Anomaly detection in Wood

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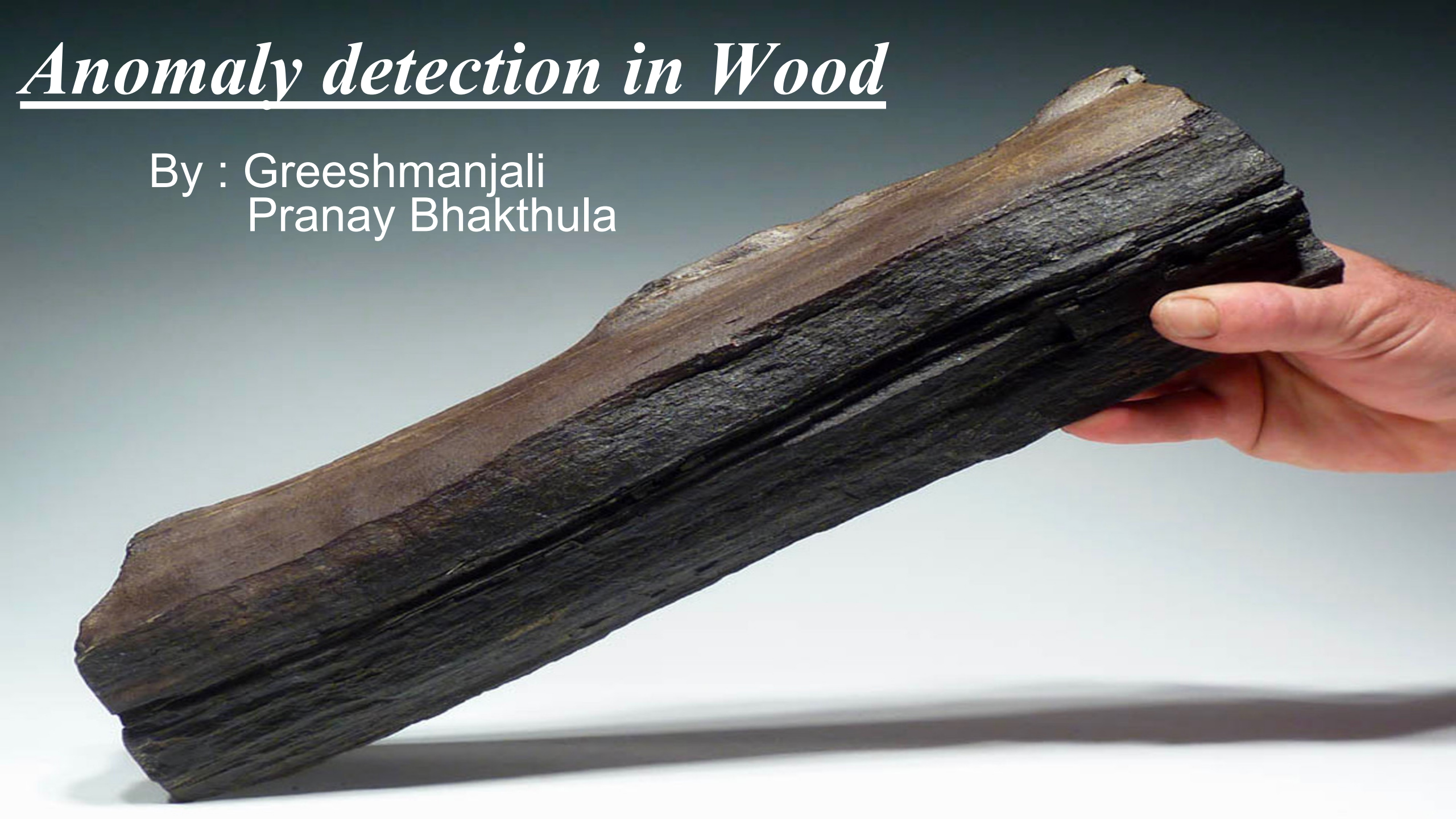


Introduction

- Based on paper ‘Chimpanzee wooden tool analysis advances the identification of percussive technology’ Co-authored by Prof. Chen Zeng .
- In this project we aim to find best method to detect anomalies in the wood; i.e, it can distinguish damaged part of the wood from the undamaged part.
- To get to know what is common and distinct among the damaged and undamaged part, and figure out the correlation among 13 haralick features for different species.

Datasets:

Dataset 1:

There are 31 different images of wood species in the dataset .

Dataset 2:

This dataset contain various images of one species named ‘Coula’.

Methods

Dataset1:

- Used python libraries to mark and trim the damaged and undamaged area.
- Generated cuts (1 mm to 9mm) on the damaged and undamaged part of the wood
- Performed EDA to generate the density plots for the 13 haralick features.

Dataset2:

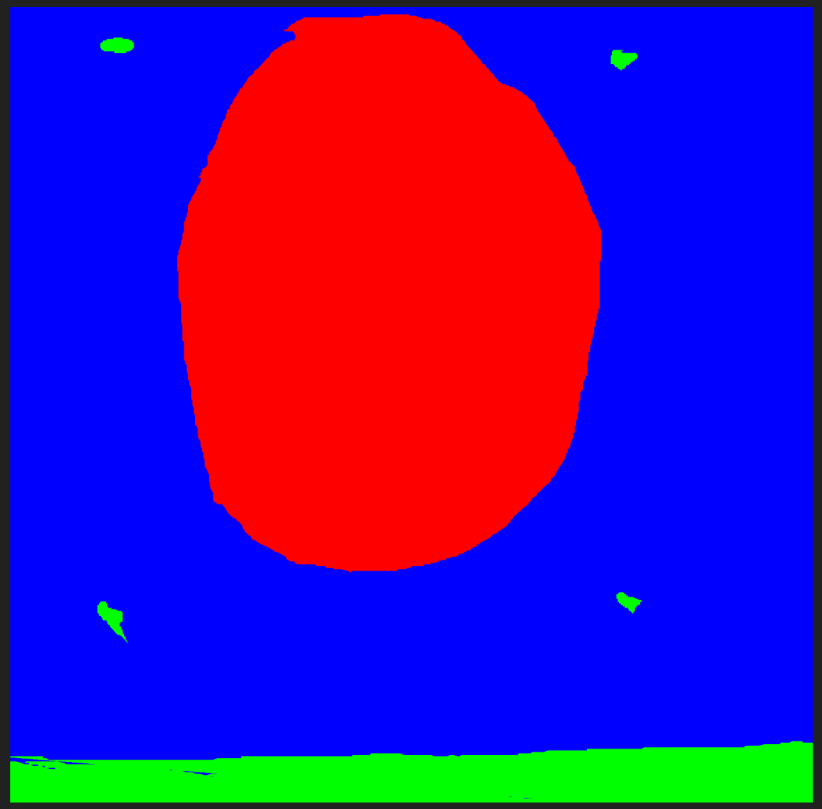
- Performed EDA to generate the density plots for the 13 haralick features.
- Calculated Gray-Level Co-occurrence Matrix (GLCM) for 13 haralick features.

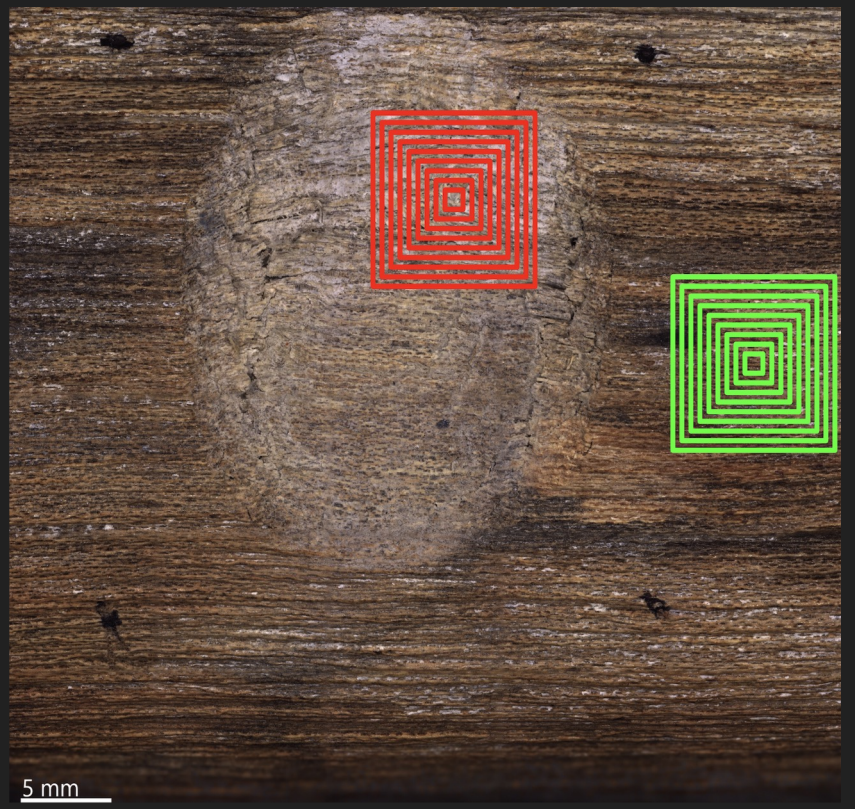
Dataset-1


5 mm


5 mm


7 mm





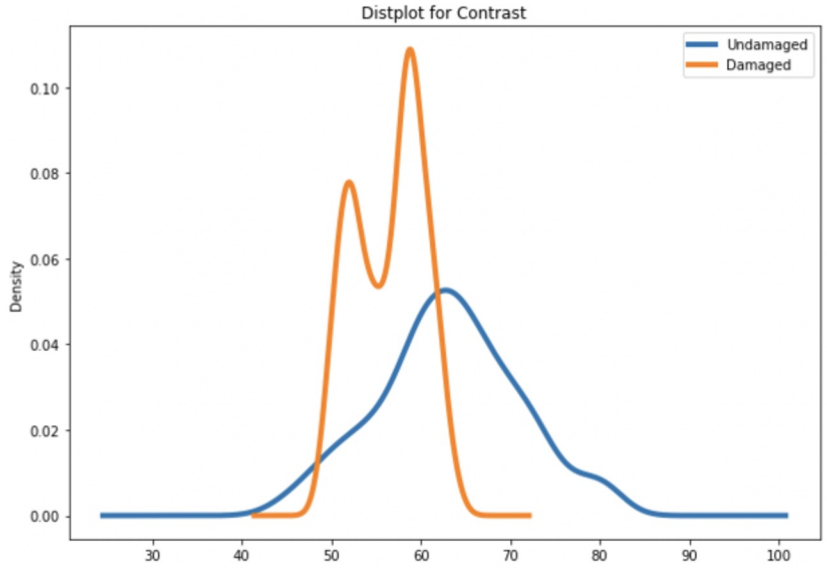
AX2_7316_747_5

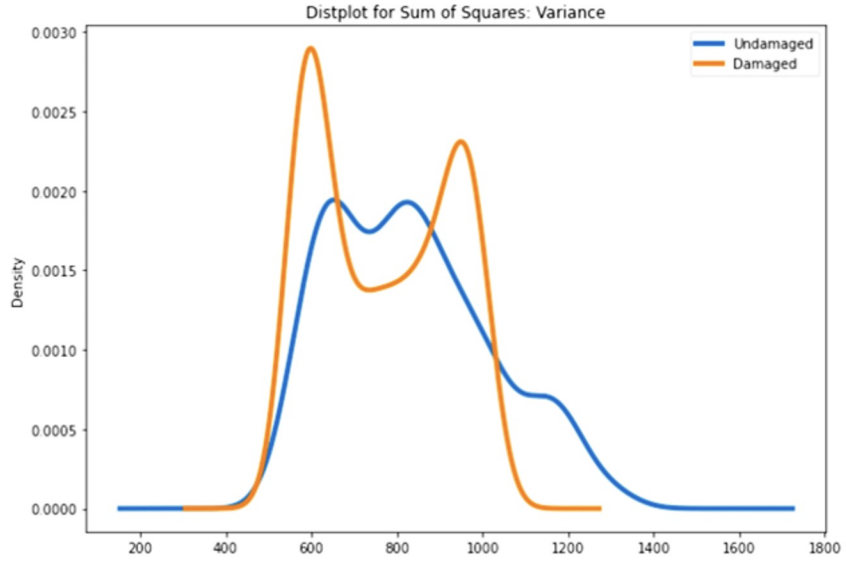
- I marked the image; here red indicates the damaged area, blue indicates the undamaged area and green is the non-wood.

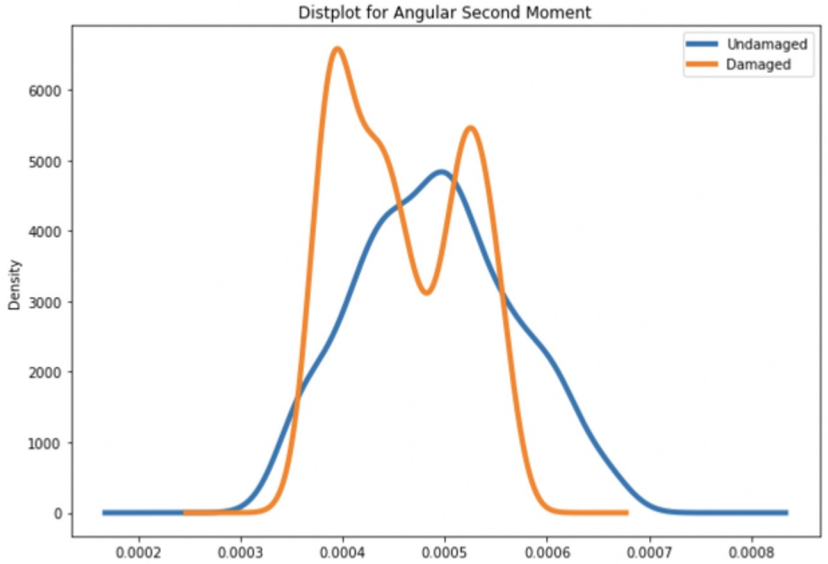
- I generated cuts from 1 mm - 9mm for all the species

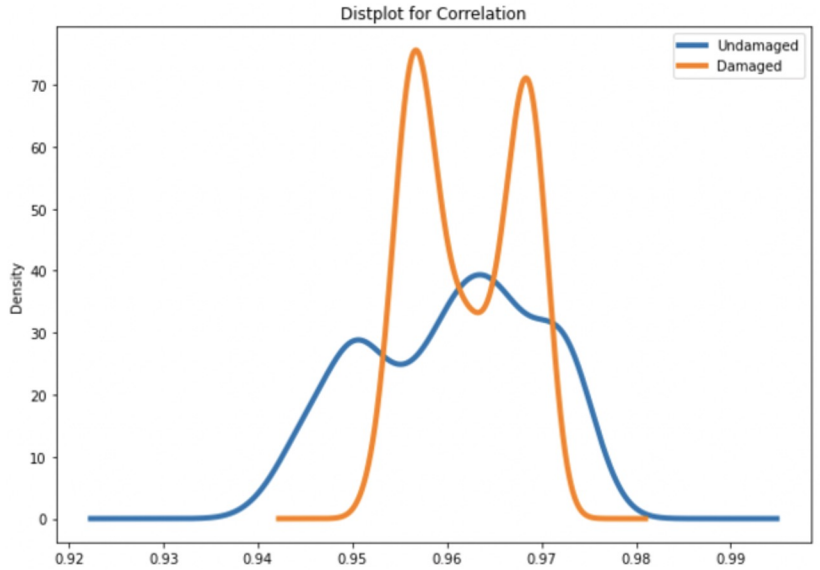
What are haralick features?

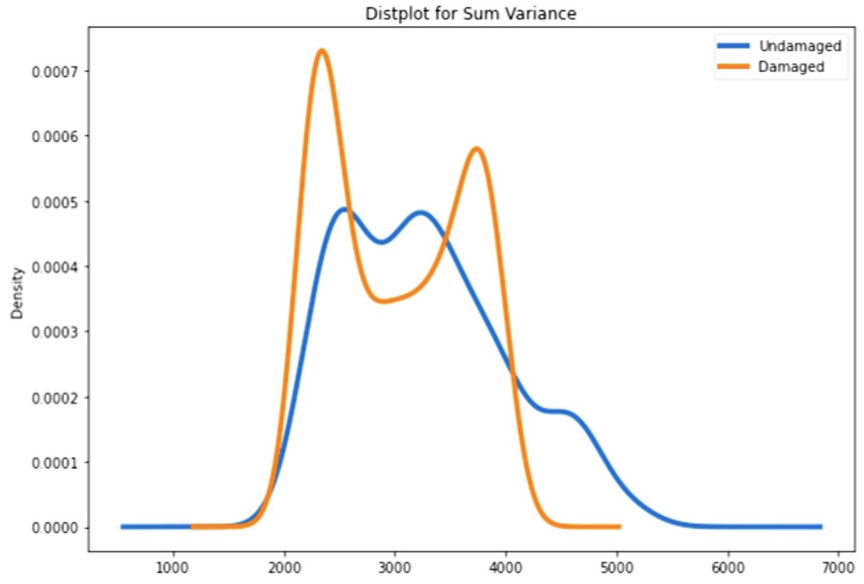
Haralick texture features are common texture descriptors in image analysis. To compute the Haralick features, the image gray-levels are reduced, a process called quantization. The resulting features depend heavily on the quantization step, so Haralick features are not reproducible unless the same quantization is performed. The Haralick texture features are functions of the normalized GLCM, where different aspects of the gray-level distribution in the ROI are represented. For example, diagonal elements in the GLCM represent voxels pairs with equal gray-levels.

