CSC 391 Project 4 Report

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1. Introduction of Project and Dataset

This project intends to build different models for classification. With an image given, the model predicts whether it is "palm" or "not palm". In Project 3, we examined the difference on the global features between palm trees and non palm trees images, using LBP and HOG. In this project, we will use these features of our training images to train the classification models and use testing images to test and see the accuracy. The models we try out in this project are support vector machine (SVM), random forest, and Kullback-Leibler divergence measure.

Going beyond Project 3, we expanded our dataset into 110 images of palms and 110 images of non palm trees. Of all 110 palm images, we have a variety of shapes, brightness condition, and scope. For example, some images contain palm leaves, some contain a whole palm tree. Of all 110 non palm images, we have a variety of regular tree leaves, branches, and brightness condition. Also, some non palm images contain no trees at all. Sample images of palms and non palms are shown below.

a. Palm Sample Images

b. Non Palm Sample Images

2. Local Binary Patterns (LBP) - Histogram

Before training the models with the images, we use LBP descriptors to see how different their features are. LBP is an effective texture operator which tells features of the texture of an image. Due to better image database than the one used in Project 3 which did not have close-up palm images, this time we are able to obtain clearer palm features.

Below in Fig [1] are 2 sample LBP histograms of palm images. Notice that they have high percentage of edges. Graphically, the bump in the middle in high. The height is determined by the amount of edges detected. This makes sense because palms are very different from its background, making their images high in edge features.

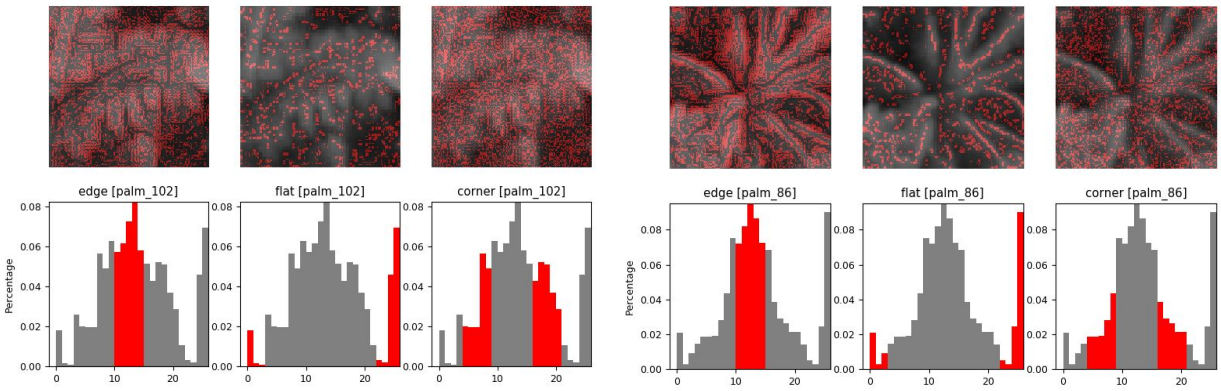


Fig [1]: Sample Palm Images and LBP Histograms

Below in Fig [2] are 2 sample LBP histograms of non palm images. Notice that they do not show high percentage in edge features, but they have high percentage in flat regions.

