Final Project
Forest Fires Training and Classification using Linear discriminant analysis

CS 559 - Machine Learning: Fundamentals and Applications

May 15, 2021

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"I pledge my honor that I have abided by the Stevens Honor System."

PROBLEM

Forest fires, also known as wildfires, are an unwanted, unplanned and uncontrolled fire in an area of combustible vegetation such as a forest. Wildfires are among the most common forms of natural disaster in some regions of the world. Forests are made of wood which is very flammable and once a forest fire starts, it can rapidly spread on to a large area causing irreparable damage to animal and human habitat, putting their lives in danger as well as causing huge amounts of emissions. Over the past few years, there have been record-breaking temperatures, droughts and fire seasons. The fires that researchers have observed over the past few years have been large, aggressive fires that are very difficult to control.

In order to suppress forest fires, they need to be detected early and controlled before they spread out onto a larger area making it uncontrollable. The challenge is that forests cover a massive land area making it virtually impossible to physically surveil them. One solution to this problem is to make use of surveillance cameras and drones that are equipped with an image processing system that takes the live image and uses machine learning to detect if there is a forest fire in the pictures, and notify authorities to its location.

The goal of this project is to design a machine learning program that takes forest images as input and detects whether or not the pictures contain instances of forest fires. Such a program can then be utilized in forest fire surveillance systems.

DATA

The data being classified consists of images of forests with and without fires. The two classes in the data are fire and no fire. The image dataset was obtained from https://data.mendeley.com/datasets/gjmr63rz2r/1. The dataset consists of 1900 images: 950 fire images and 950 no fire images[1]. They are 3-channeled with a resolution of 250 × 250 retrieved by searching various search terms in multiple search engines.

An example of an image with fire (left) and no fire (right) is shown below:


METHODOLOGY

Our dataset consists of 1900 images: 950 fire images and 950 no fire images [1]. In order to parse the images into readable data, we used the feature extraction HOG method in order to parse the data into histograms with 8-bins. These images were parsed into an ‘aggregate.csv’ file, which contained the histograms of each image. Each histogram contains the number of pixels in the blue, green, red color channels in each of the 8bins. It also makes sure that the pixels are counted exactly three times. At the end of each row, we allocated a class label ‘1’ denoting that the image contains a fire, and ‘0’ denoting that the image does not have fire.

The histogram data was then read from the csv file. The data was randomized and split into two 50:50 sets of training and testing data. Principal component analysis was performed on the training data projecting the onto various numbers of axes. The same PCA projection is then applied on to the testing data. The testing data was then used to train a classifier using Maximum Likelihood Estimation using the following formula: $f(x) = \frac{1}{\sqrt{(2\pi)^3 det(\Sigma)}} e^{\frac{-(x-\mu)^T \Sigma^{-1}(x-\mu)}{2}}$.

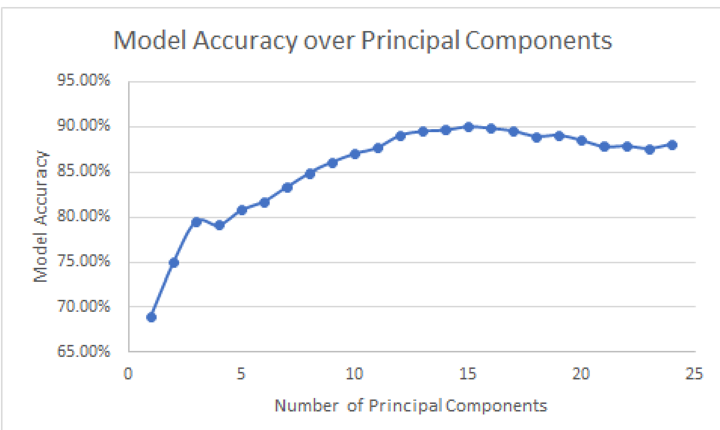
The model accuracy was then calculated. This process was repeated for 100 trials, each with different randomizations of the data. This procedure was conducted again, but this time using Fisher Linear Discriminant Analysis, instead of using PCA.

We repeated this approach, while changing different parameters, such as the number of axes and number of bins to see if we get more accurate results.

RESULTS

Comparing Different Number of Principal Components

PCA finds the direction with the largest variability and projects the data points onto the line. The best principal component was found to be 15. Adding more principal components caused the model accuracy to plateau and decrease slightly.



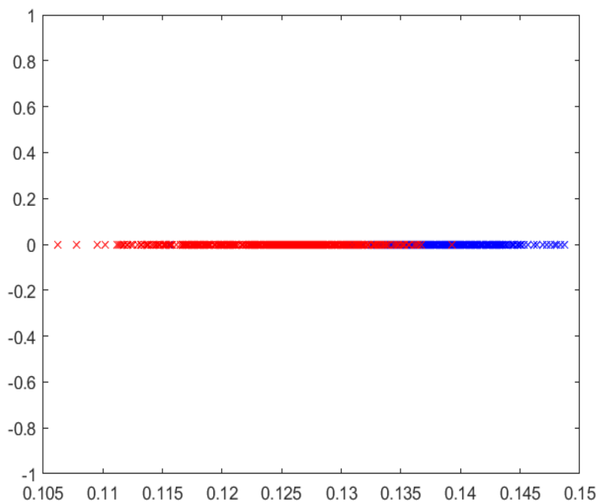
Axes	1	2	3	4	5	6	7	8	9	10	11	12
Accuracy	68.90%	74.85%	79.42%	79.02%	80.70%	81.66%	83.26%	84.83%	86.00%	86.93%	87.62%	88.97%
Std Dev	1.0283	1.2045	1.0698	1.0971	0.961	1.0871	1.1604	1.0681	1.0702	1.0182	1.0007	0.9468
Axes	13	14	15	16	17	18	19	20	21	22	23	24
Accuracy	89.44%	89.56%	89.95%	89.77%	89.49%	88.87%	89.00%	88.46%	87.74%	87.80%	87.53%	88.02%
Std Dev	0.9271	0.8391	0.7906	0.8704	0.8984	1.0736	1.1577	1.3056	1.2161	1.4903	1.2888	1.3689