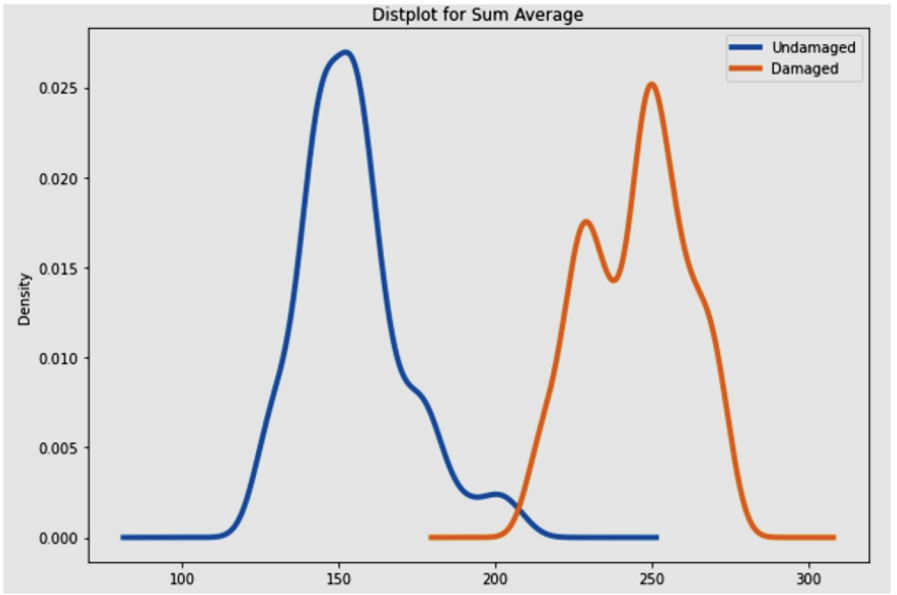

Distplot for Contrast
Undamaged
Damaged
Density
0.10
0.08
0.06
0.04
0.02
0.00
30
40
50
60
70
80
90
100

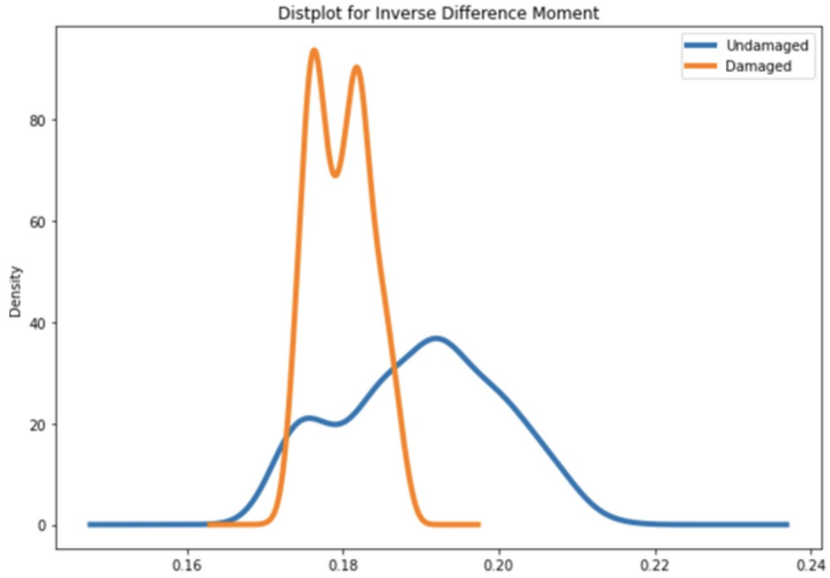

Distplot for Sum of Squares: Variance
Undamaged
Damaged
Density
0.0030
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
200
400
600
800
1000
1200
1400
1600
1800

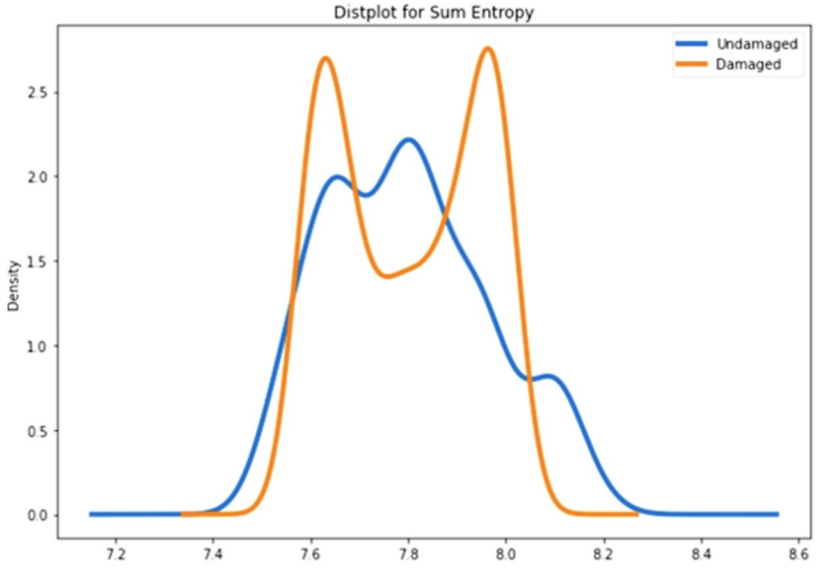

Distplot for Angular Second Moment
Undamaged
Damaged
Density
6000
5000
4000
3000
2000
1000
0
0.0002
0.0003
0.0004
0.0005
0.0006
0.0007
0.0008

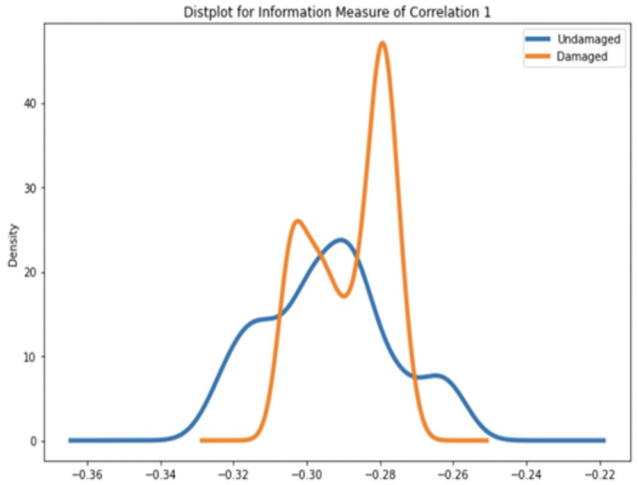

Distplot for Correlation
Undamaged
Damaged
Density
70
60
50
40
30
20
10
0
0.92
0.93
0.94
0.95
0.96
0.97
0.98
0.99

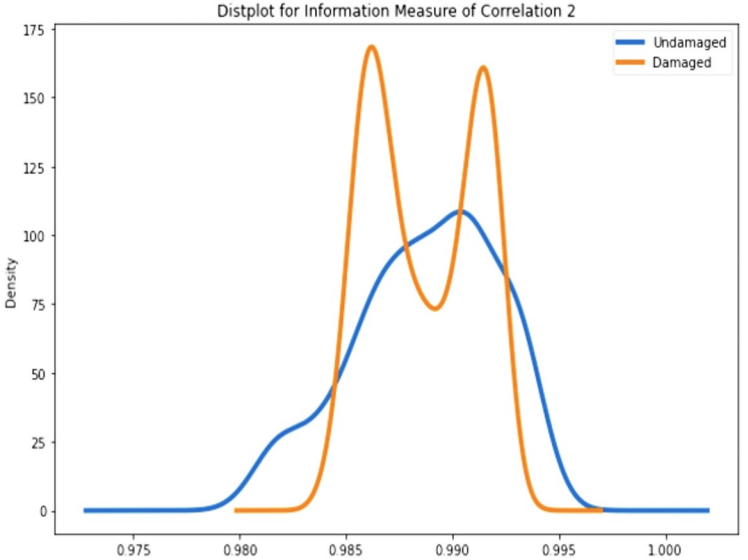

Distplot for Sum Variance
Undamaged
Damaged
Density
0.0007
0.0006
0.0005
0.0004
0.0003
0.0002
0.0001
0.0000
1000
2000
3000
4000
5000
6000
7000

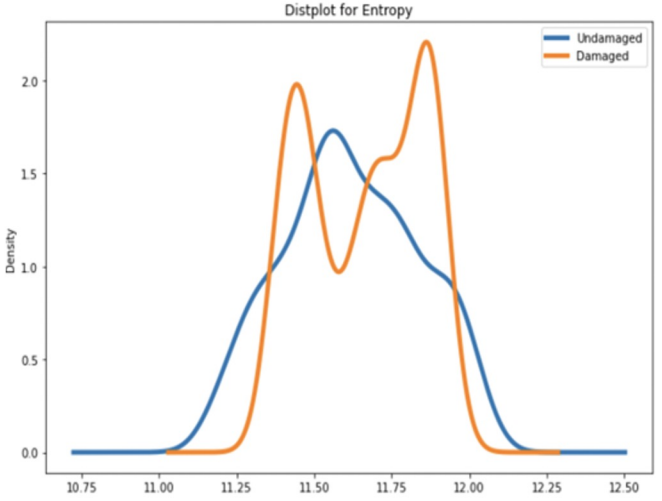

Distplot for Sum Average
Undamaged
Damaged
Density
0.025
0.020
0.015
0.010
0.005
0.000
100
150
200
250
300

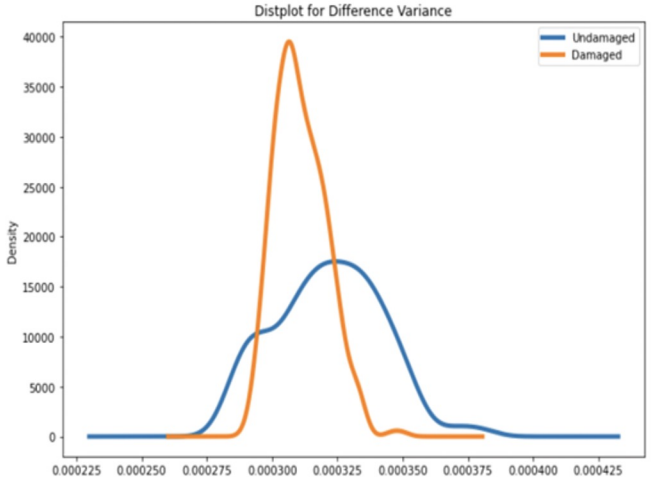

Distplot for Inverse Difference Moment
Undamaged
Damaged
Density
80
60
40
20
0
0.16
0.18
0.20
0.22
0.24

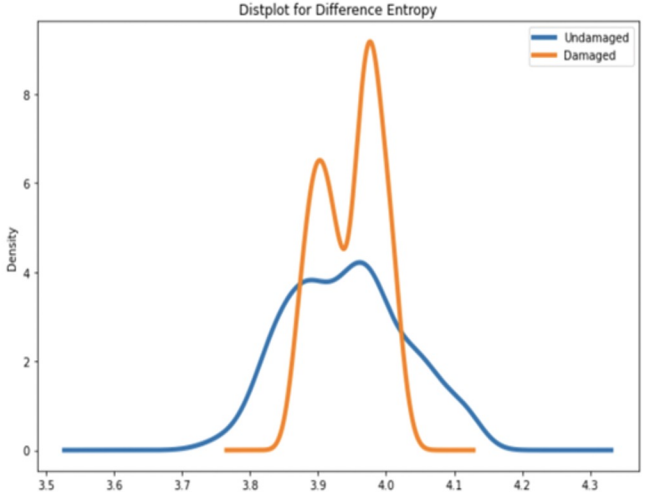

Distplot for Sum Entropy
Undamaged
Damaged
Density
2.5
2.0
1.5
1.0
0.5
0.0
7.2
7.4
7.6
7.8
8.0
8.2
8.4
8.6


Distplot for Information Measure of Correlation 1
Undamaged
Damaged
Density
40
30
20
10
0
−0.36
−0.34
−0.32
−0.30
−0.28
−0.26
−0.24
−0.22


Distplot for Information Measure of Correlation 2
Undamaged
Damaged
Density
175
150
125
100
75
50
25
0
0.975
0.980
0.985
0.990
0.995
1.000


Distplot for Entropy
Undamaged
Damaged
Density
2.0
1.5
1.0
0.5
0.0
10.75
11.00
11.25
11.50
11.75
12.00
12.25
12.50


Distplot for Difference Variance
Undamaged
Damaged
Density
40000
35000
30000
25000
20000
15000
10000
5000
0
0.000225
0.000250
0.000275
0.000300
0.000325
0.000350
0.000375
0.000400
0.000425

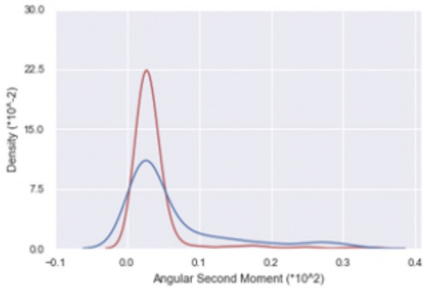

Distplot for Difference Entropy
Undamaged
Damaged
Density
8
6
4
2
0
3.5
3.6
3.7
3.8
3.9
4.0
4.1
4.2
4.3