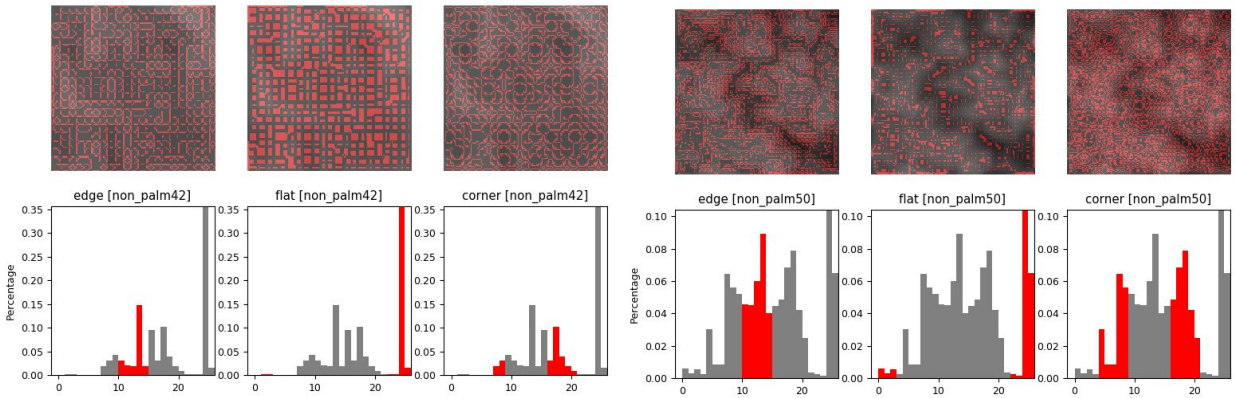


Fig [2]: Sample Non Palm Images and LBP Histogram

Below in Fig [3] are 2 sample irregular LBP histograms of non palm images. They have high percentage in edge features, just like palms. The left one is probably due to its branches that cause a lot of edges to be detected. The right one is the most common irregularity in which the image is clearly non palm but still have high percentage in edge features. This might be due to the fact that these images are very blurred. Thus, any small difference could be detected as edges. Even though the edge features are similar to those of palms, these non palm images also have high percentage in corners, while palms are usually low in corners. This difference in corner may help classify palm and non palms when their features look alike.

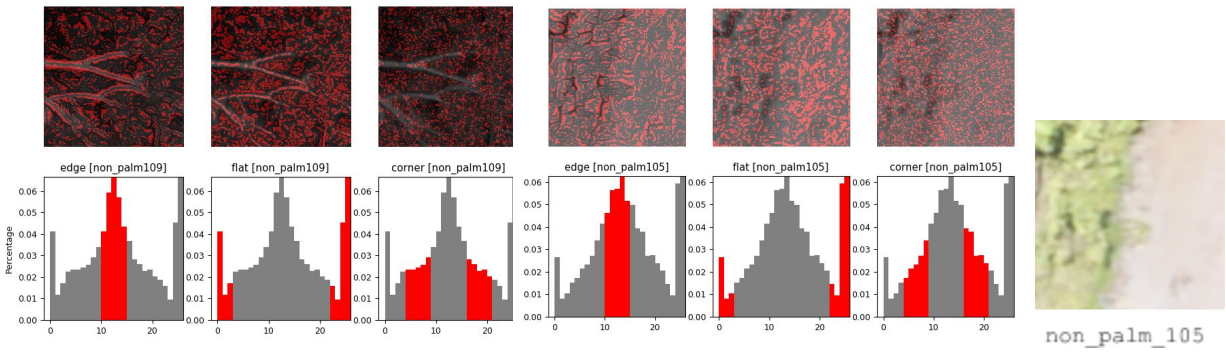


Fig [3]: Irregular Sample Non Palm Images and LBP Histogram

3. Support Vector Machine with LBP Descriptors

We used random number generator to generate 55 numbers from 0 to 219, which is ¼ of the total data, to be the testing set, and the rest is the training set. Then we use the LBP values from the training set to fit the SVM machine with the default RBF kernel. Afterwards, we put the LBP values from the testing set into the SVM to predict the classification and thus we can see the accuracy of this model. The result turns out to be pretty high, in which 92% of the non palms are correctly classified and 90% of the palms are correctly classified.

	precision	recall	f1-score	support
non_palm	0.92	0.88	0.90	26
palm	0.90	0.93	0.92	29
micro avg	0.91	0.91	0.91	55
macro avg	0.91	0.91	0.91	55
weighted avg	0.91	0.91	0.91	55

Fig [4]: SVM with LBP Output

Below is the confusion matrix, which shows that of all 25 non palms detected, 23 turn out to be correct; of all 30 palms detected, 27 turn out to be correct. Visually, we focus on the upper left and bottom right block. The darker the blocks are the more images are correctly classified.

