Project Title and Members

Wood classification in computer vision: A Survey

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https://github.com/haroldle/feature_engineering_class_project

Idea description

Benchmarking multiple state-of-the-art deep learning models (VGG16, ResNet, Vision Transformer) and traditional computer vision models to understand how each feature extraction technique affects the prediction. Traditional Computer vision techniques include LBP - Local Binary Pattern with variants with SVM - Support Vector Machine, and using feature fusion technique (fusing LBP with SIFT - Scale Invariant Feature Transform descriptor); inspired by [4]

Goals and Objectives:

Goal: This paper aims to answer two questions: Can deep learning models perform better than the proposed method in An automatic recognition system? How does each feature extraction technique affect the performance of the models?

Objectives: In answering those questions, these are the objectives:

1. Understanding the image dataset
2. Recreating the model from D. V. Souza *et al* [2]
3. Creating a simple feature fusion model (SIFT with LBP) that is based on Feng Yang, Zheng Ma, and Mei Xie [3]
4. Doing Transferred Learning on VGG16, Siamese Net, Vision Transformer.

Motivation

Computer vision based on wood classification is a small area in wood science [5]. This paper could be an inspiration for expanding computer vision based on wood classification.

Significance

The significance of this paper is trying to introduce wood anatomists to a better way to classify wood. According to Hwang SW, Sugiyama J [5], the wood classification process is still manual work. Besides that, classifying wood correctly is “the fundamental aspect for the conservation flora.” [2]

Features

The dataset is from D. V. Souza *et al* [2]. It contains 46 different wood species. For each species, there are roughly 17 images.

The feature extraction techniques that we are going to use are:

1. Local Binary Pattern (texture feature), [2, 5, 7]
2. SIFT (local feature), [1]
3. Feature fusion (fusing multiple features for classifying) (SIFT with LBP) or (LBP with multiple variation),; inspired [4]
4. CNN (convolutional neural network - vanilla VGG), [8]
5. Siamese - calculating distance between feature vectors (two CNN models) [6]
6. Transformers (discarding CNN and only using an attention mechanism to learn; in this case, it learns the image pixel directly without doing any convolutional technique.) [3]

We have done 1 and 3. In three we specifically only did with 1 with some variance.