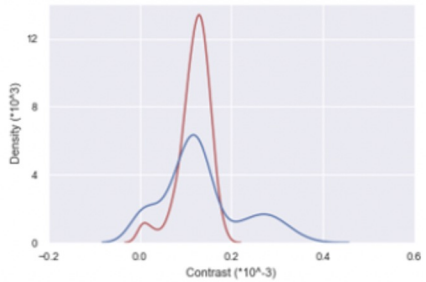
Dataset 2

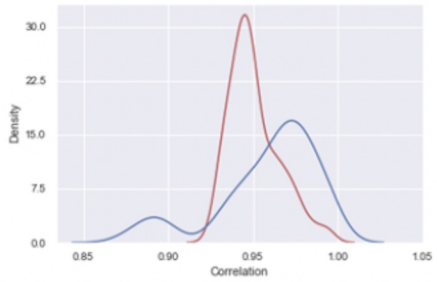

7 mm

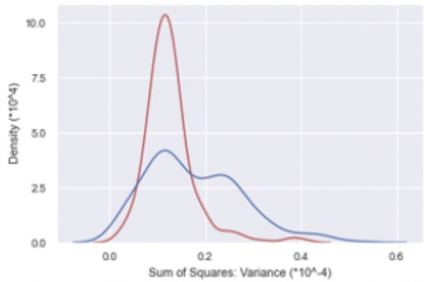

7 mm

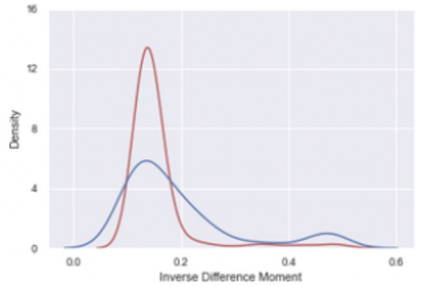

6 mm

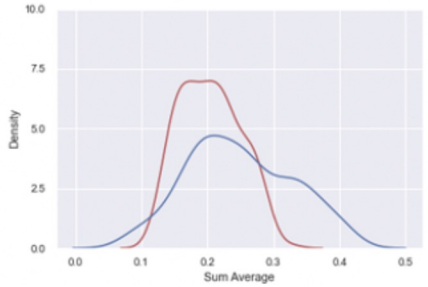


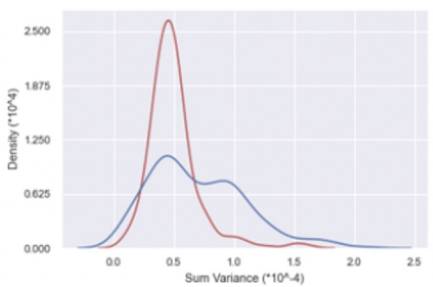


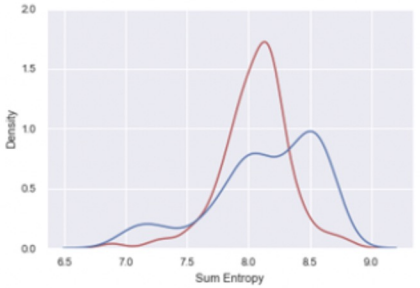


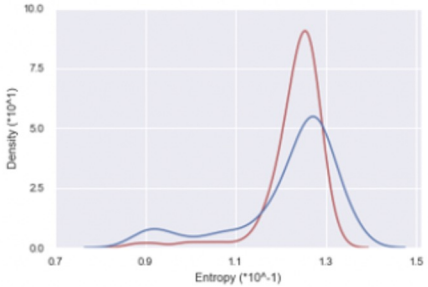


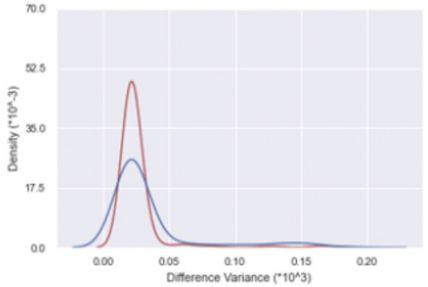


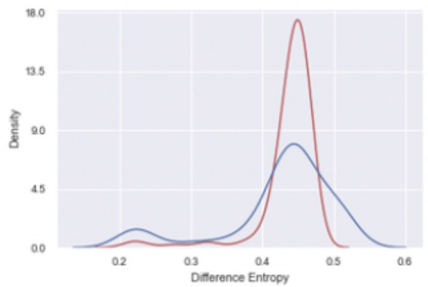


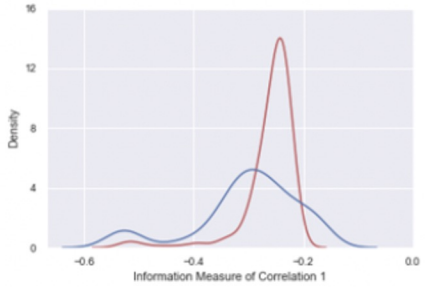


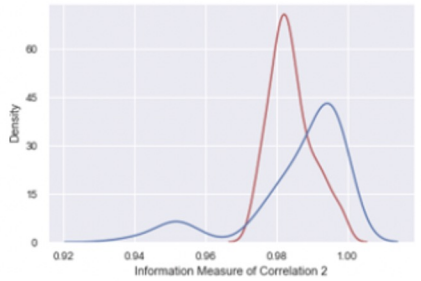




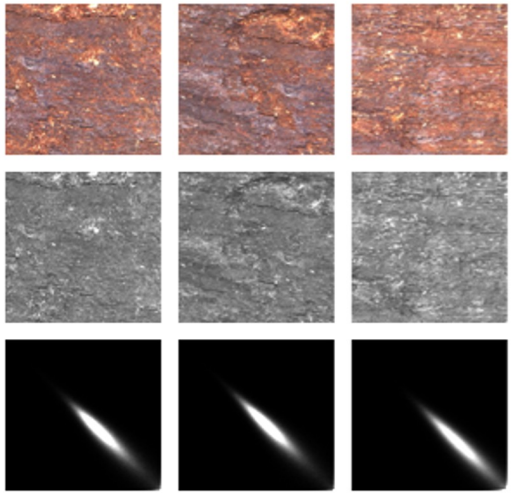




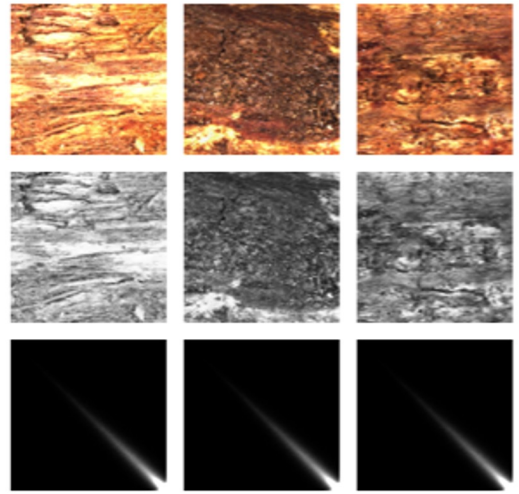




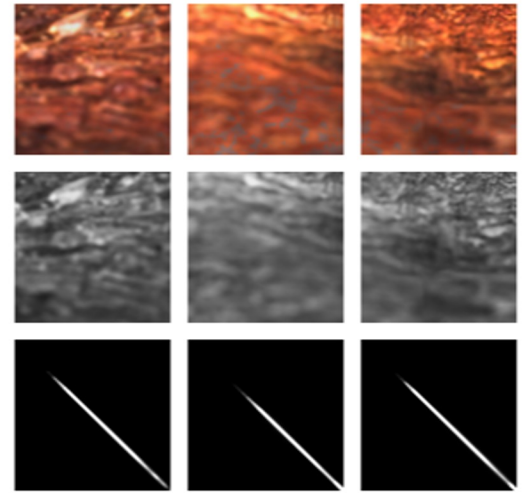
Density plots



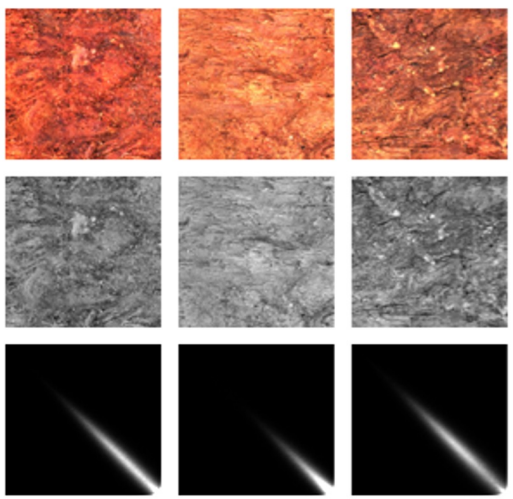
Undamaged Min Value



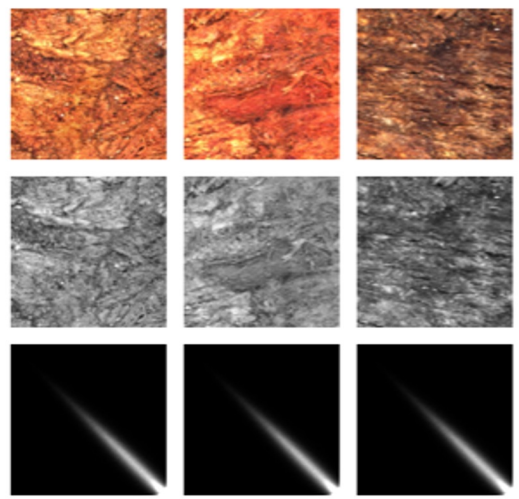
Undamaged Mid Value



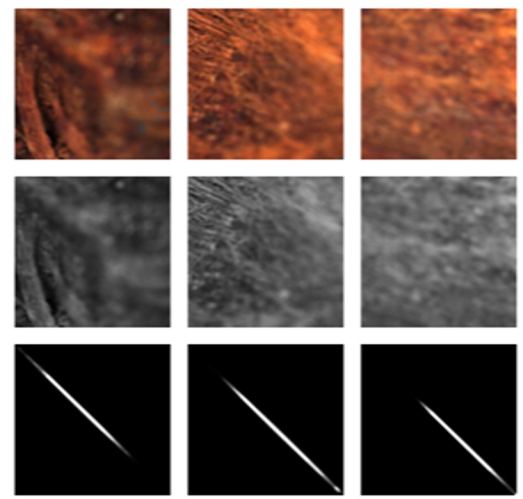
Undamaged Max Value



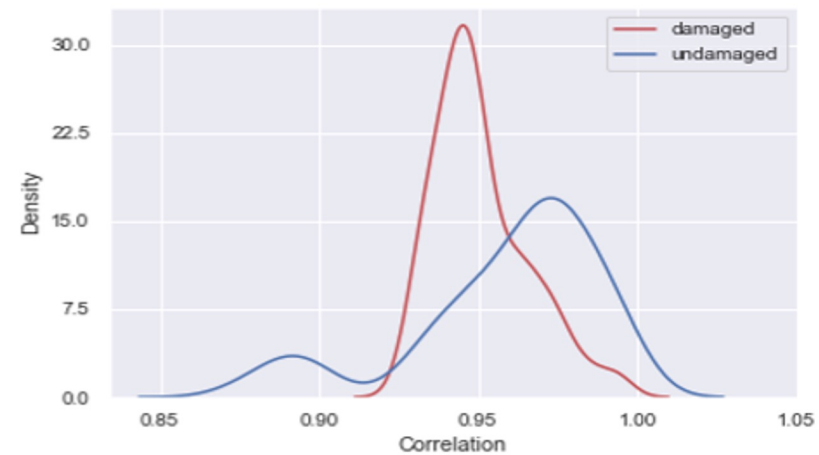
Damaged Min Value

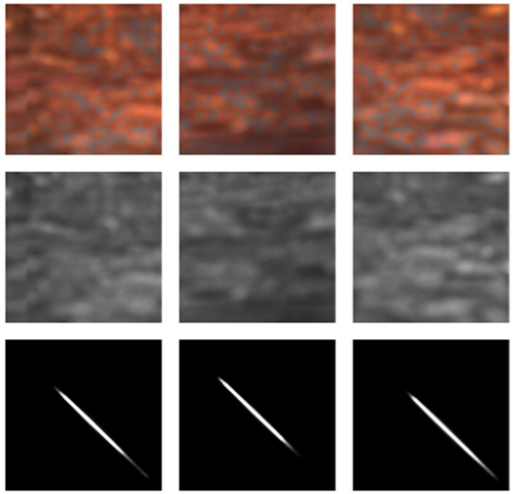


Damaged Mid Value

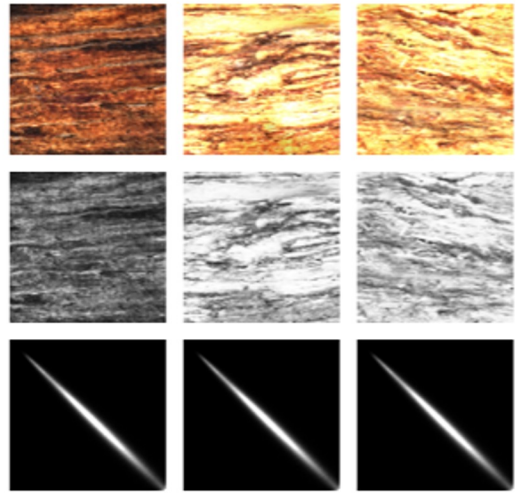


Damaged Max Value

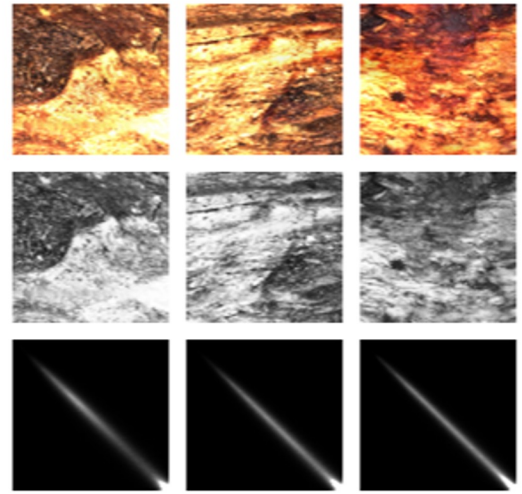




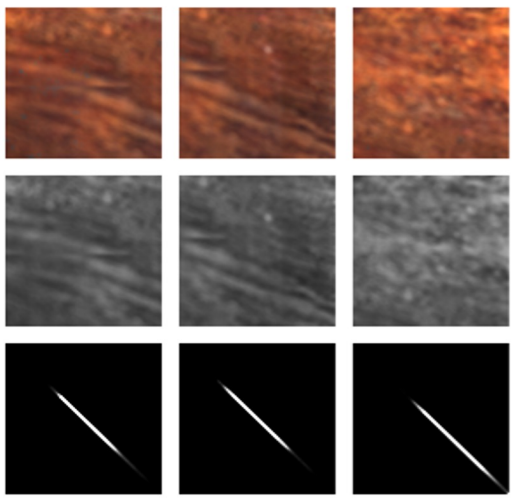
Undamaged Min Value



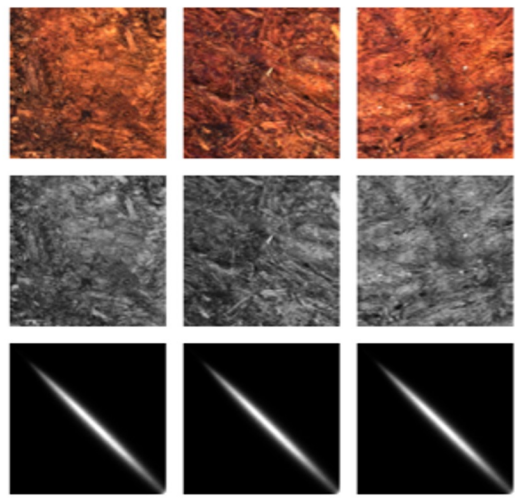
Undamaged Mid Value



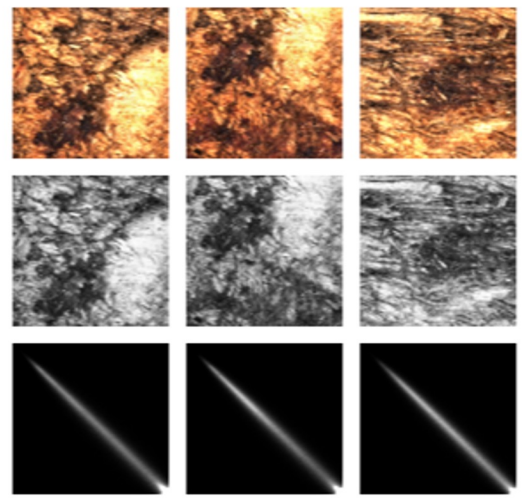
Undamaged Max Value



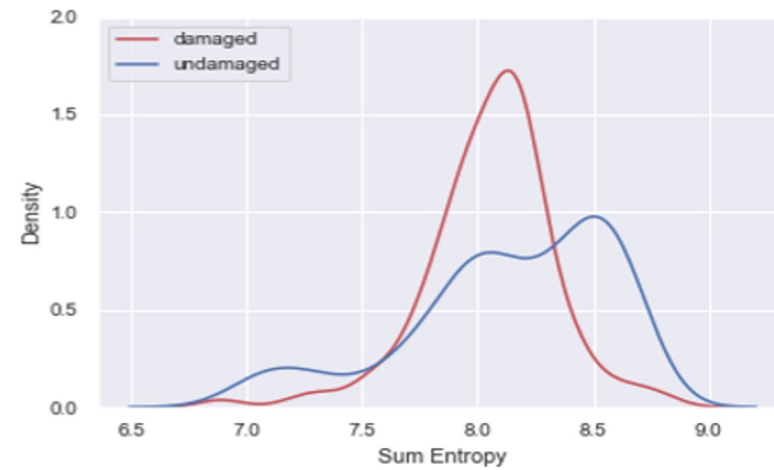
Damaged Min Value