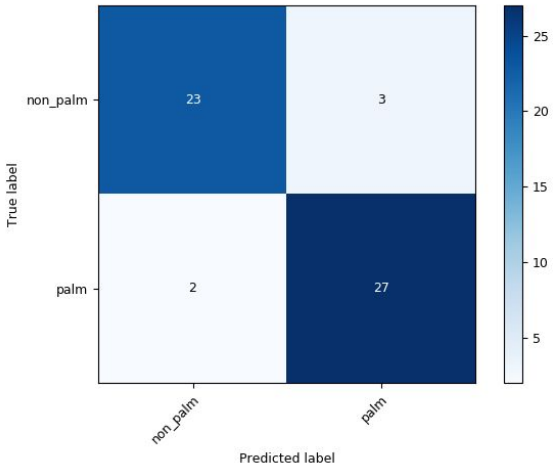


Fig [5]: SVM with LBP Confusion Matrix

4. Support Vector Machine with HOG Descriptors

We used a similar approach for SVM with Hog descriptors. Here the variable we use to train the SVM is the feature descriptor (fd) stored in `fd, hog_image = hog(image_resized, ...`. The accuracy of the model is shown below. The precision for non palms is 86%, and 96% for palms.

	precision	recall	f1-score	support
non_palm	0.86	0.96	0.91	26
palm	0.96	0.86	0.91	29
micro avg	0.91	0.91	0.91	55
macro avg	0.91	0.91	0.91	55
weighted avg	0.91	0.91	0.91	55

Fig [6]: SVM with HOG Output

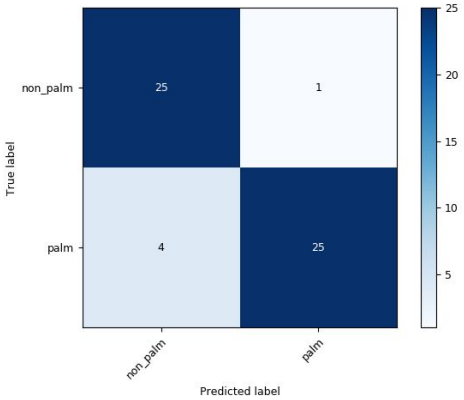


Fig [7]: SVM with HOG Confusion Matrix

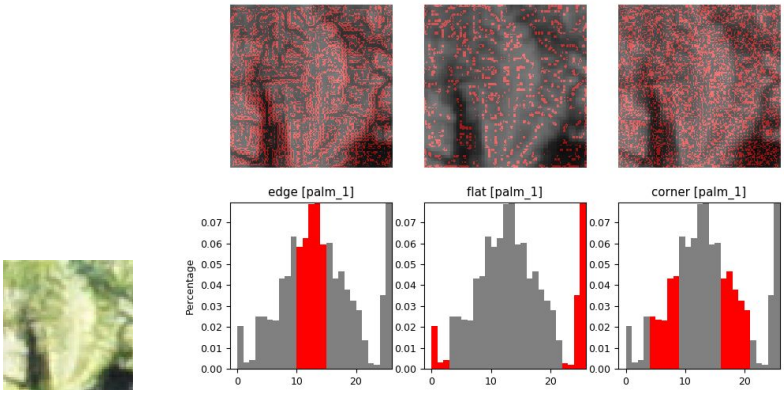
5. Misclassified Images Using Support Vector Machine

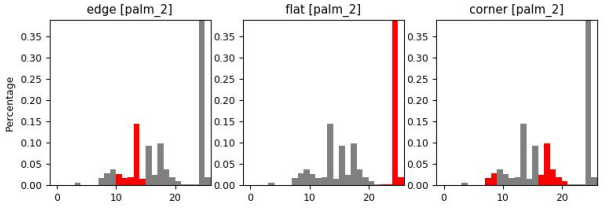
After the classification process, the program outputs a list of images that are misclassified. The output is shown below. The numbers are the index in the image array in which 0 to 109 are the palm images and 110 - 219 are the non palm images.

