Encinas, Michael
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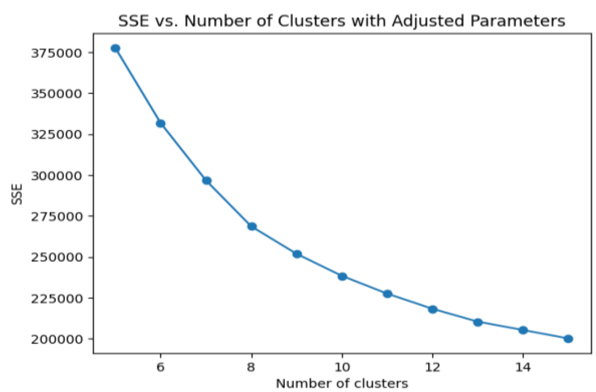
Final Project Machine Learning
CSE 546

For this project I was given a dataset (FLIR Thermal Data) that contains 5k images from 5 classes [‘person’, ‘sign’, ‘bike’, ‘bus’, ‘car’]. The files that I was given will contain the 256 features that are extracted from all the provided 5k images (using CNN) and the image folder which contains 5 files for the different classes to look up images to those specific data sample.

For the beginning of this project, I will be using unsupervised training to see if I can reduce my features, use PCA, and find trends that might increase my ARI and Silhouette Scores which will give me more ideas on how this preprocessing will help me when I select 4 different types of classifiers later. I will be using python in Jupyter notebook.

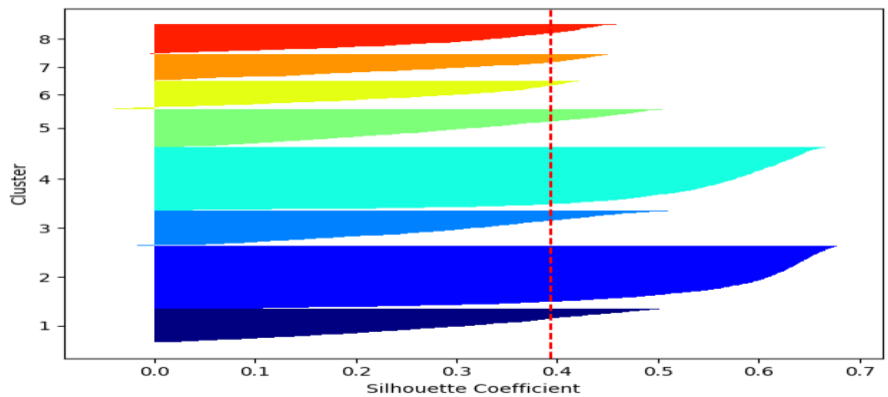
To first start off on my project I went ahead and uploaded the data and image files to my notebook. I looked at no scaling at first with SSE vs Number of Clusters to get an idea on how many clusters I might need.

Figure 1



Just based on the figure 1 display I use the ‘elbow’ method and decided that cluster 8 will be the cluster I am going with. I then printed out the silhouette scores to get an idea of my clusters.

Figure 2



Cluster 4 and Cluster 2 appear to have big separation, but the other cluster don't have good silhouette scores which makes me think that using unscaled data with no feature selection or even PCA is going to give me optimal ARI scores.

When checking ARI I got .7523 with clusters at 8 with unscaled which is pretty good I believe considering I kept all features and have not normalized anything to see if it can change. However, I am trying to optimize my ARI and Silhouette scores so I will be mixing up my parameters. When printed out my clusters with its 5 core samples and 2 boundary samples I noticed that Cluster 2 is person and Cluster 4 is sign which shows that it might be easier to distinguish those clusters. Some of the clusters like in Cluster 8 have a bike with a bike on it which might be confusing to distinguish which ones which so have a sub section is also practical. I also observe that car is easier to spot on the images compared to busses. Even for boundary samples the images appear to be blurry.

I was missing 940 images from Class 5(signs) so I only displayed those images on what I had to display. I do wonder if I start to change my parameters if the images, I get are off better quality since I am getting core and boundary which could mean that the blurriness on some of the images can be improved since it might select blurry photos for core now.