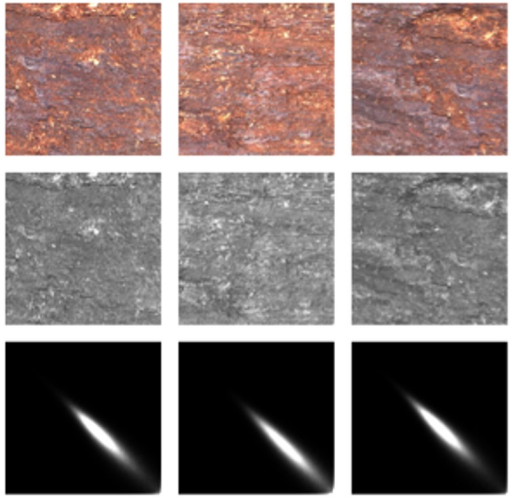


Damaged Mid Value

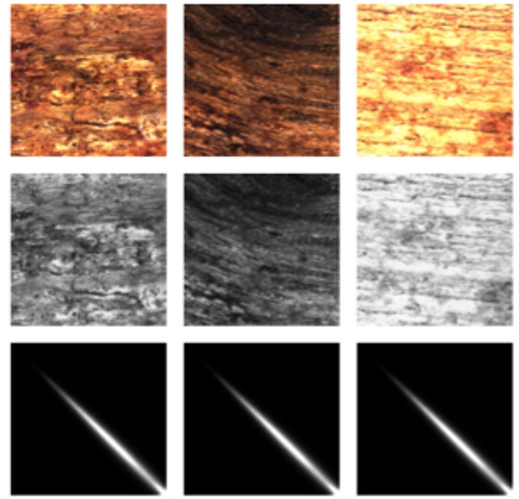


Damaged Max Value

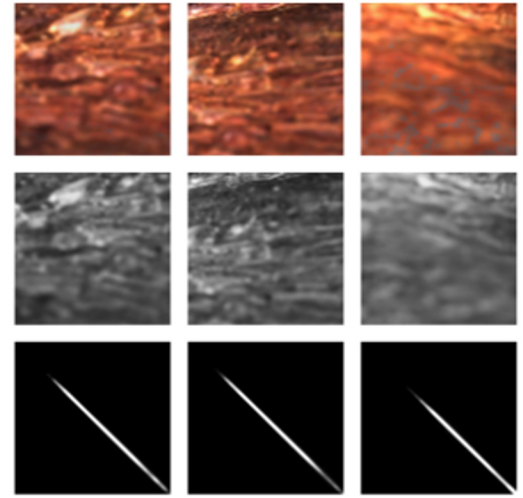




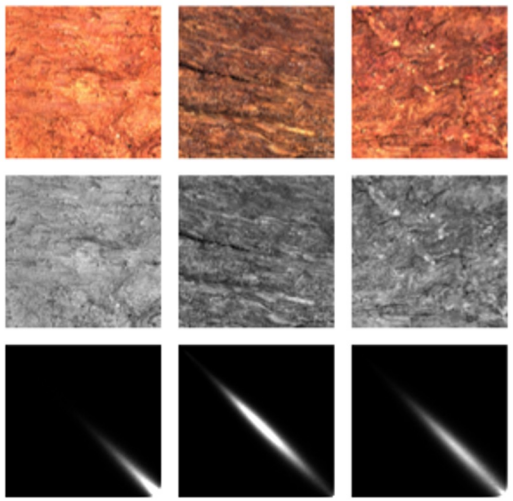
Undamaged Min Value



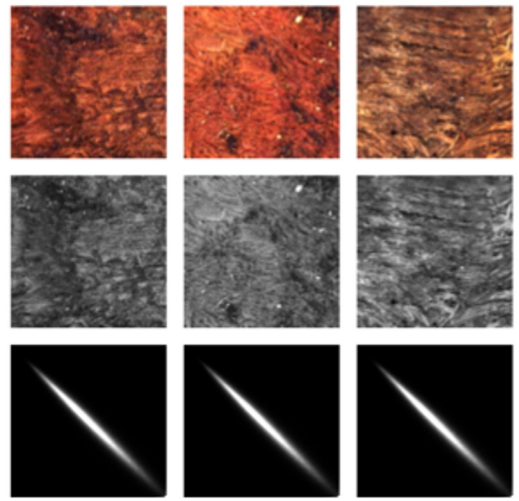
Undamaged Mid Value



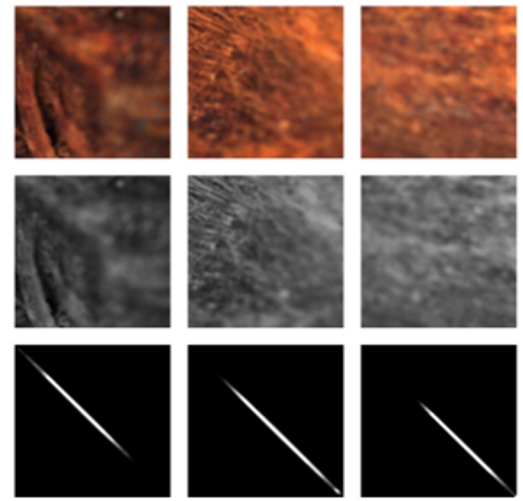
Undamaged Max Value



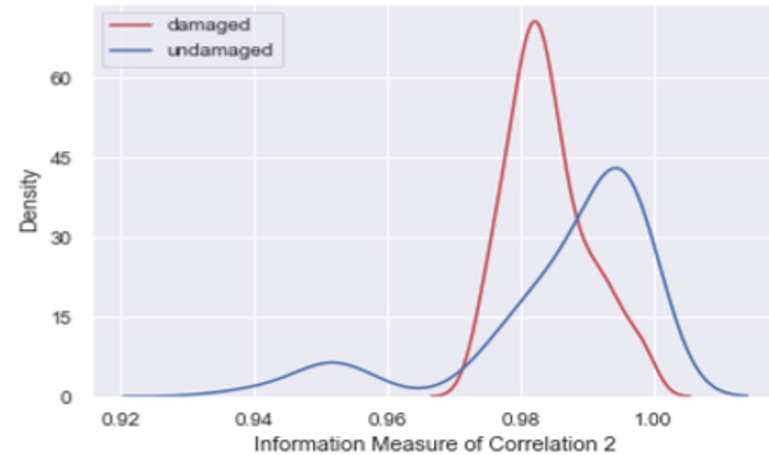
Damaged Min Value



Damaged Mid Value



Damaged Max Value



Dataset : Fossil wood

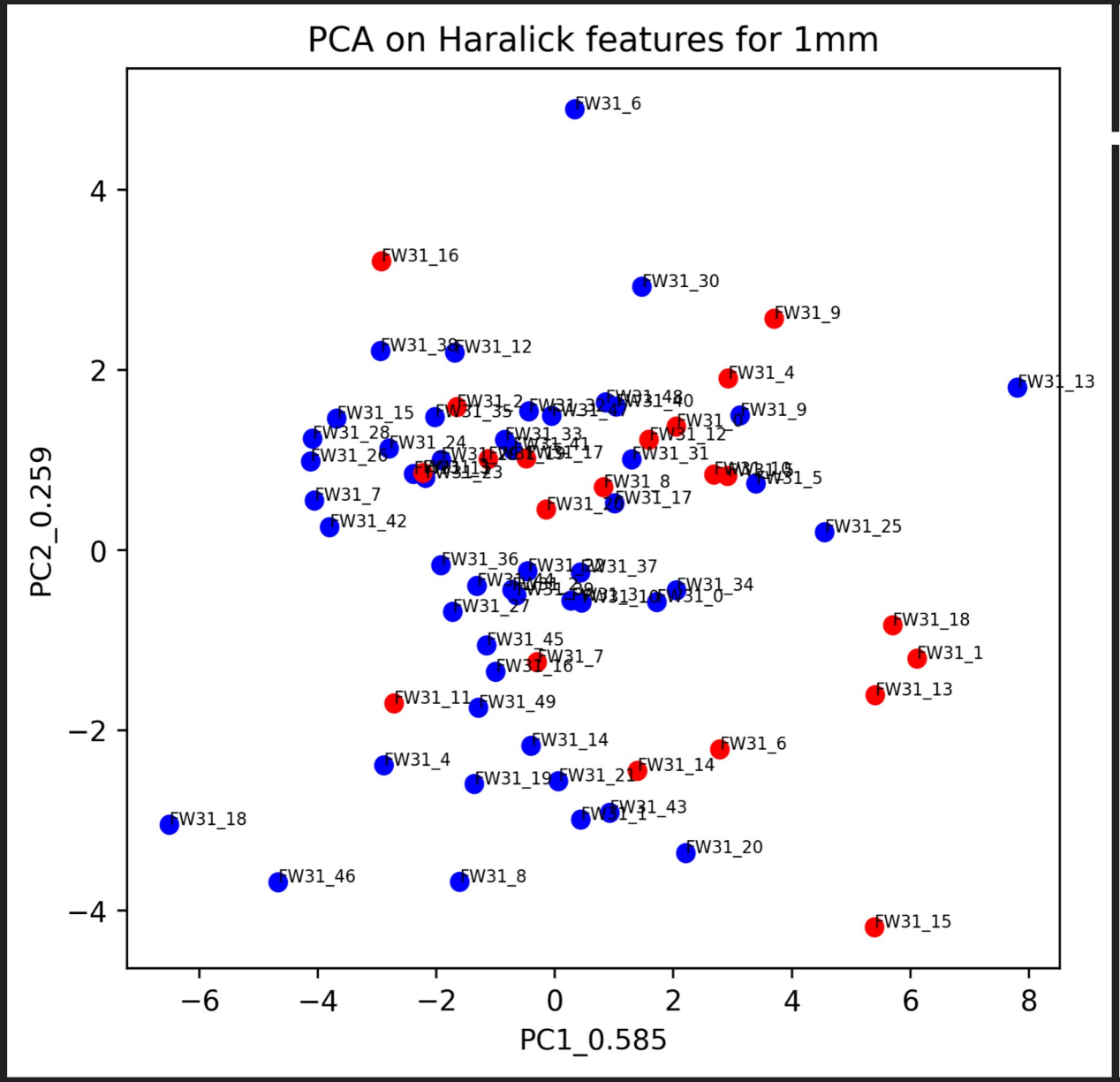
- The dataset contains images of 7 different types of fossil woods. Of them 6 are undamaged fossils and 1 is damaged fossil which is the target image on which we will do our analysis on.
- The fossil woods are over 4 million years ago.

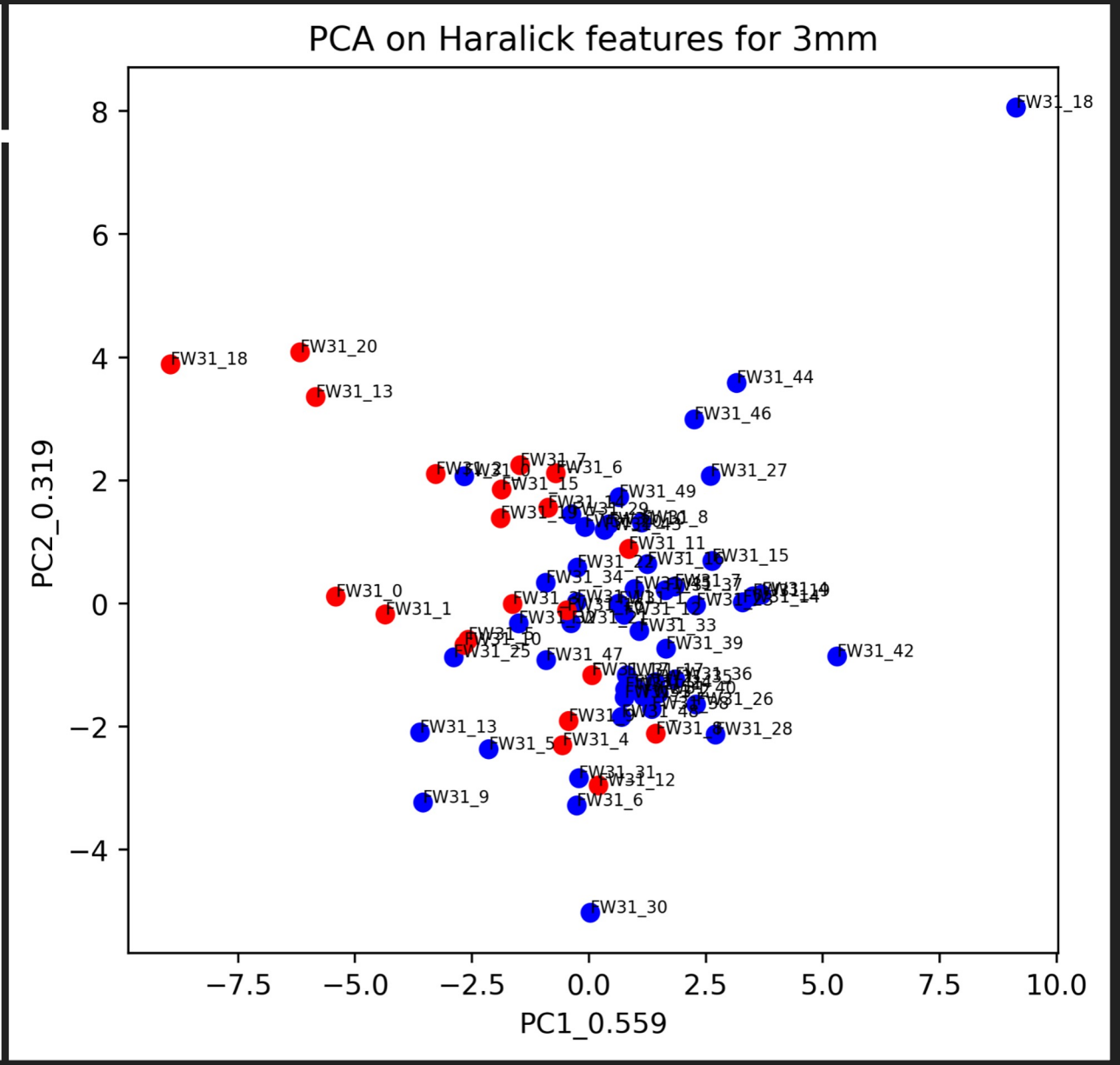
- The damaged part of the image is inside the painted region.
- Rest of the image is undamaged part
- Created a dataset with 1mm, 3mm, 5mm and 7mm cut images of damaged and undamaged parts

Methods

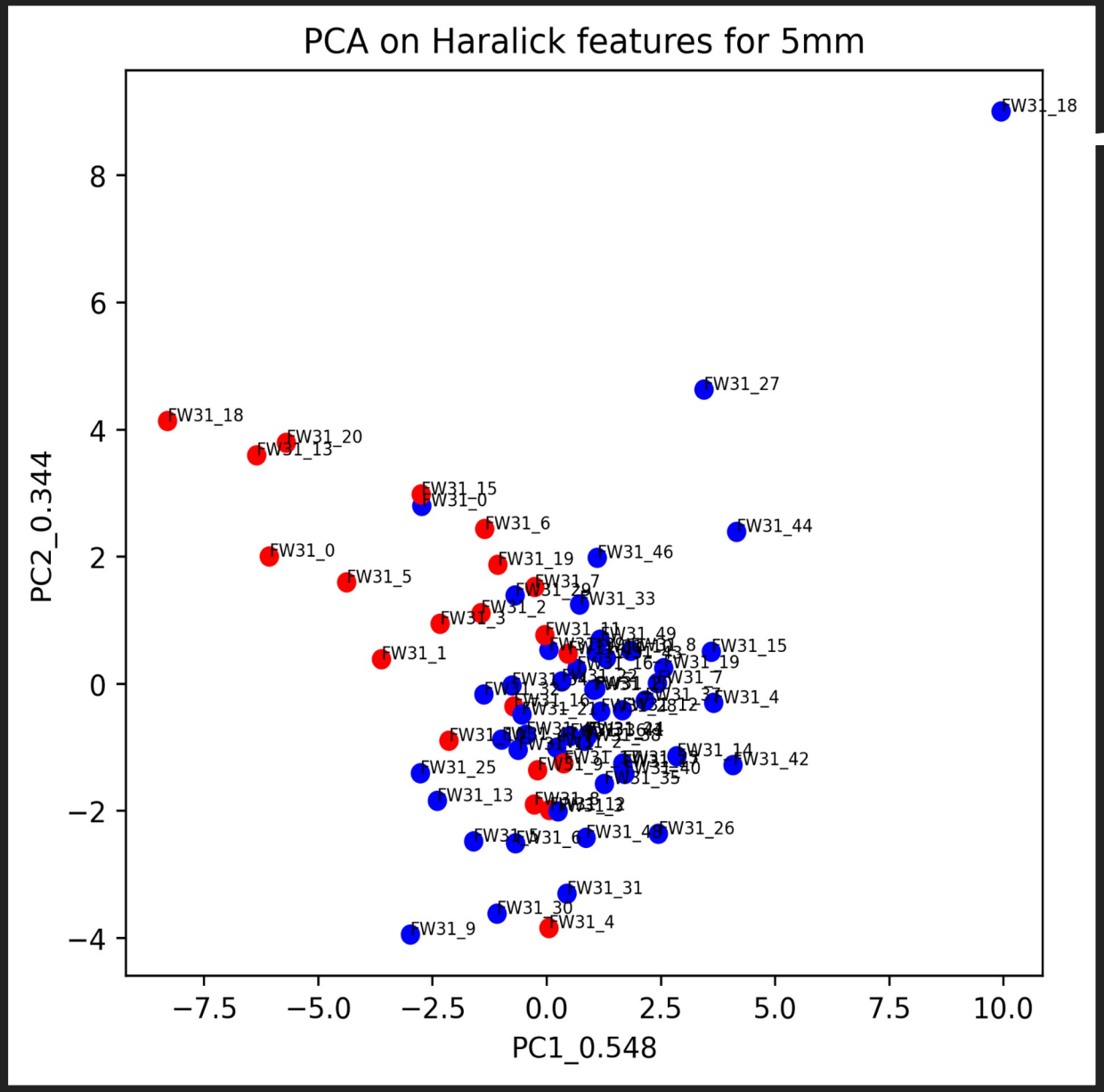
- Extracted haralick features and applied PCA to distinguish between damaged and undamaged part of the image
- Applied Gram matrix on outputs of pre-trained models like Resnet50 and VGG19 to extract patterns of the image and used PCA to distinguish between damaged and undamaged part of the image.