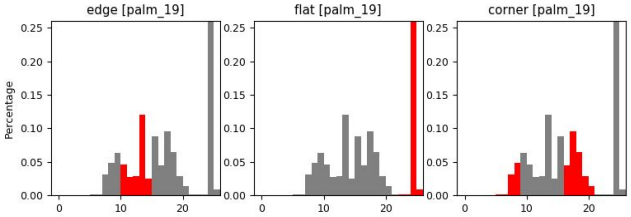
```
Missclassified SVM LBP:  210
Missclassified SVM LBP:  188
Missclassified SVM LBP:  19
Missclassified SVM HOG:  19
Missclassified SVM HOG:  59
Missclassified SVM HOG:  185
Missclassified SVM HOG:  1
Missclassified SVM LBP:  2
Missclassified SVM HOG:  2
Missclassified SVM LBP:  198
```

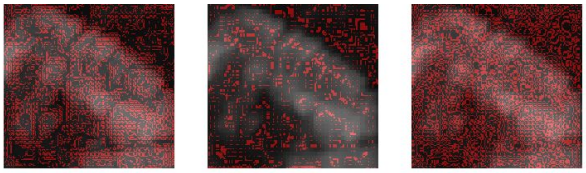
Fig [8]: Images Misclassified by SVM

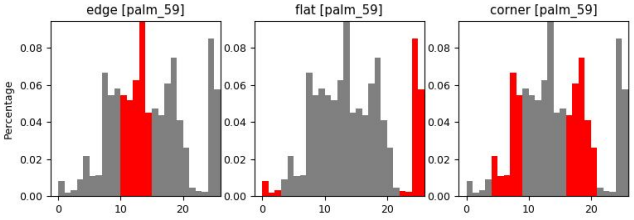
From here we can get those misclassified images and see why they are misclassified.