Explanation of Results

As we increase the number of axes used for the PCA, we receive a better result in mean accuracy. By changing the number of axes, we will get varying results on accuracy of classification. For example, by performing the PCA on 1 axis, we received a mean accuracy of 68%, whereas increasing the number of axes to 10 gave us a mean accuracy of 87%. The best accuracy is found around 15 axes which is perhaps the most optimal number of principal components that should be used for this model.

Comparing LFDA vs PCA

When Fisher Linear Discriminant Analysis was applied to project the data before training a classifier using MLE, over 100 trials, the model accuracy was 85.72% and the standard deviation was 6.97. A scatter plot of the projection of one of the runs is shown below with red points representing images with the class label “fire” and blue representing “no fire”:



The LFDA projected model was successfully able to create a classification between the two data sets. There is a clear distinction between the two classes visually represented in the chart to the left.

LFDA produces a comparable model accuracy compared to PCA. Even though PCA has better overall accuracy over multiple axes, LFDA is able to produce a very accurate model on a single dimension linear axis. The benefit of such a model is that it allows us to visualize the data whereas when using PCA, it is difficult to visualize the data that is over 3 dimensions. That being said, the objective of the program is to have the highest accuracy possible so that forest fires can be detected with precision. The visualization of the data is not a necessity of the model. The model accuracy using the LFDA model had a much larger standard deviation indicating that there is still variability depending on what data is used for training and testing.

Comparing the number of bins

	PCA			LFDA	
Bins	**Axes**	**Accuracy**	**Std Dev**	**Accuracy**	**Std Dev**
4	9	90.22%	0.79	86.02%	8.28
8	15	90.00%	0.91	85.72%	6.97
16	23	88.62%	0.96	82.87%	9.34

The previous 2 models using PCA and LFDA were run on image data that split the frequency of each color channel, red, blue and green into 8 bins each. It is important to examine the effect of using different numbers of bins on the model. It was found that the lowest number of bins produced the marginally better results in the model. We found that if we have too many bins, the data distribution will look rough and it would be difficult to differentiate between the signal from the noise. On the contrary, using too few bins would make the histogram lose certain details that are needed to find important patterns in the data.

Tuning Parameters

For this project we tested results against various different parameters. By tuning different axes and various numbers of bins, we were able to see changes in our accuracy. As the number of axes grew for PCA, the higher accuracy we received until after 15, where it began to plateau. On the contrary, 4-8 bins were optimal for the image histograms which provided us marginally higher levels of accuracy. Other potential ways to tune parameters is by using a red filter to filter all the images first to extract just the red components of the images and run the PCA using the filtered images to see how it would impact accuracy. We could also filter the image using segmentation so that the small fire areas are more visible in the forest. Using these methods would most likely increase the accuracy of the model as the fire areas in the image become more apparent.

CONCLUSIONS AND RECOMMENDATIONS

We learned various valuable insights while completing this project. First, there are many different factors such as bin sizes, feature extraction methods, and types of machine learning analysis that can be altered in order to get better accuracy and more valuable information. We found that by increasing the number of axes used during the PCA, we get a larger mean accuracy. However, this increase gets diminishing returns in mean accuracy after 10 axes.

One issue with this study was that some of the images in the dataset were irrelevant to the problem that we are trying to tackle which is detecting forest fires. We had many images of the coast, bodies of water, and mountains where forest fires would not be possible. So in an ideal situation where we are able to collect and change our own dataset of images, we would only create the training and testing models based on forest images with either a fire or no fire.

For the purpose of this project, HOG was used as the method to parameterize the images and train a model on them. However there are other technique s such as segmentation that could be used that might improve the results. Alternatively, instead an infrared camera can be used to collect the image data as infrared has a much wider range than the visual spectrum.

We could also couple image data with ambient sensors associated with the surveillance camera that detect local temperature, humidity, wind speed, rain to produce a better model. Using these sensors would also give us more valuable information such as the probability of a fire occurring given a combination of different classifiers. For future research and development of this project, using a larger dataset consisting of different variables and applying other ML techniques would ensure a better model for predicting forest fires.

In conclusion, the best model to achieve the highest model accuracy was found to be using HOG to breakdown image data into histograms with 4 bins for each channel, projecting the data using PCA on to 9 principal components and finally using MLE to train a classifier in order to detect forest fires from image data. The model can be improved by making various enhancements such as segmentation, filters and additional ambient sensors.

REFERENCES

[1] Khan, Ali; Hassan, Bilal (2020), “Dataset for Forest Fire Detection”, Mendeley Data, V1, doi: 10.17632/gjmr63rz2r.1

[2] Shlens, Jonathon (2014), “A Tutorial on Principal Component Analysis”, Google Research Mountain View, CA 94043, V.3.02, https://arxiv.org/pdf/1404.1100.pdf