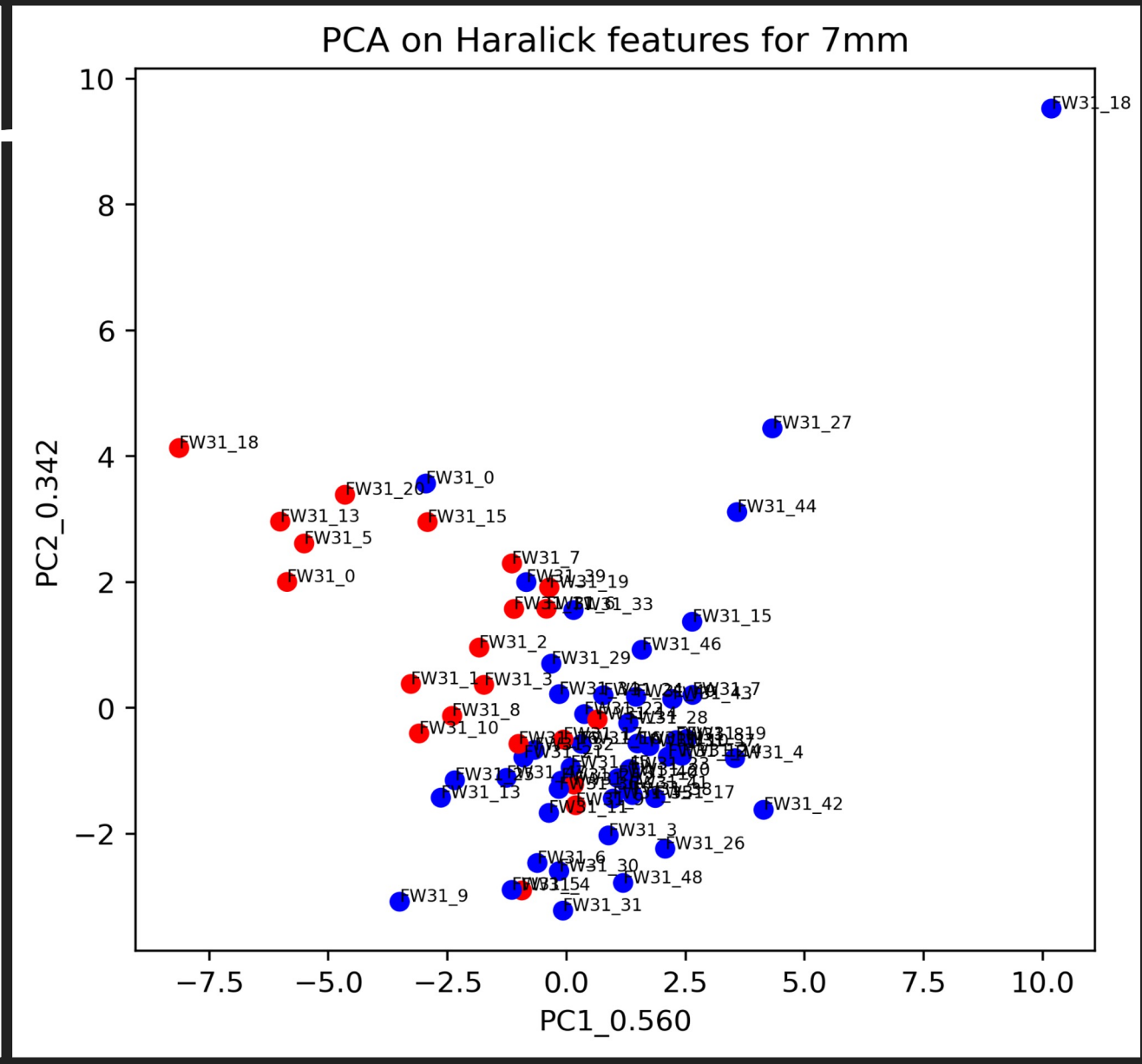
PCA on Haralick features



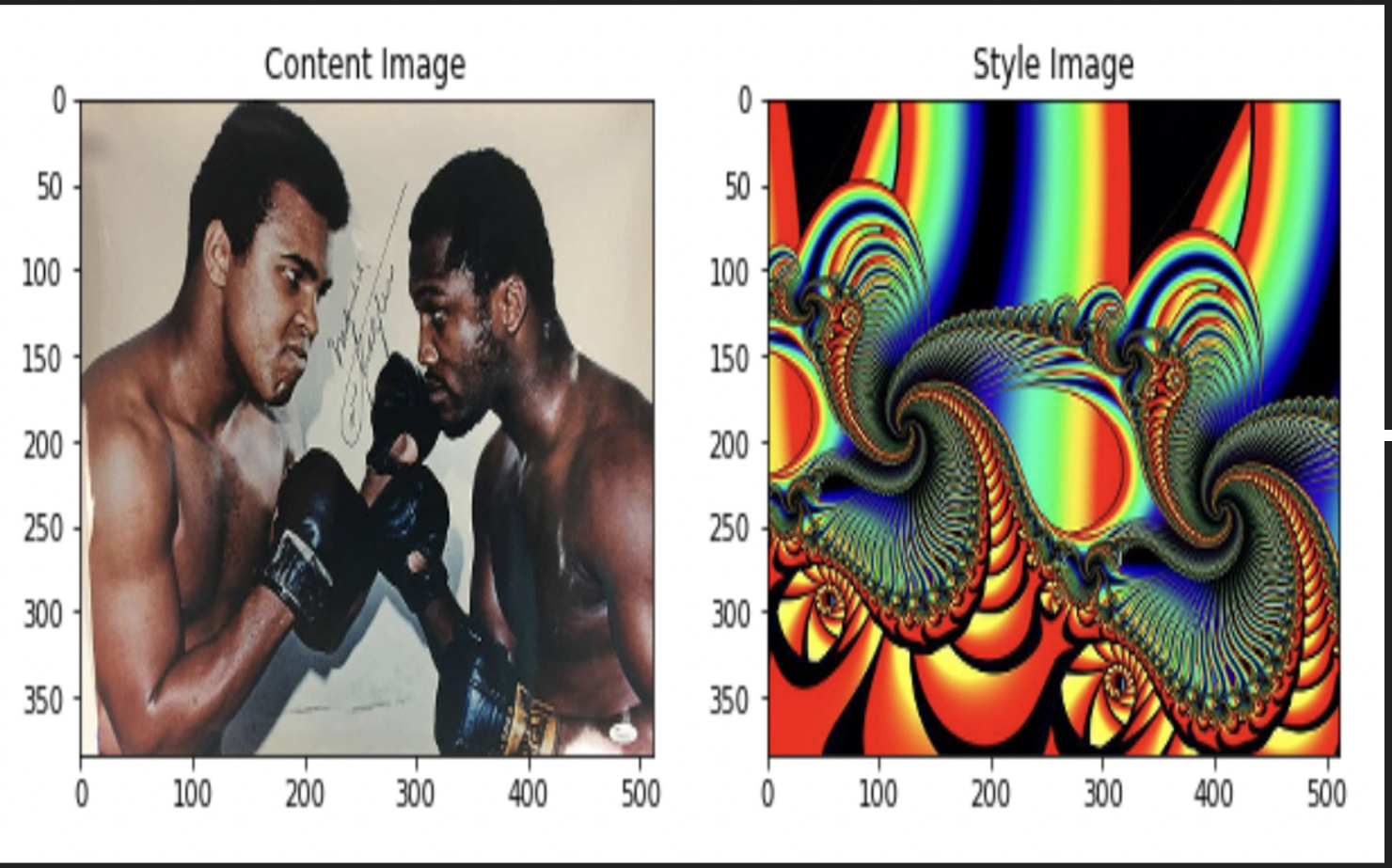


PCA on Haralick features

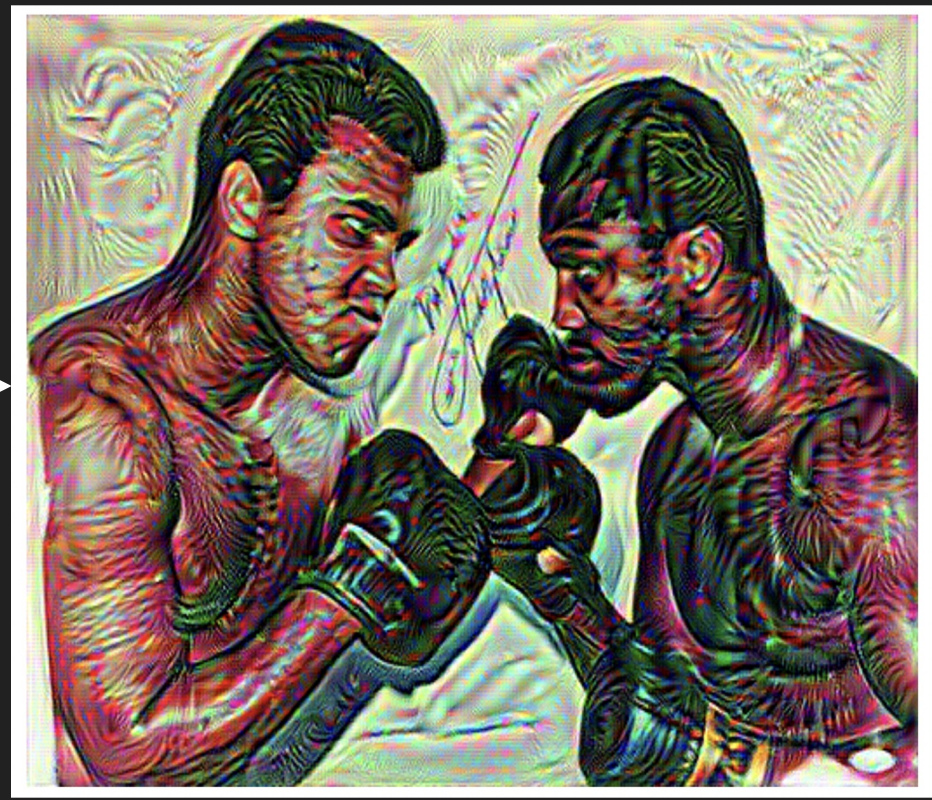




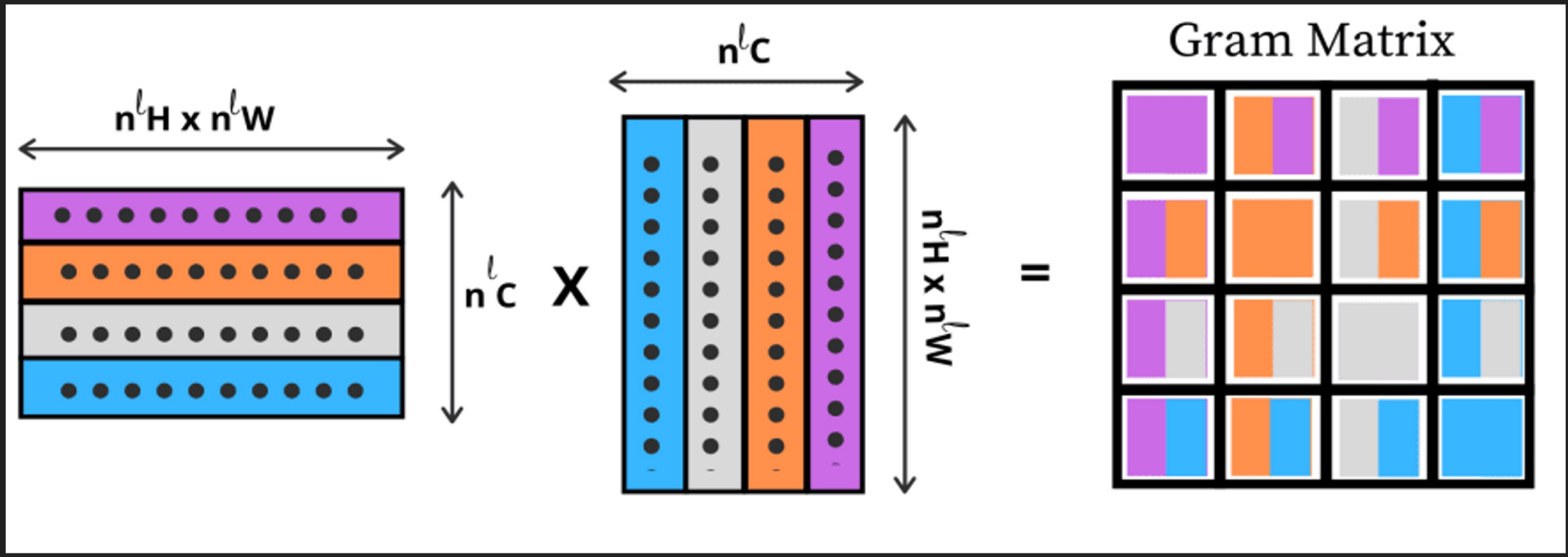
Neural style transfer



Output image



Gram matrix

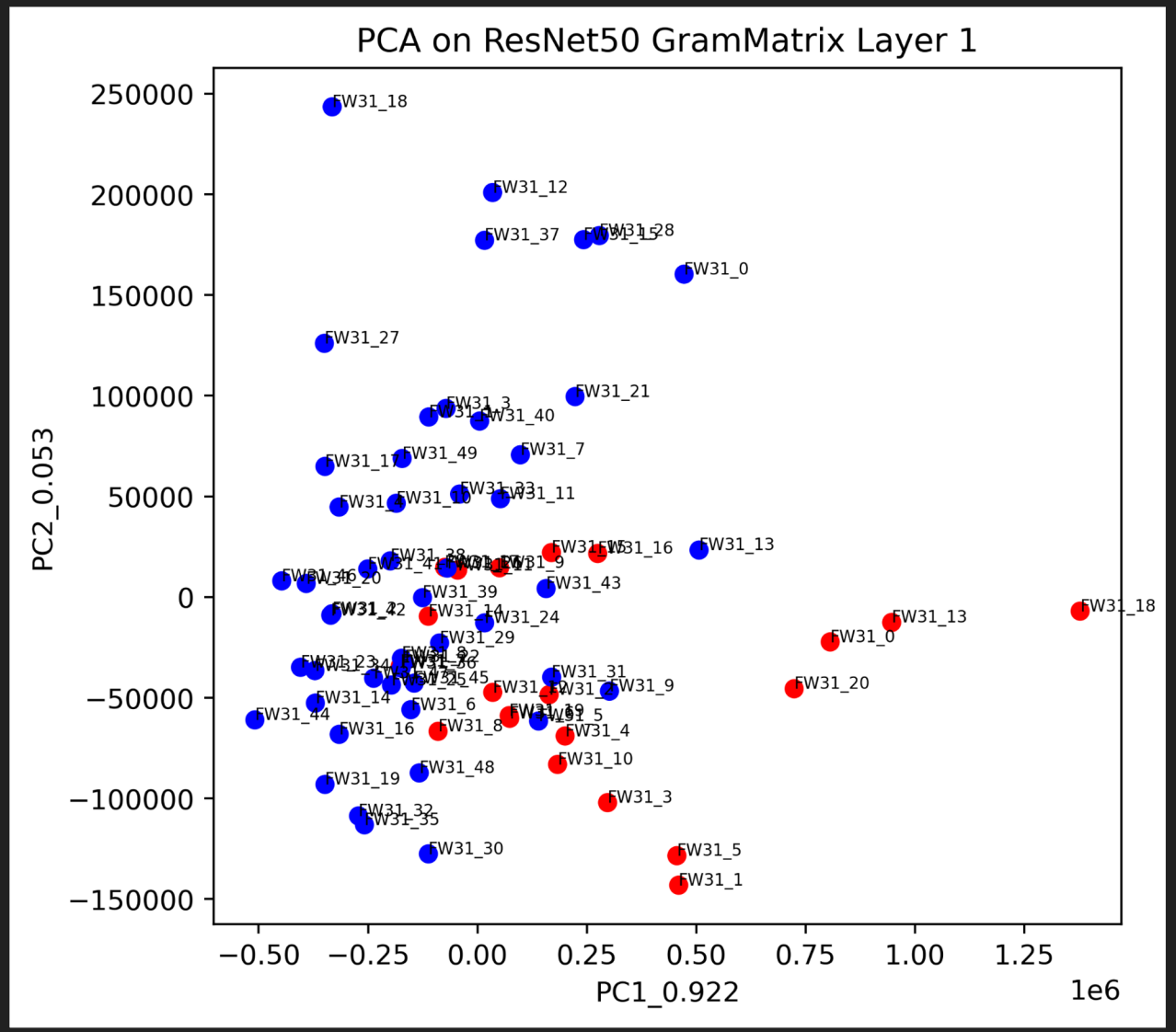


$$g_{ij} = \mathbf{v}_i^T \mathbf{v}_j.$$

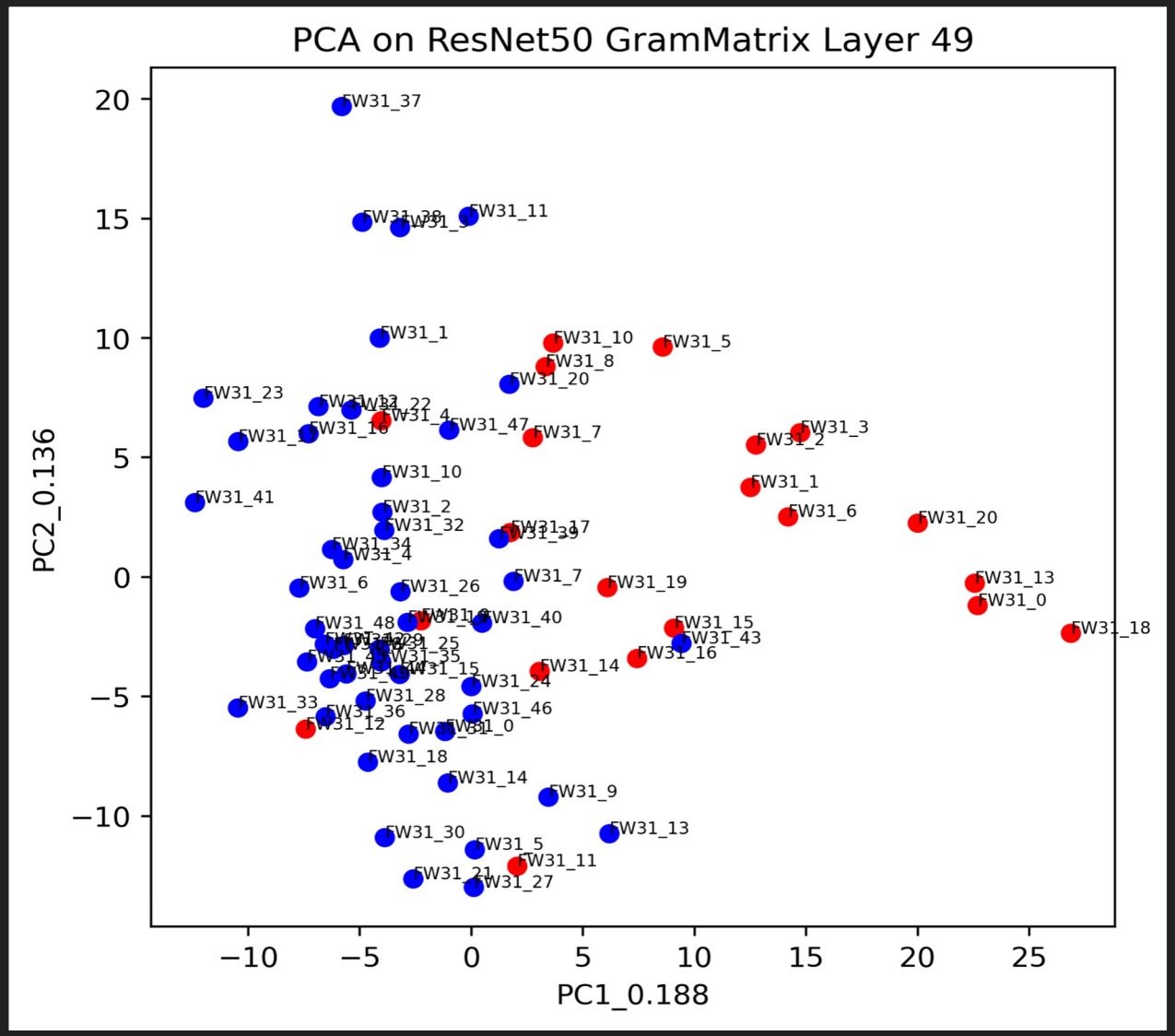
Resnet50 and VGG19

- VGG19 and Resnet50 are pre-trained Machine learning models.
- VGG19 contains 19 layers on convolution layers while Resnet50 contains 50 layers of convolutional layers
- Resnet50 is faster because it produces less parameters than VGG19

