Using a SVB model for forest fire image classification

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1. Overall context for your project

Wildfires have become an increasingly common occurrence in recent years, with an average of 61,410 wildfires and 7.2 million acres impacted annually from 2013 to 2022. These devastating events can have significant impacts on both the environment and human communities, destroying habitats, homes, and infrastructure. Early detection of forest fires is critical for limiting destruction, as it allows for swift and effective mitigation efforts to be put in place. However, current detection methods, such as NOAA's AVHRR satellite images, have a significant delay between image capture and wildfire detection, which can hinder timely response.

By leveraging the power of machine learning, my aim is to create an algorithm to accurately and efficiently identify wildfires in photos, allowing for faster and more effective response times if implemented in the real world. The development of such these kinds of technologies is particularly important given the frequency and scale of wildfires in recent years, which have challenged traditional detection and response methods.

2. Problem definition

Develop an algorithm that can effectively and accurately identify the presence of wildfires in images, with the same level of proficiency as human observers. This requires the analysis of a diverse set of images, labeled as either "fire" or "not fire," in order to train a machine learning model that can differentiate between the two categories with a high degree of accuracy. A reasonable goal for this project and the somewhat limited data set I have to work with is a F1 score of .60.

3. Project motivation – why should we care?

Developing an algorithm that can effectively and accurately detect wildfires in images is a critical task with significant real-world implications. Wildfires are a major threat to ecosystems, human settlements, and infrastructure, causing devastating damage and loss of life. Early detection of these fires is crucial for minimizing their impact and enabling rapid response efforts. However, relying solely on human observers to identify and report wildfires is a daunting task, given the vast areas that need to be monitored, as well as the potential for human error and delays in reporting.

4. Project methodology

a. First key characteristics of the images (features) need to be identified so we can create a model that uses this features to detect fires.
b. After the features are decided on a function must be created for each one, that takes in a single image as input and returns the values for the feature.
c. Then the training images must be looped through and the features for each one assigned.
d. Once we have the features they need to be normalized
e. We need to select the top features
f. Then we need to define a classifier here we use a linear SVB.
g. Now that our model is trained we can loop through the test folder in order to calculate important stats like accuracy and f1
h. If the final accuracy is not satisfactory we must go back and modify the parameters and model until it is.

5. Data source

https://www.kaggle.com/datasets/alik05/forest-fire-dataset

Description (From Kaggle): “This dataset is curated to address the forest fire detection problem. All images in the dataset are 3-channeled with resolution of 250 × 250. The images were retrieved by searching various search terms in multiple search engines. Afterwards, these images are thoroughly investigated to crop and remove the inappropriate components such as people, fire-extinguishing machinery etc in order to ensure that each image only contain the relevant fire region. The dataset is designed for binary problem of Fire and No-Fire detection in the forests landscape. It is a balanced dataset consisting of 1900 images in total, where 950 images belong to each class. The dataset is divided into 80:20 for training and testing purposes in the proposed study.”

6. Data analyses

Initial observations:

The data consists of two folders test and train, this is a 80-20 split of the total image set of 1900 images. Each image is of a size 250x250 so they will not need to resized in order to be interpreted.

- Feature extraction
  a. Color observations:
     i. On visual inspection the fire photos have much more red and orange colors. By extracting the mean RGB value from each image we can detect the overall color patterns of the image.
     ii. To implement this feature we can use this line of code
         1. img.convert('RGB').resize((1, 1)).getpixel((0, 0))
     iii. Which resizes the image to a 1 by 1 image and returns the color effectively averages every pixel to get the mean color
  b. Texture observations:
     i. The feature of image texture may be a good indicator of if fire is present in the image.
     ii. Based on research the best practice for this is using a local binary pattern on the greyscale as explained here.[1]
  c. Lines observations
     i. It is possible that there are more or less lines in the fire/nofire photos so we can use hough lines to extract this feature from the images.
     ii. By using a Hough transform[2] we can extract the points of all straight lines in the image.
     iii. The relevant feature is the count of how many of these lines exist in each image

7. Exploratory data analyses

- Feature EDA

  a. Color features:

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[1] Bedi, A.K., Sunkaria, R.K. Mean distance local binary pattern: a novel technique for color and texture image retrieval for liver ultrasound images. *Multimed Tools Appl* **80**, 20773–20802 (2021). https://doi.org/10.1007/s11042-021-10758-7

[2] Shehata, Allam & Mohammad, Sherien & Abdallah, Mohamed & Ragab, Mohammad. (2015). A Survey on Hough Transform, Theory, Techniques and Applications.