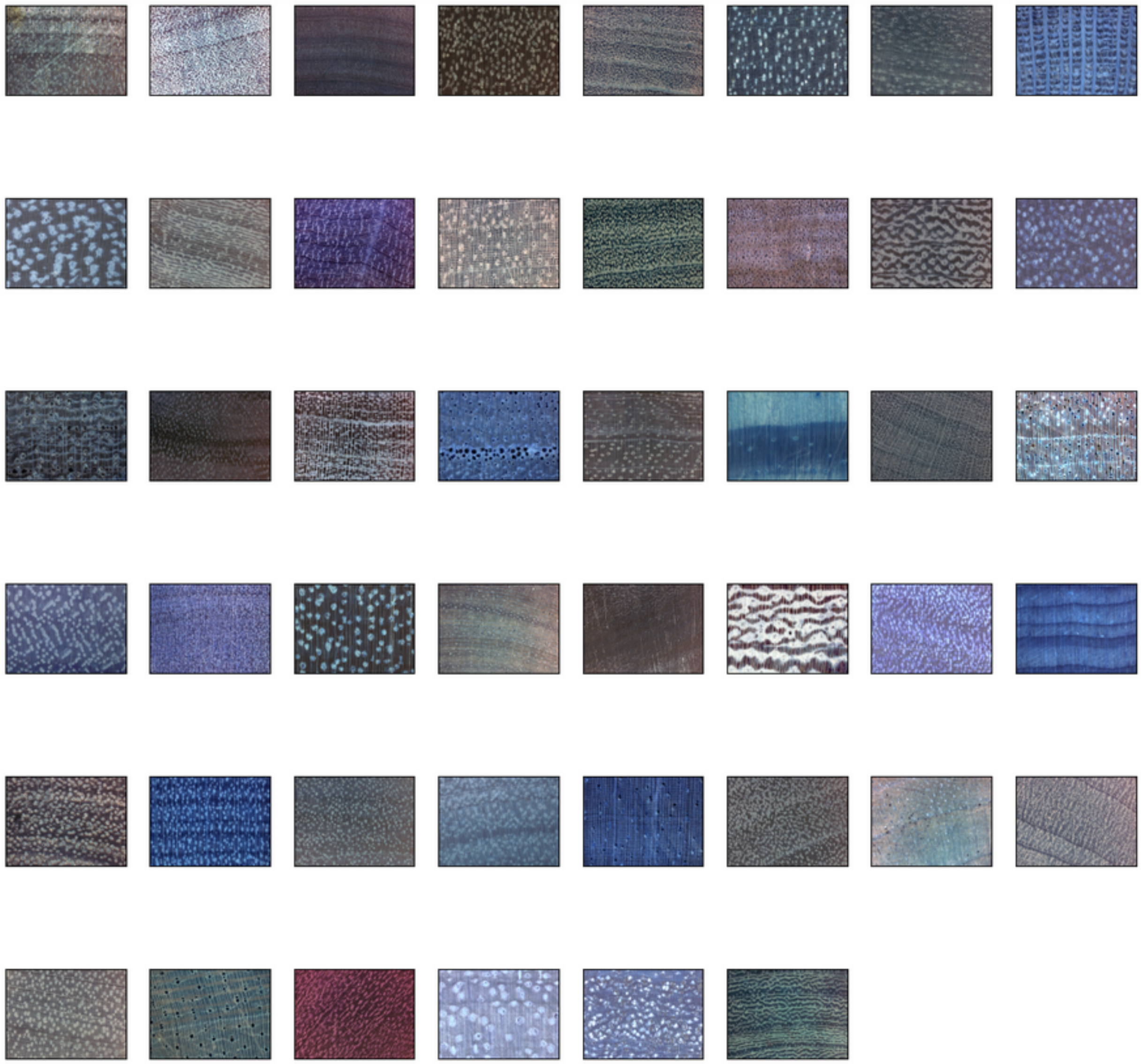
Related work

LBP (multiple variants). LBP has been used intensively in wood classification [2, 5] and defection [7]. By fusing LBP variants, the machine learning model performances greatly increase [2].

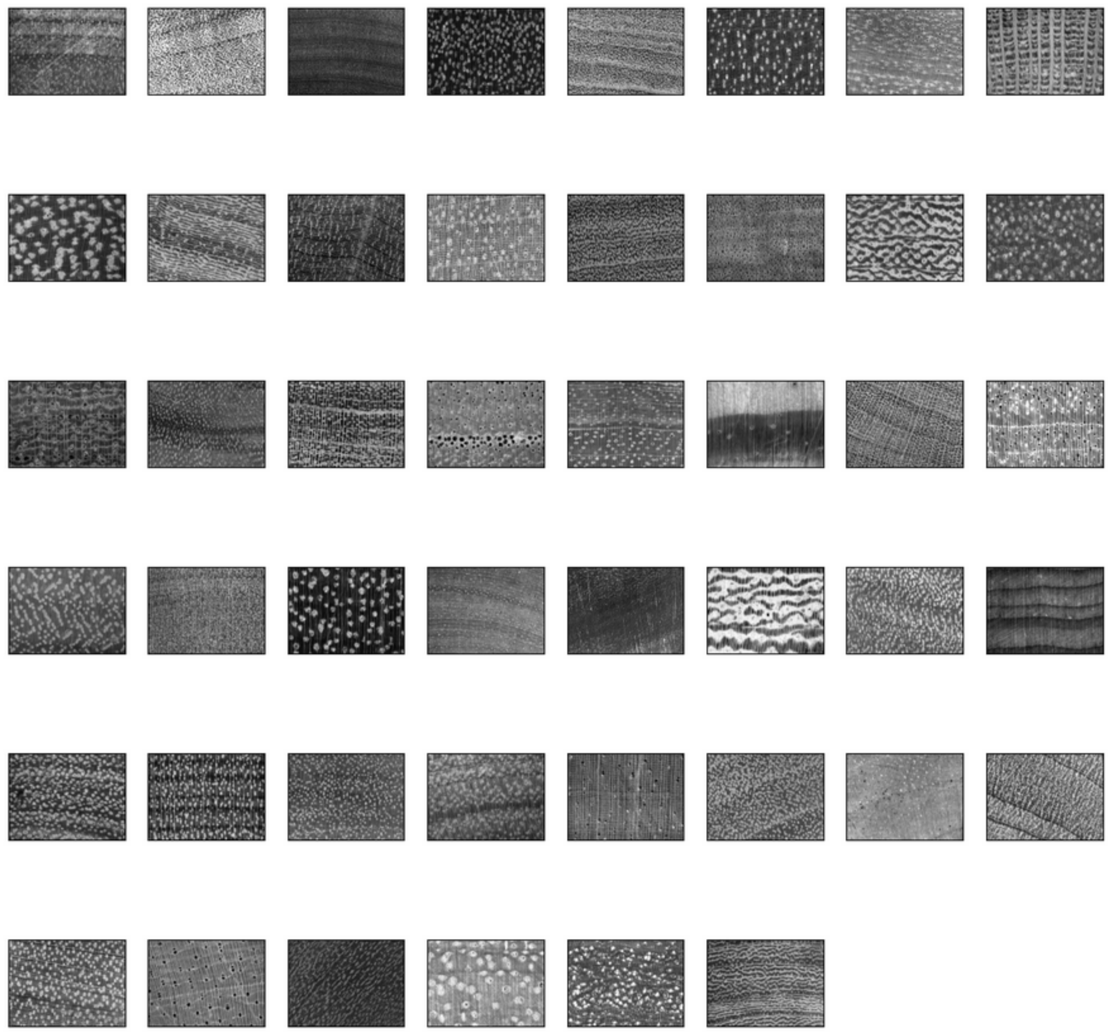
Vanilla CNN. Vanilla CNN - (VGG16 and ResNet) - is used in wood classification [5]. These models have a potential in learning the feature patterns of the woods' images.