I will include on my PDF files I created to look at with no normalization and then my final pdf file with my features, PCA etc. at end of the unsupervised training section of this report.

Below are just two core samples examples of different clusters to get an idea on what I am discussing. Figure 3 and Figure 4 as reference.

Figure 3

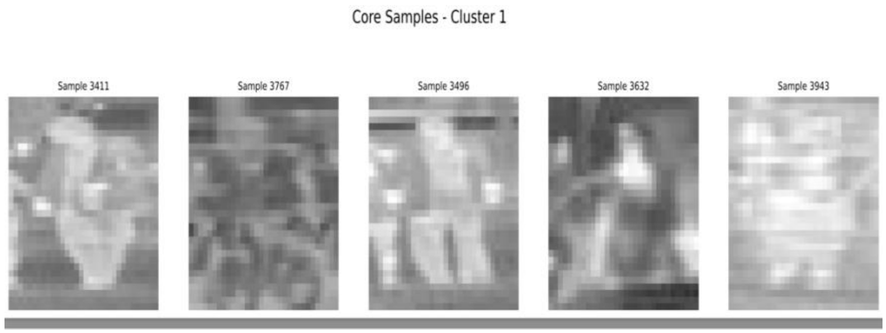
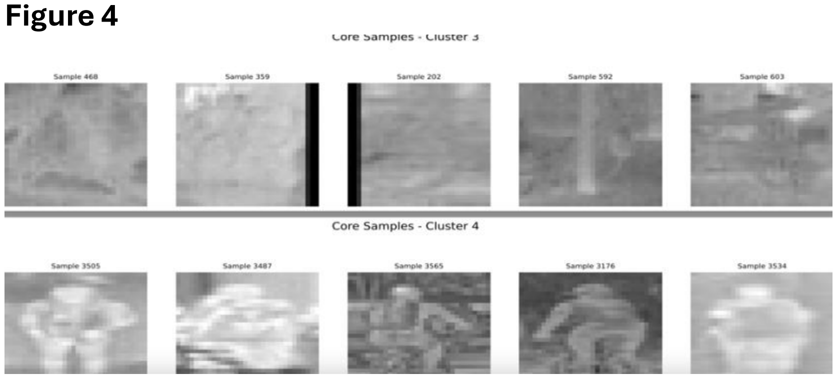
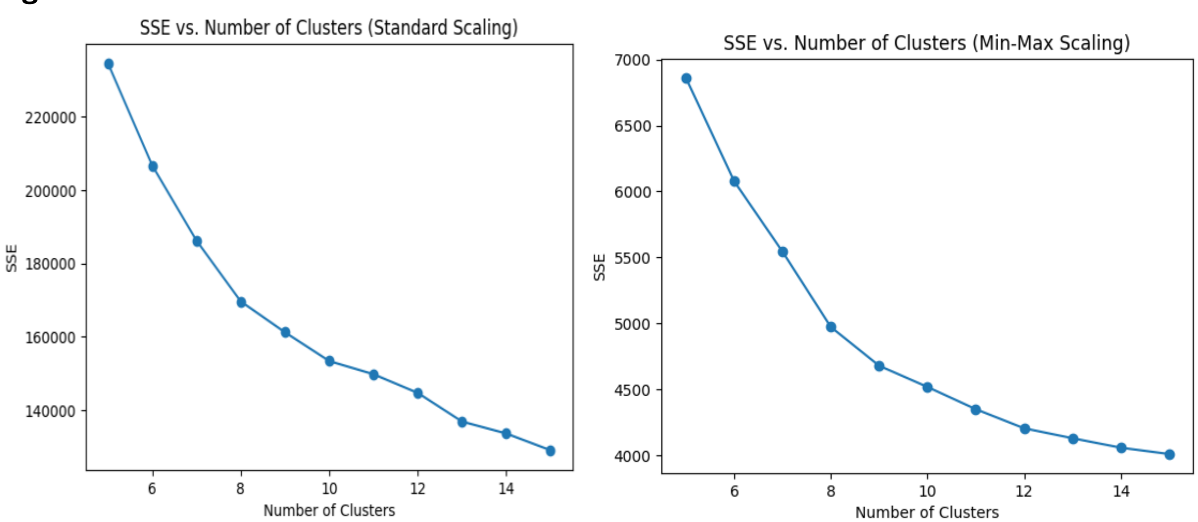


