affect the accuracy of our CNN model is very important.

Dataset and Epochs

Table one shows the relationship between dataset size and our model's accuracy. It was found that when our model trained on a larger amount of images, such as 500 or 700 photos, the accuracy of our model significantly increased. For example, the accuracy increased from an average of 50% with 10 pictures to 74.62% with 700 pictures over 25 epochs. It is suggested, based on these results, that a larger dataset provides better training data for our model, enabling the model to generalize better and distinguish between images of fires and non-fires.

The number of epochs also significantly influences our model's performance, with the highest epochs being observed at several intermediate epochs. For example, using 700 photos, accuracy peaked at 74.50% at 5 epochs and slightly fluctuated as epochs increased. Although the accuracy varied depending on the epochs, for every row in the table, the accuracy was always higher for the most amount of the epochs used, compared to when the fewest number of epochs were used. From this information, it is indicated that it is important to find the right balance, as too few epochs may underfit the model, while too many epochs may lead to overfitting of the model. It is suggested to start with a higher amount of epochs as it, usually, leads to a good accuracy for the model.

Performance at Specific Epochs

Table two shows that the model achieved the highest accuracy by using 700 photos for training and testing data across different epochs. The model could also reach 100% accuracy as early as epoch 15 and maintain this level throughout the rest of the epochs. Our CNN can effectively learn to classify wildfire images accurately, starting from the range around epoch 15.

This is extraordinary, as we know our model can reach perfect accuracy, with a sufficient dataset and an appropriate amount of epochs.

The Impact of Image Resolution

Table three illustrates how image resolution can affect our model's accuracy. Images resized to 100x100 pixels achieved the highest accuracy of 73.43% across three trials, outperforming smaller resolutions of 10x10 and even larger resolutions of 250x250. These findings indicate for our dataset that medium-resolution images provide a balance between preserving sufficient detail for feature extraction and minimizing computational demands. Extremely low-resolution images can lose critical features, while extremely high-resolution images can introduce noise or overcomplicating factors for our model. This goes against the common belief that increasing the resolution of a photo always increases the accuracy of a machine-learning model.

Implications for Wildfire Detection

It is confirmed that machine learning models, such as CNNs, can be very effective in early wildfire detection. By changing certain factors, such as dataset size, the number of epochs, and image resolution, these models can achieve high levels of accuracy. The early classification of a wildfire can save many lives, protect people's property, and reduce environmental damage.

Limitations and Potential Error

Our project was only done on one specific dataset. This may not take into account all the situations in the world, which could cause these results to be slightly different based on other

datasets. We could also continue to try to optimize the structure of the CNN to converge to an optimal accuracy earlier.

Future Work

In the future, more research can be done on our model to maximize its accuracy even further to predict whether something is a wildfire. We advise future research to be on questions such as: Does the model still have a high percentage in predicting wildfires from lower-quality images? How well can the model perform under certain weather conditions in the place where the pictures are being taken? What are the common causes of false positives and false negatives in the predictions from our model, and how could this be minimized? Can the model be utilized for real-time detection of wildfires, using video streams?

Conclusion

Our research shows the effectiveness of the CNN model in accurately detecting wildfires from images, with the optimization of factors such as dataset size, epochs, and image resolution. Unlike traditional methods that detect wildfires, which depend on delayed reporting, our approach illustrates the speed and precision of dating wildfires using a CNN model. Our research addresses the research question by affirming that CNN models can serve as an effective tool for wildfire detection when properly trained and optimized. This supports our hypothesis, as changing specific factors can significantly improve the model's accuracy. For example, our experiment shows that larger datasets and increased epochs can result in better performance. Our model can be applied to the real world, using drones and satellites, to enhance the capability of detecting wildfires at an early stage, before severe damage occurs. Future advancements can lead

to the increased performance of our model. To conclude, our research shows ways that machine learning models, specifically CNN models, can be an effective solution in saving lives and protecting the environment.

References

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Abstract

Wildfires have devastating impacts on lives and the environment, so it is important to detect them at an early stage. Conventional detection approaches are based on the slow process of human reporting or restricted sensor information, which results in late action. This situation highlights the importance of developing smart and efficient wildfire detection systems.

We propose a Convolutional Neural Network (CNN) for the automatic classification of images for the purpose of detecting wildfires. The image dataset was labeled as 'fire' and 'no-fire,' and the preprocessing step of resizing was applied to all images. The CNN was trained and tested in different conditions: The effects of dataset size, image resolution, and the number of training iterations were also taken into consideration to check their impact on detection performance.

Our CNN has had a high success rate in identifying images that are associated with wildfire. With the increasing size of training data, the performance increased. Using the biggest dataset (approx. 700 images) and a sufficient number of epochs, the model could almost classify correctly, while with minimal amounts of training sets (e.g. 10 images), it was approximately 50%. The moderate image resolution of about 100×100 pixels was optimal, better than low and high resolutions. These results indicate that the CNN is capable of identifying crucial characteristics of wildfires and that sufficient data and proper image quality are important for this.

The CNN-based approach can be useful to improve the current early wildfire warning systems by quickly and accurately detecting fires compared to conventional systems. This research also shows that with adequate amounts of training data and optimization, CNN models can be applied efficiently for real-time wildfire detection. Future work will focus on the generality of the approach across various scenarios and its integration with the operational monitoring systems.