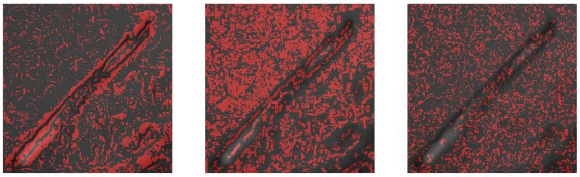


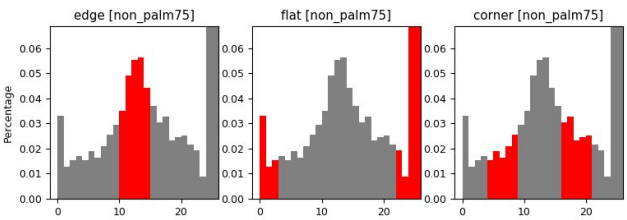

edge [palm_2]
flat [palm_2]
corner [palm_2]
Percentage


edge [palm_19]
flat [palm_19]
corner [palm_19]
Percentage




edge [palm_59]
flat [palm_59]
corner [palm_59]
Percentage




edge [non_palm75]
flat [non_palm75]
corner [non_palm75]
Percentage

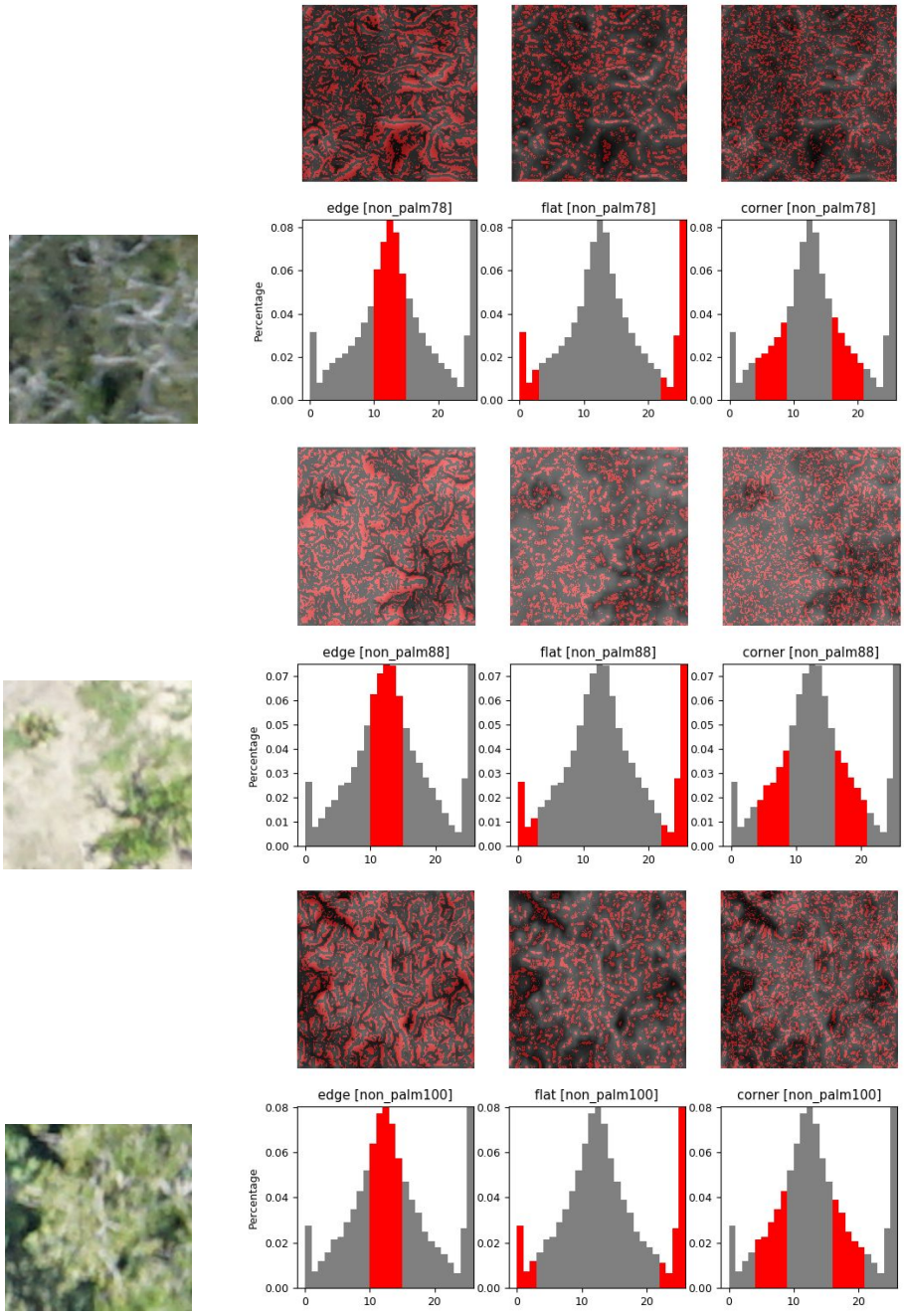


Fig [9]: 8 Misclassified Images

One pattern we can conclude is that SVM tends to misclassify when palm images have high percentage in corner and non palm images have high percentage in edges.

6. Random Forest with LBP and HOG Descriptors

The second method we use for classification is random forest. The accuracy is shown below. We can see that it is lower than the result by SVM.

```
RF LBP Accuracy: 0.7272727272727273
RF HOG Accuracy: 0.8
```

Fig [10]: Random Forest Results

7. Kullback-Leibler Divergence Measure with LBP Descriptors

Last but not least, we use Kullback-Leibler Divergence Measure with LBP Descriptors to match the testing set with one in the "database". The database is the training set we used for SVM and random forest. This method matches a testing image with one of the image in the database based on the similarity of their LBP features. This method computes a score for all images in database and outputs the highest score that matches the testing image.

```
accuracy:  0.4909090909090909
```

Fig [11]: Kullback-Leibler Result

The accuracy is the lowest among the three.

8. Comparison Conclusion

Overall, SVM is the best with high accuracy using both LBP and HOG features. Random forest is the second and Kullback-Leibler has low accuracy.