Resnet50 output of 5mm cut

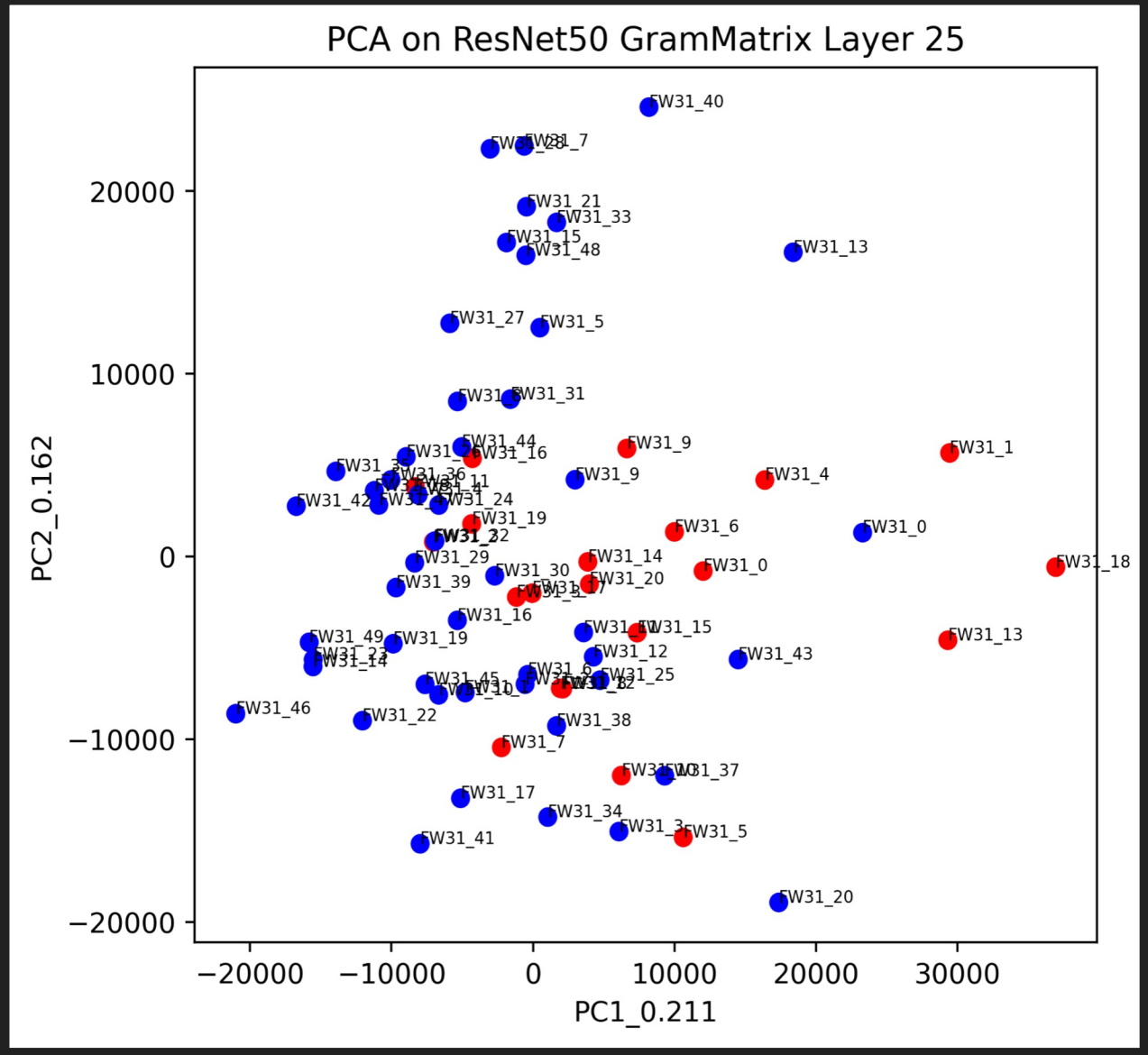


1st layer of 5mm images

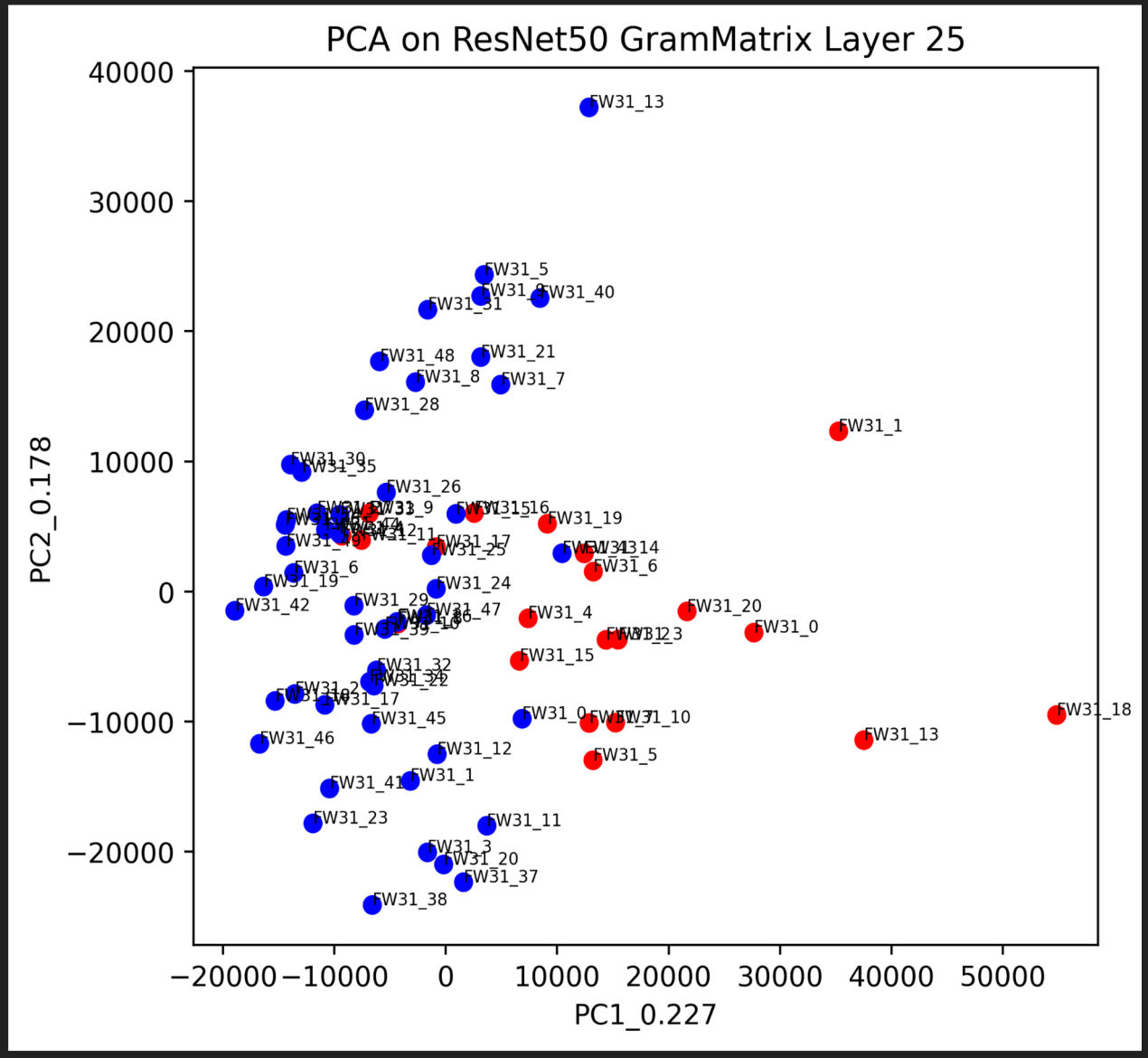


49th layer of 5mm images

Resnet50 output of 1mm and 3mm cut

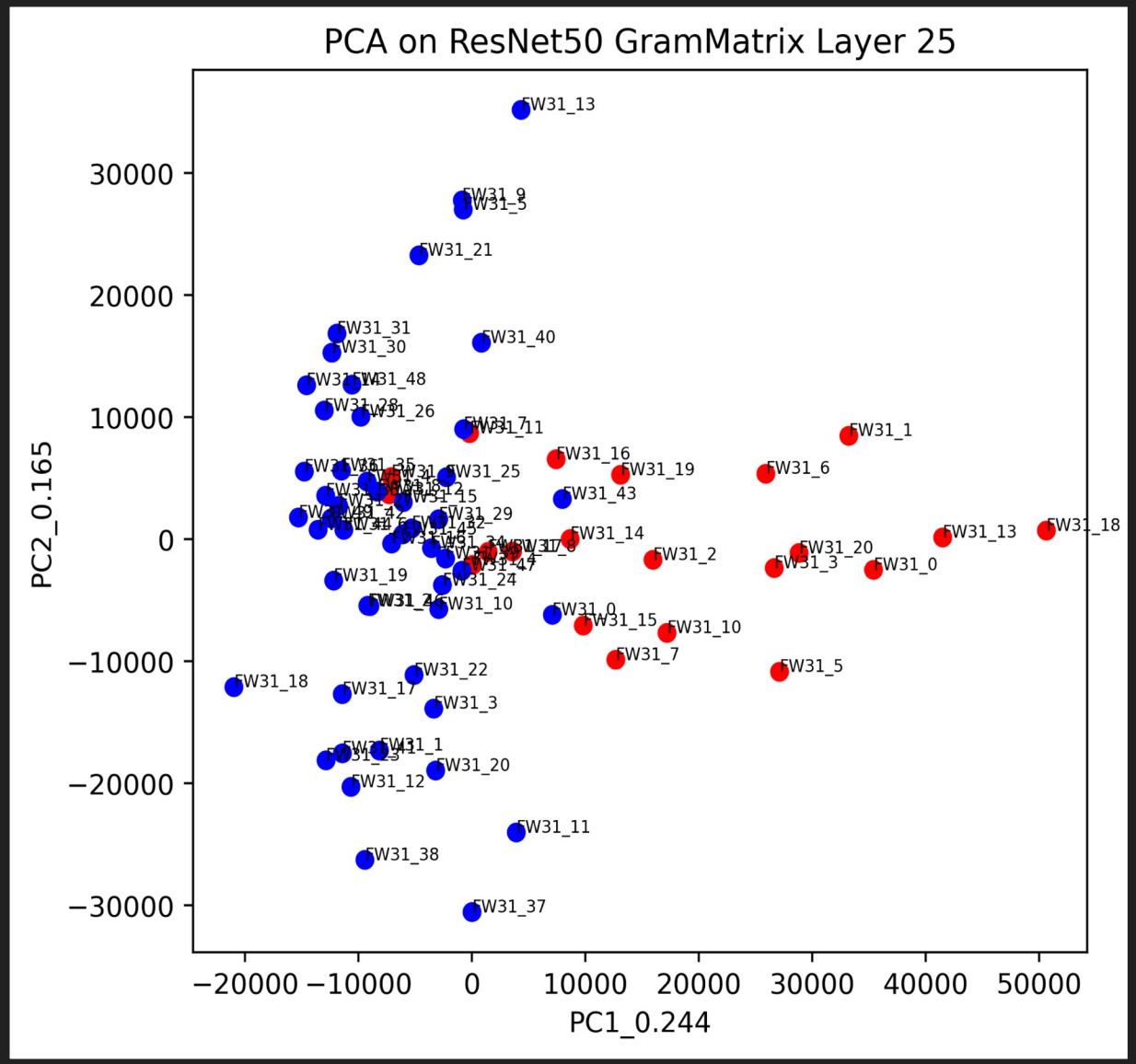


25th layer of 1mm images

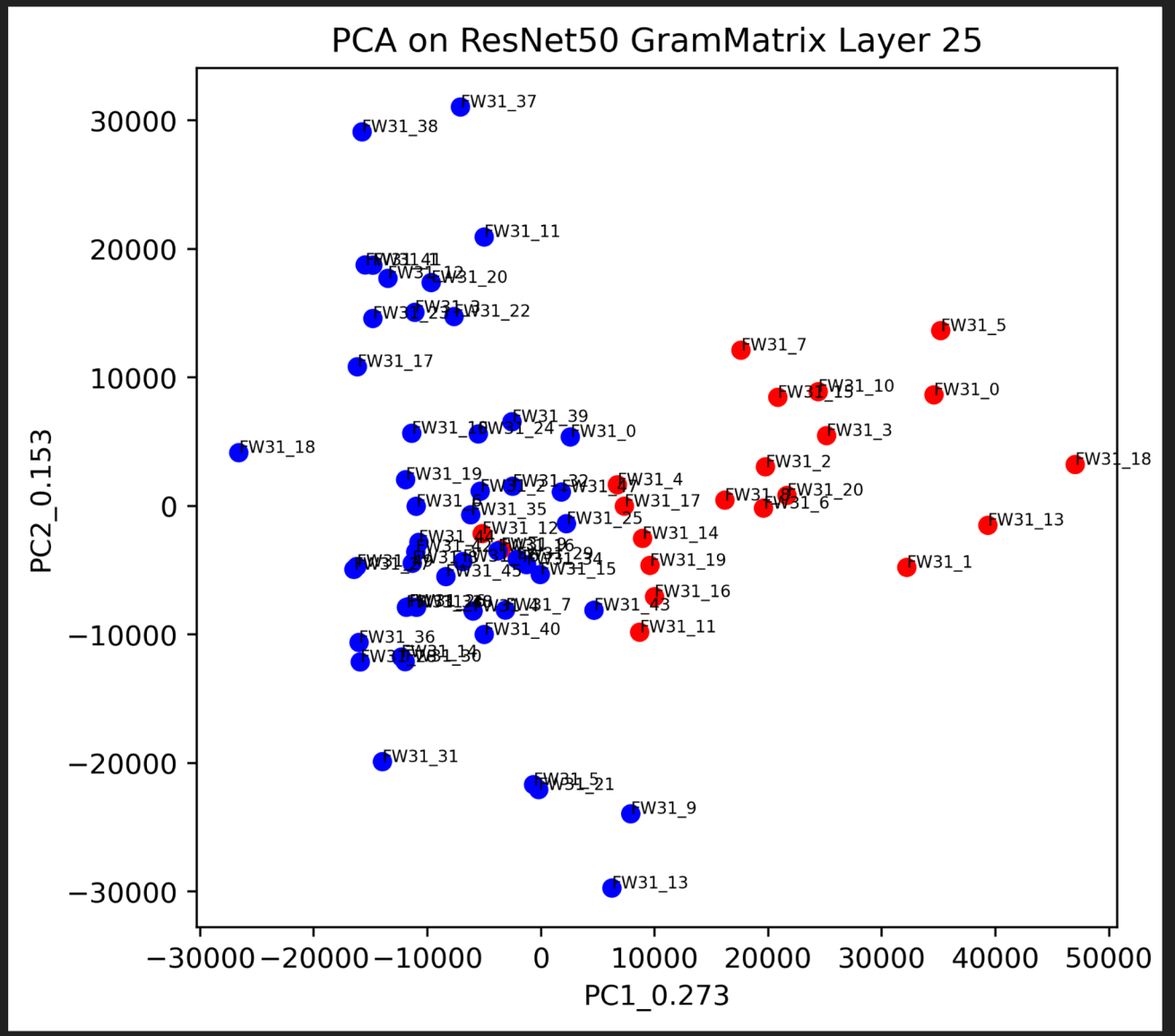


25th layer of 3mm images

Resnet50 output of 5mm and 7mm cut

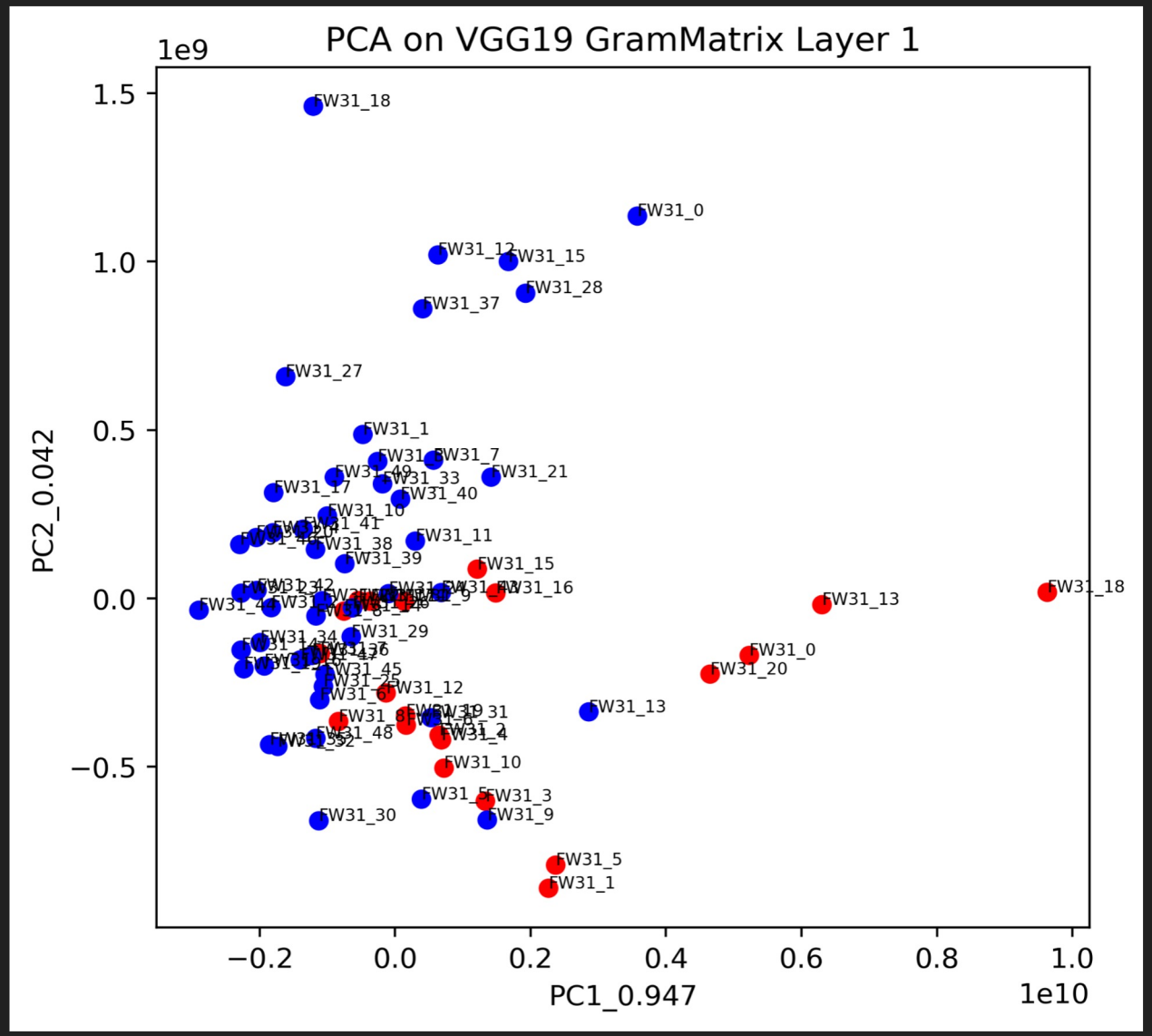


25th layer of 5mm images

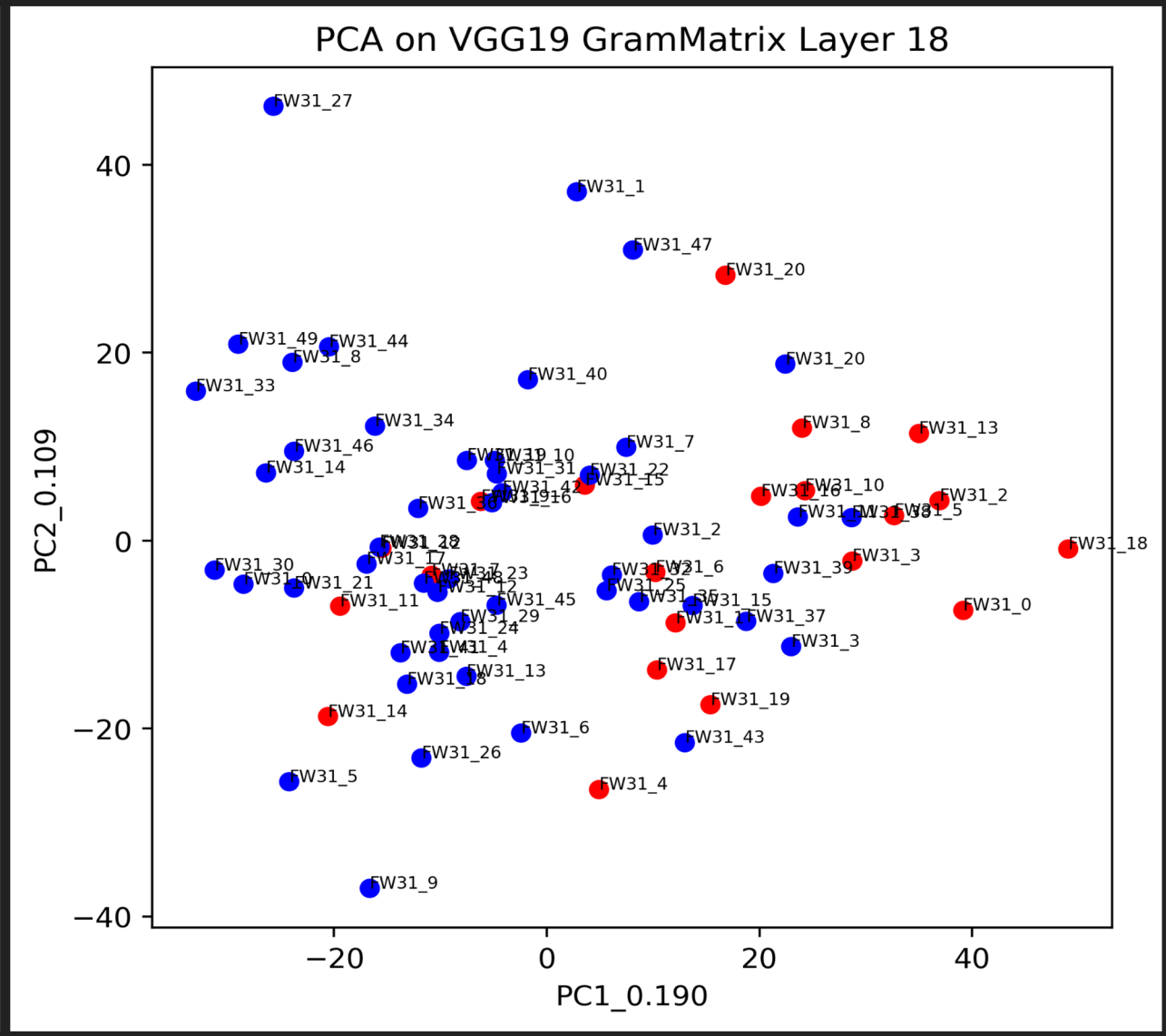


25th layer of 7mm images

VGG19 output of 5mm cut

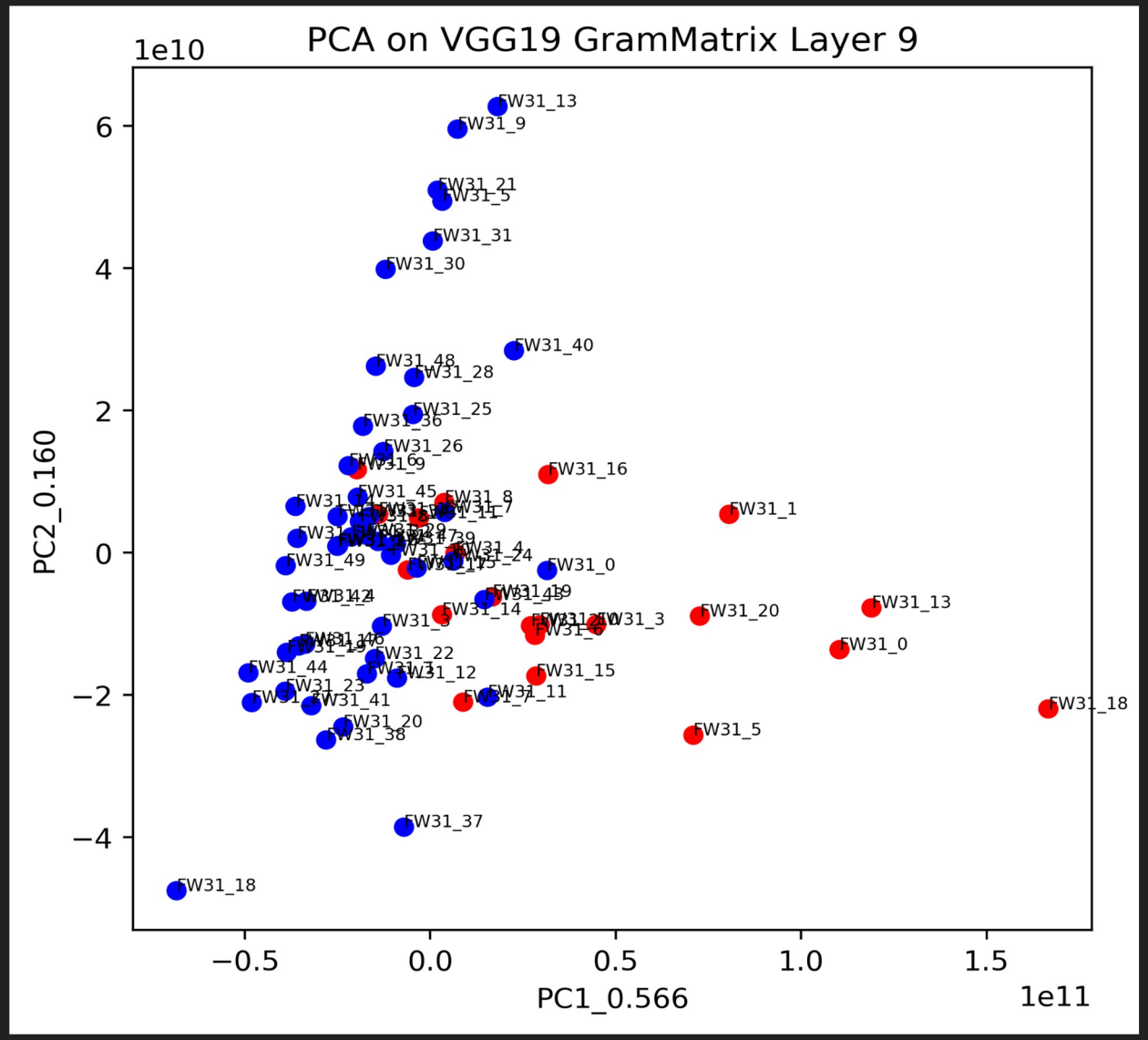


1st layer of 5mm images

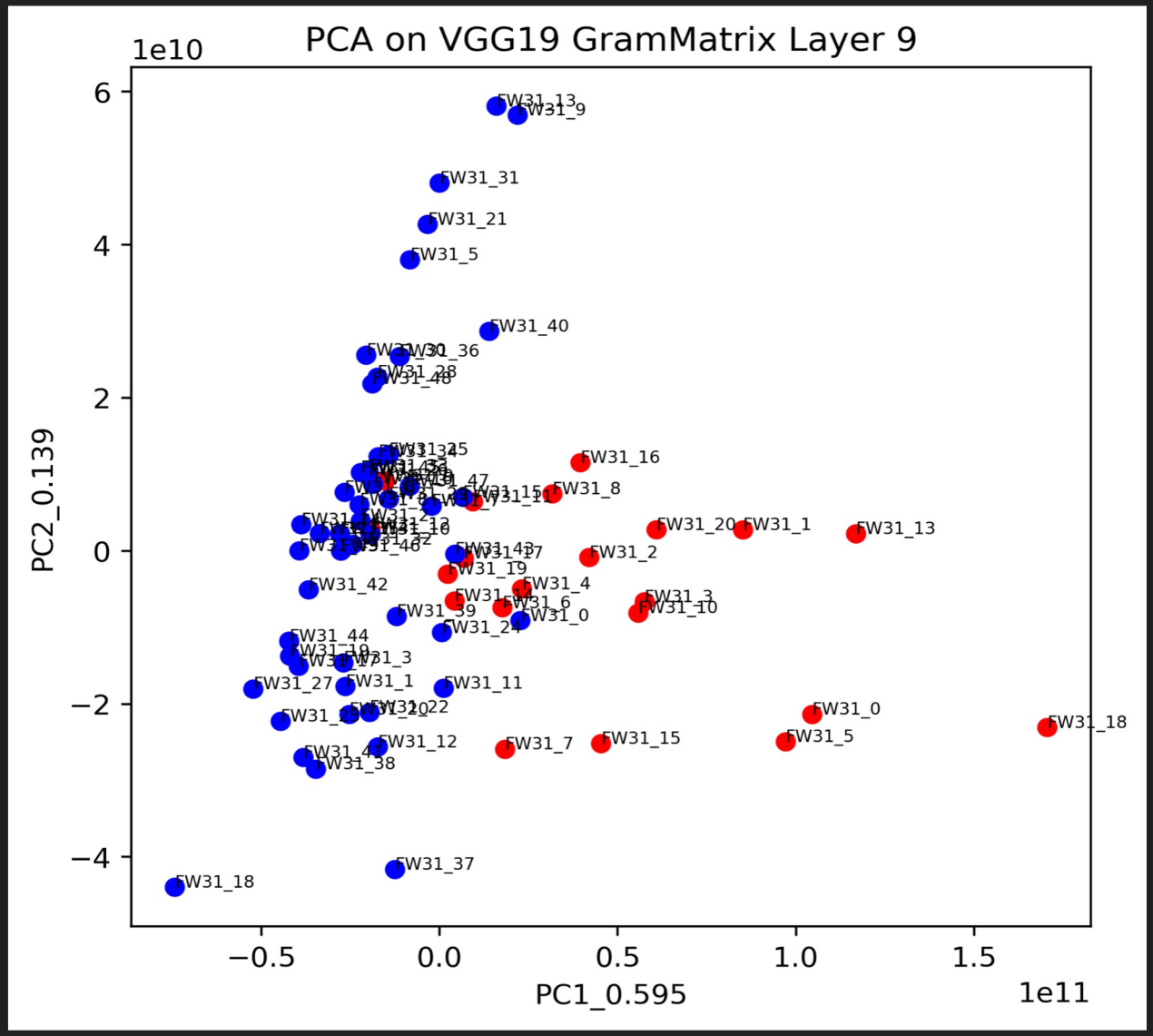


18th layer of 5mm images

VGG19 output of 5mm and 7mm cut



9th layer of 5mm images