Dataset

The dataset is from D. V. Souza *et al* [2]. It contains 46 different wood species. For each species, there are roughly 17 images. A picture of all wood species can be seen on the next page.

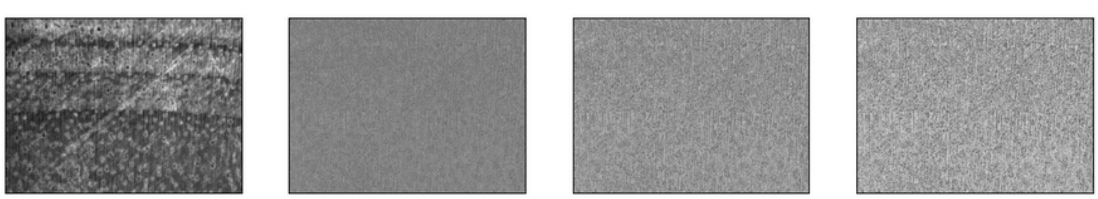


Detail design of Features



The above image shows all the images as grayscale which is the first step for getting the features.

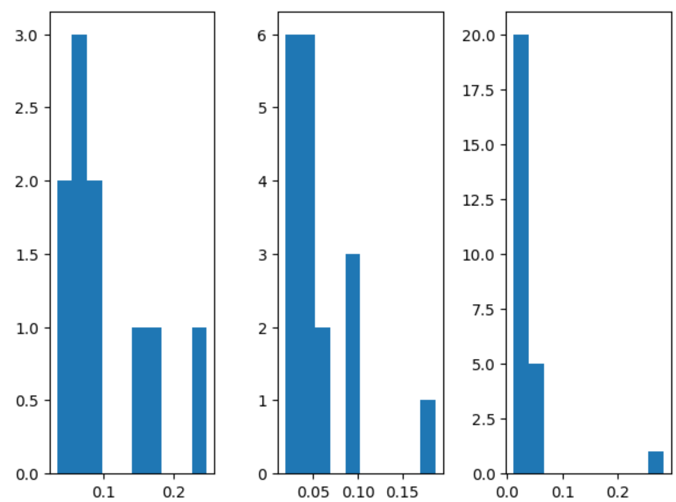
```
FROM LEFT TO RIGHT
ORIGINAL IMAGE => LBP 8 POINTS WITH RADIUS OF 1 => LBP 16 POINTS WITH RADIUS OF 2 => LBP 24 POINTS WITH RADIUS OF 3
Out[5]: <matplotlib.image.AxesImage at 0x7f86ec4b7fa0>
```



The image above is an example of Local Binary Pattern(LBP) being performed on an image. In this case we are doing rotation invariant uniform images. We also performed for non rotation invariant uniform images but the result looks similar and one must look closely to see a difference.