i. Fire

1. Mean Color(RGB): [124.55131579 76.58157895 49.30526316]
2. Rendered: 

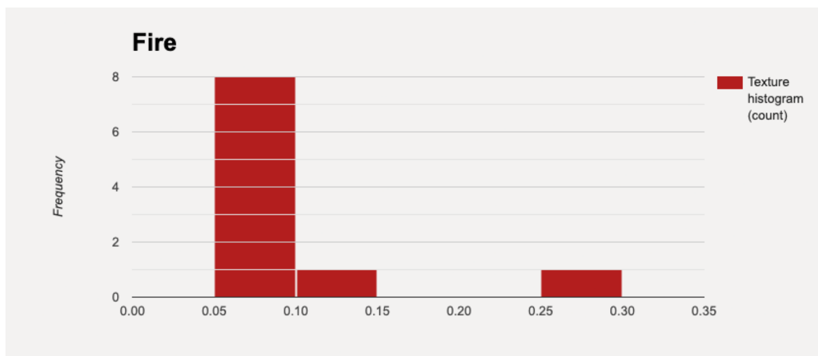
ii. No fire

1. Mean Color(RGB): [109.98618421 91.30592105 70.79473684]
2. Rendered: 

b. Texture features:

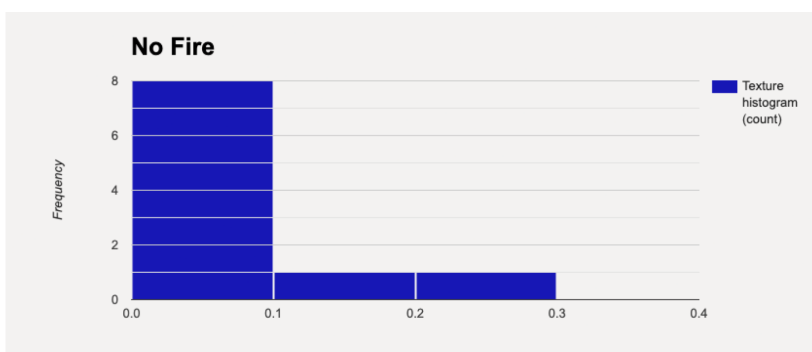
i. Fire

1. Mean texture histogram: [0.06006507 0.07980676 0.05662059 0.08273629 0.11452417 0.0981992, 0.0633392 0.09152522 0.09808499 0.25509851]
2. Graphed:

a. 

ii. No fire

1. Mean texture histogram: [0.07102698 0.08730452 0.0527248 0.06955737 0.09504303 0.0856665, 0.05804594 0.0956014 0.10015458 0.28487489]
2. Graphed:

a. 

c. Lines features:

i. Fire

            1. Mean line count: 145.51
        ii. No fire
            1. Mean line count: 565.99

8. ML model design

The ML model I created is a Support Vector Machines (SVM) used to classify images as either containing a forest fire or not. The was designed as follows:

1. Concatenate features into a single feature vector for each image and append the feature vector to a list.
2. Split the data into training and testing sets.
3. Normalize the features.
4. Select the top k features using the SelectKBest function from scikit-learn library.
5. Define the SVM classifier with a linear kernel.
6. Train the classifier using the training set.
7. Evaluate the performance of the model on the testing set by predicting the labels and computing accuracy and F1 scores.

9. Key insights/findings and ML model

The key figures used to evaluate the performance of the model was accuracy and f1; Accuracy which measures the percentage of correctly classified images out of all the images in the test set. The model achieved an accuracy of 0.78421, indicating that it was able to classify nearly 78.4% of the images in the test set correctly.

In addition to accuracy, the f1 score was also calculated to evaluate the model's performance. The f1 score is a weighted average of precision and recall, which are two other important metrics for classification tasks. The f1 score takes into account both the false positives and false negatives. The SVB model I created achieved an f1 score of 0.78418, which is very close to the accuracy score and indicates that the model is performing well.

Overall, these results suggest that the ML model developed in this code is a promising solution for the task of forest fire detection. However, further experimentation may be necessary to determine whether the model can generalize well to new datasets or if there are any particular image features or characteristics that the model struggles with.

10. Potential real-world applications of project

The real-world applications of this project are very intuitive and practical. The most obvious of these is that the model can be used to automatically detect the presence of a fire in images captured by aerial or ground-based cameras. This can allow firefighters and emergency responders to quickly locate and respond to forest fires, potentially reducing the amount of damage that the fire can cause. Right now satellite images and humans in fire towers are the main solution for this, so by using this model paired with a wirelessly connected imaging device forest fires would be able to be detected sooner.

11. Limitations of project work

The dataset for this project is fairly limited; it is limited by size and quality. With only 1900 images total it is a relatively small dataset and the model would be more accurate with more training data. Additionally, the images mostly depict fairly drastic forest fires and not subtle fires or smoke, this means that the ability of the model to early detect fires is limited because it was not trained on this information. The model being a SVB model is also fairly simplistic this makes it fast but with the relative nuance of forest fire detection a more complex model could be more appropriate.

12. Conclusion

In conclusion the model I created is very strong at assessing and predicting the fire status of the test set provided. Its relative effectiveness on real world fire images is still unknown but there is definitely potential for a model similar to this one. Future research in this area could focus on experimenting with different model designs and architectures, including neural networks, to see if there are ways to improve the model's performance. Additionally, more extensive testing on real-world images could be conducted to determine how the model performs under different conditions and environments. Overall, while the developed model shows promise in detecting forest fires from images, further research is needed to fully assess its potential for practical applications.[3]

[3] https://github.com/LeoSipowicz/ML_forrest_fire_detection