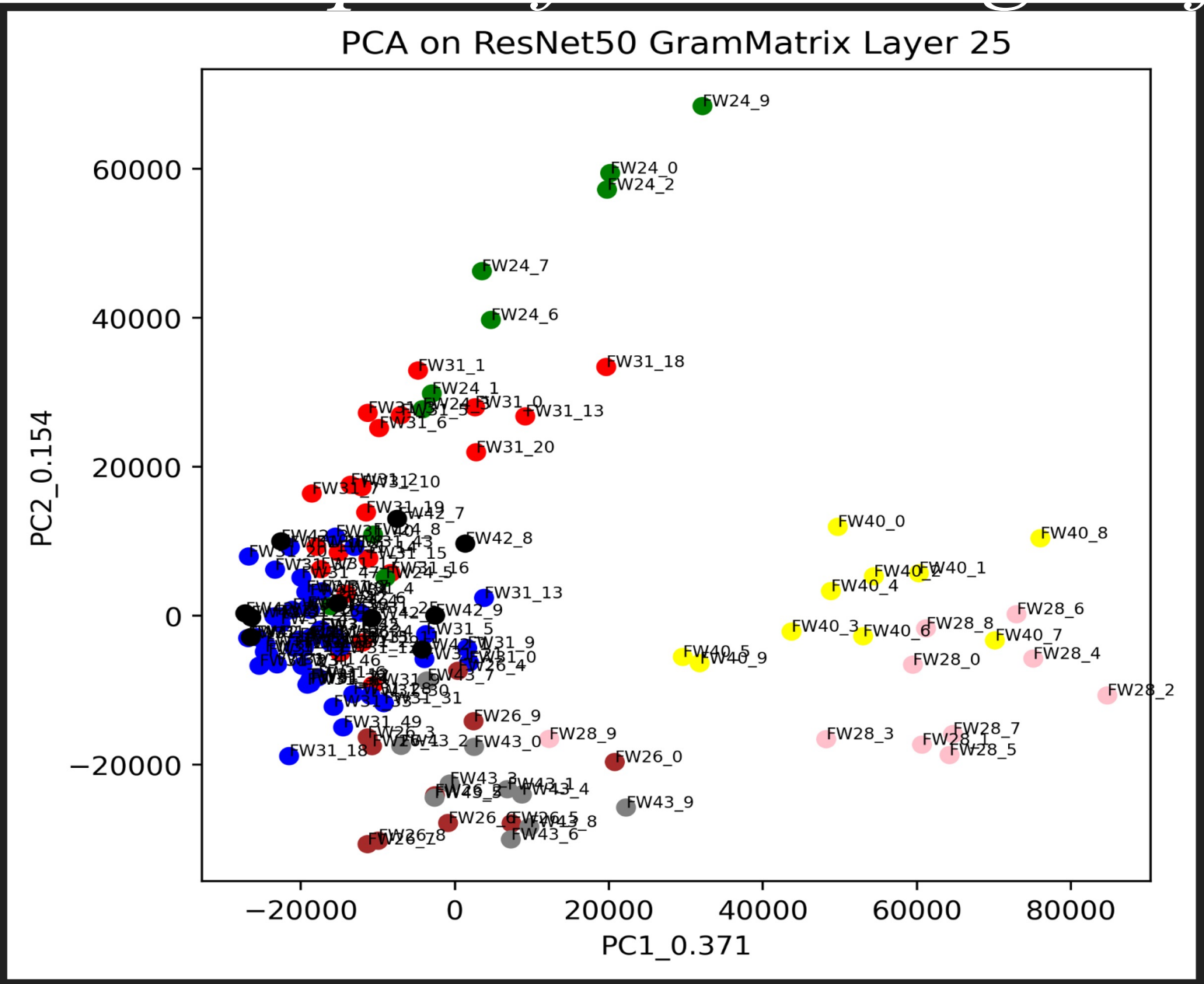


9th layer of 7mm images

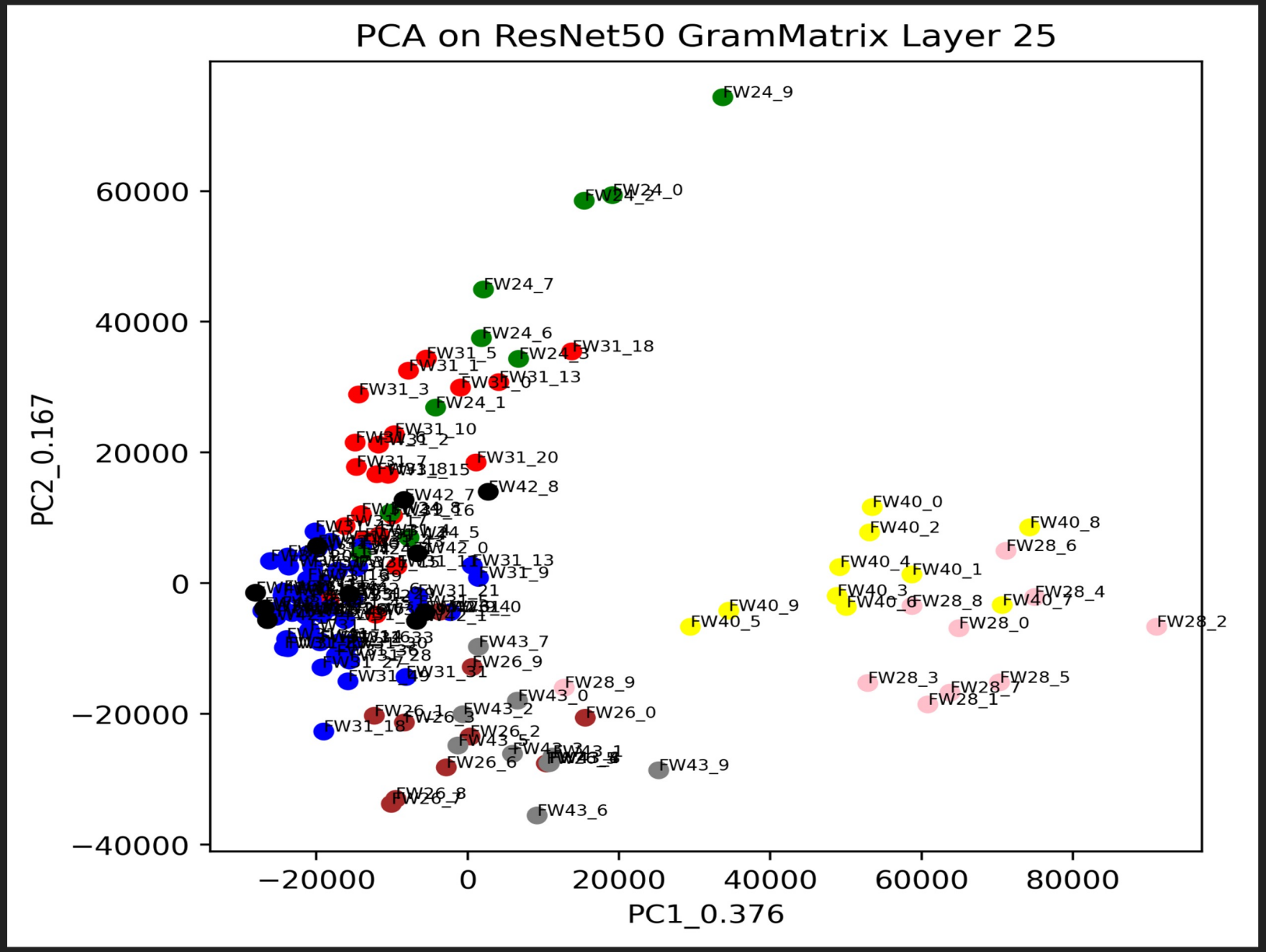
t-test on PCA values of Resnet50 model of all image sizes

t-test (p-values) for 25th layer		
	PC1	PC2
1mm	0.00255	0.19394
3mm	0.0001	0.41366
5mm	4.12E-06	0.93813
7mm	3.35E-08	0.38144

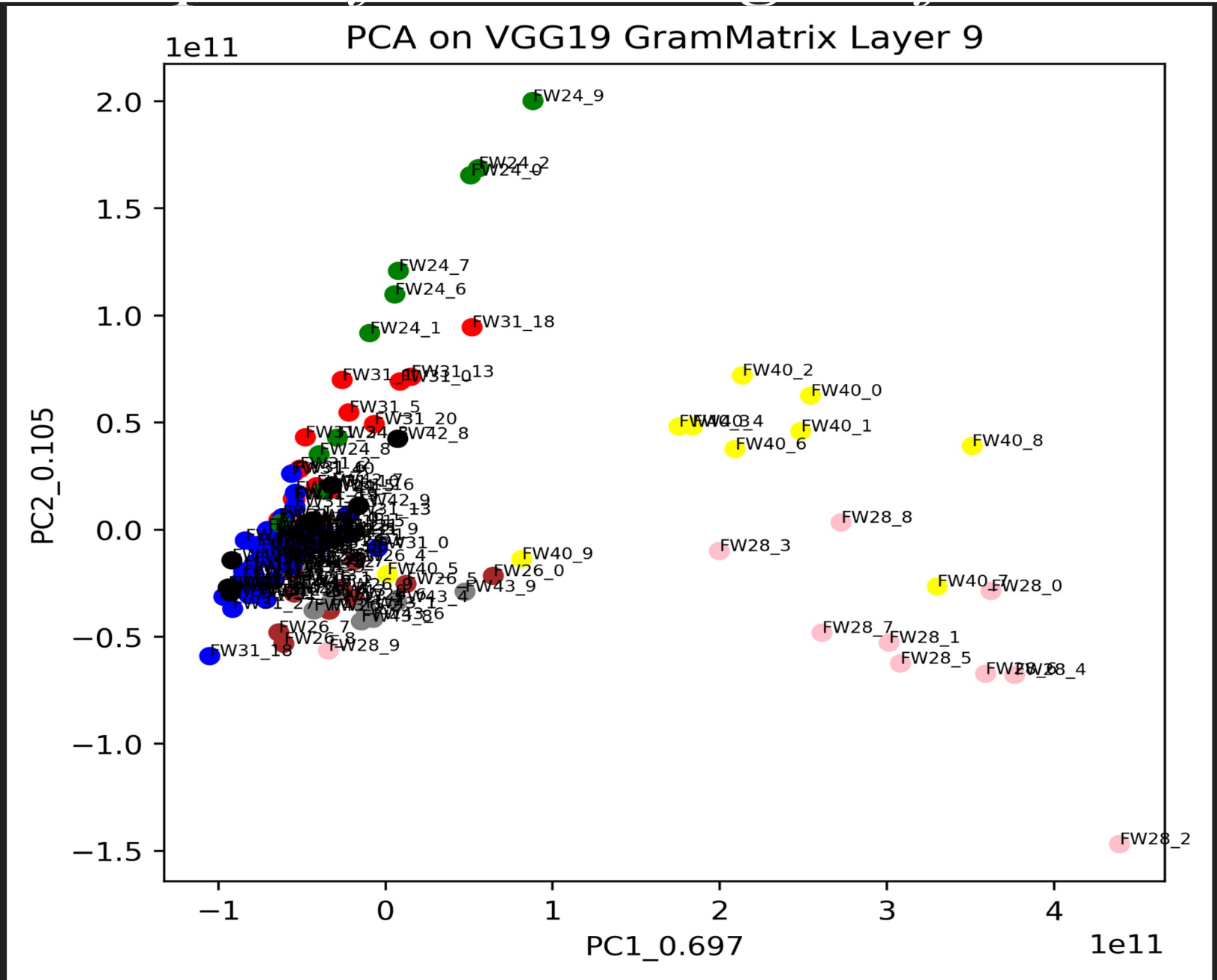
Resnet50 output of 5mm images of all wood



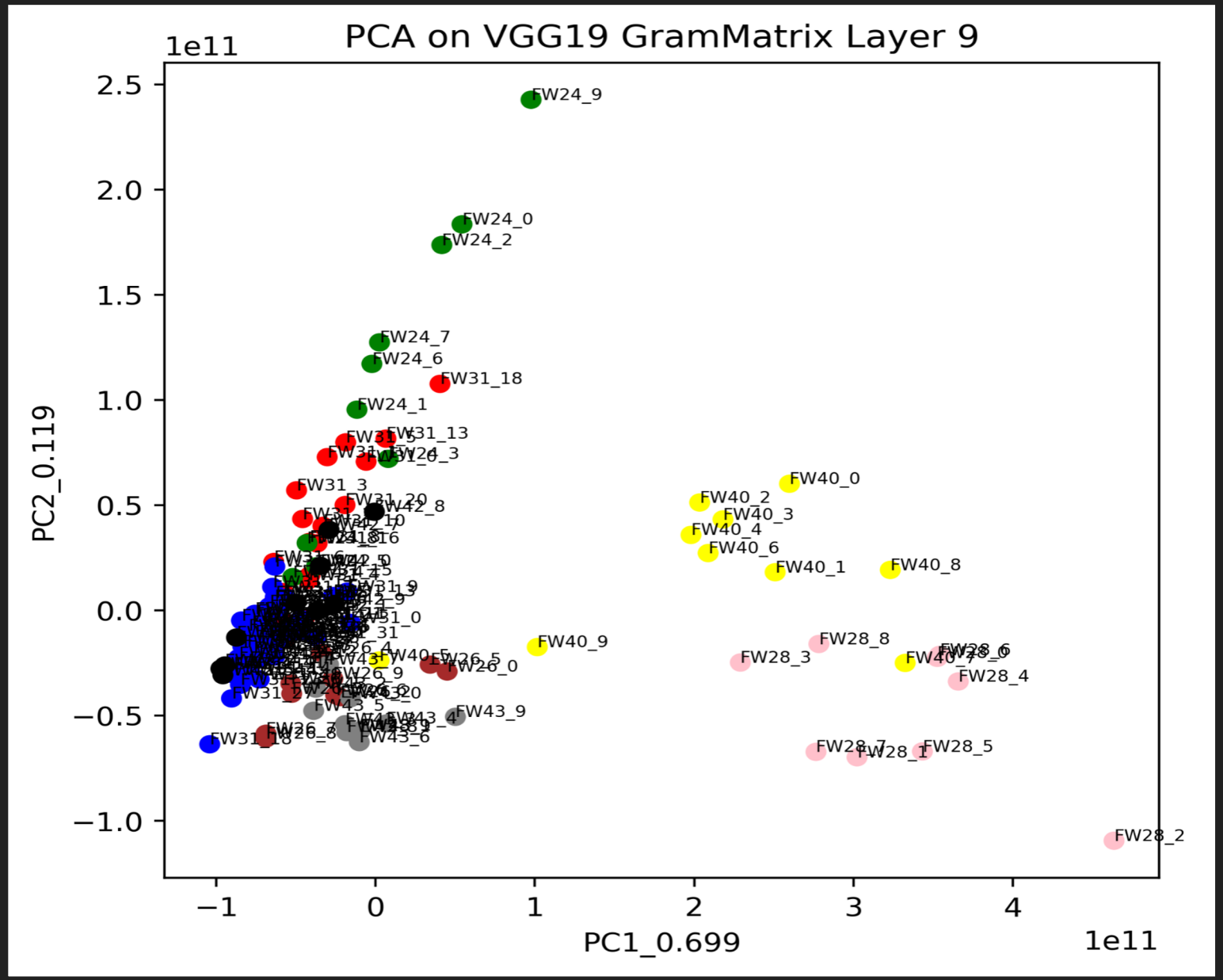
Resnet50 output of 7mm images of all wood



VGG19 output of 5mm images of all wood



VGG19 output of 7mm images of all wood



Conclusions

- It is observed that Correlation, Sum entropy, Information measure of correlation-2 are the best out of the 13 haralick features for coula species.
- Found out a method to use GLCM to return the matrix images which measures intensity contrast between a pixel and its neighbour pixel over the whole image.
- From the results it shows us there is high intensity in the diagonals and the thicker lines shows the variation between the pixels of both the damaged and undamaged area.

Conclusions

- Using PCA on pre-trained models is better than using PCA on haralick features to distinguish patterns in image
- Middle layer (25th for Resnet50 and 9th for VGG19) is better than first and last layer
- We can observe that using larger images like 5mm,7mm images give better results than 1mm and 3mm images.
- We can observe that using Resnet50 model for classification is better than using VGG19 model.

Thank you