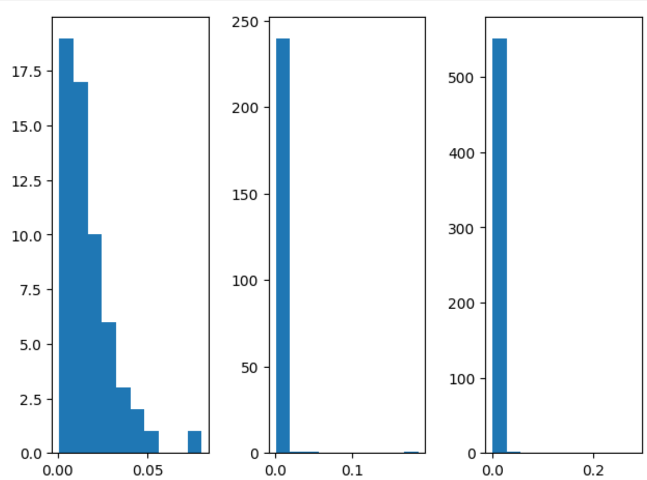
Below we can see a histogram of LBP rotation invariant with the left histogram being for 8 points with a radius of 1, the middle is the LBP rotation invariant for 16 and a radius 2, and the right histogram is LBP rotation invariant of 24 and a radius of 3.

```
In [7]: fig, ax = plt.subplots(1, 3)
        fig.tight_layout()
        ax[0].hist(extract(an_image, 8, 1.0, 'uniform'))
        ax[1].hist(extract(an_image, 16, 2.0, 'uniform'))
        ax[2].hist(extract(an_image, 24, 3.0, 'uniform'))
        plt.show()
```



Below we have histograms of LBP non-rotation invariant with the same setup as the above.

```
In [10]: fig, ax = plt.subplots(1, 3)
         fig.tight_layout()
         ax[0].hist(extract(an_image, 8, 1.0, 'nri_uniform'))
         ax[1].hist(extract(an_image, 16, 2.0, 'nri_uniform'))
         ax[2].hist(extract(an_image, 24, 3.0, 'nri_uniform'))
         plt.show()
```



Analysis & Implementation

The local binary pattern (LBP) requires a grayscale image. This process is done by comparing the center pixel to the surrounding neighbor pixels. For each surrounding pixel we compare it to the center and if the center is larger than the neighbor than the neighbor get assigned 1 and in the reverse gets assigned a 0. Then after that is done for each neighbor then it is flattened out and numbered by the index. This gets raised to power of 2 which then gives the decimal number which is the LBP value. This value is then placed in the output array. This technique extracts local features in the image and since we are doing tissue we care more about local features than about global features. We care about local features as with global features all the tissues will look the same. We perform basic fusion for the radiuses of 1,2, and 3 of 8,16, and 24 points. We perform it twice, once for rotation invariant uniform and non rotation invariant uniform.

We created Random Forest and Support Vector Machine models to classify the 46 classes of wood tissue. We looked at the accuracy of these models and the accuracy from the paper. These models were done twice, one time for non rotation invariant uniform images and second for the rotation invariant uniform images.

Preliminary Results

For each result we are showing the accuracy, macro average, and weighted average of the overall model for precision, recall, f1-score, and support. We have it for each wood species as well but are only showing the overall models here as there are 46 classes and would be really long to see here. The full results can be seen in https://github.com/haroldle/feature_engineering_class_project/blob/main/Classification%20report.ipynb.

Below we have a screenshot of the accuracy of Random Forest for non rotation invariant uniform images.

accuracy	0.897260	0.897260	0.897260	0.89726
macro avg	0.902413	0.887320	0.883882	438.00000
weighted avg	0.915166	0.897260	0.896519	438.00000

Below we have a screenshot of the accuracy of Random Forest for uniform images.

accuracy	0.840183	0.840183	0.840183	0.840183
macro avg	0.838656	0.833783	0.821604	438.000000
weighted avg	0.855396	0.840183	0.834999	438.000000

Below we have a screenshot of the accuracy of Support Vector Machine for non rotation invariant uniform images.

accuracy	0.888128	0.888128	0.888128	0.888128
macro avg	0.887396	0.886959	0.880041	438.000000
weighted avg	0.903899	0.888128	0.890186	438.000000

Below we have a screenshot of the accuracy of Support Vector Machine for uniform images.

accuracy	0.956621	0.956621	0.956621	0.956621
macro avg	0.948903	0.953359	0.946784	438.000000
weighted avg	0.962870	0.956621	0.956783	438.000000

We can see from these results that the SVM model for uniform images performs the images. We could not reach the level of accuracy for the models D. V. Souza *et al* [2] which had an accuracy of 97 percent.

Project Management

Work completed and Description:

Based on the objectives we have completed 1 and 2. Sarah did the model training and classification report on SVM and Random Forest for 100%. Le did the data understanding and LBP feature extraction for 100%. Sarah has done 100% of the document while Le did 100% of the video and source code description.

Issues/Concerns:

We are a little further behind than we thought we would be. We figured we should be almost done with part 3 but we have not started it because it took longer to understand the dataset and do the LBP feature extraction than we originally planned. Therefore we will be skipping part 3 for now and begin working on the Siamese Net and compare. If we have time we will come back to part 3 to implement and compare with the other models.

References

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