Figure 4



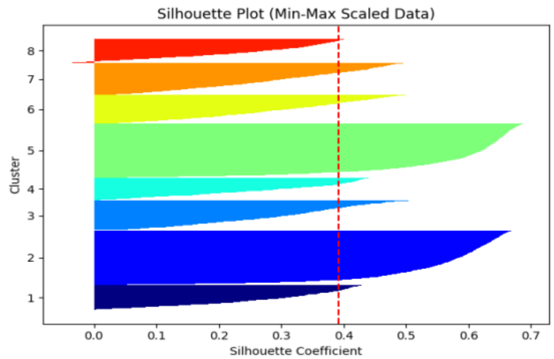
Next, I wanted to normalize my data using min_max and standard_scandard scaler to see If my clusters might change in numbers or if my ARI and Silhouette Scores might increase or decrease.

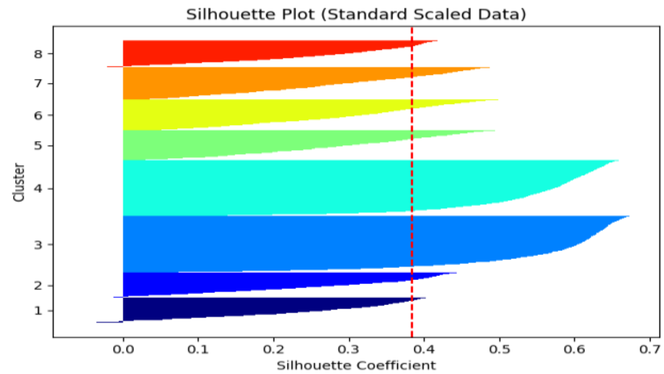
Figure 5



Clusters appear to be the same with 8 being the drop off. Even my Silhouette scores appear to be like unscaled data. Figure 6 as reference.

Figure 6





However, min_max does have a slightly better ARI with a score of .76433 compared to standard_scaler with .75998 and unscaled .76020.

I then tried DBSCAN clustering and went with min_max and standard_scaler due to wanting to keep to normalizing my data. I varied my EPS values from .05, .1, .2, .4, .5, .7, .8, .9, 1.0, 1.1 and my min_samples_values from 2,3,5,10,15, and 20.

I printed out my top ten DBSCAN scores based on ARI and my silhouette scores, and ARI scores are low compared to K-means clustering. Based on the results below in Figure 7 I will be using K-means clustering to see if I can improve that score while PCA and feature selection.

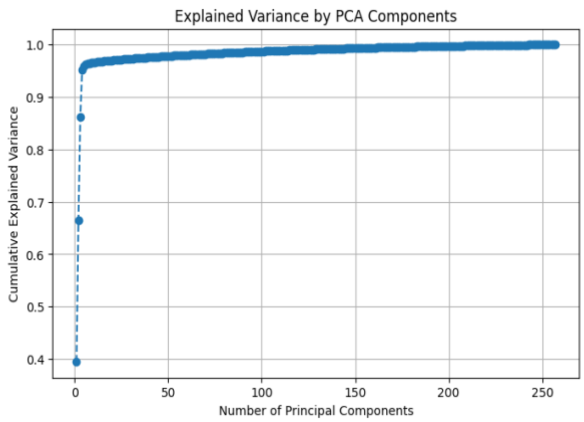
Figure 7

	Scaler	eps	min_samples	ARI	Silhouette Score
94	MinMaxScaler	0.7	15	0.454529	0.026738
95	MinMaxScaler	0.7	20	0.433850	0.120074
93	MinMaxScaler	0.7	10	0.385707	-0.008860
101	MinMaxScaler	0.8	20	0.360767	0.194773
100	MinMaxScaler	0.8	15	0.357603	0.093210
92	MinMaxScaler	0.7	5	0.352074	-0.031331
91	MinMaxScaler	0.7	3	0.344588	-0.252654
90	MinMaxScaler	0.7	2	0.344218	-0.427817
99	MinMaxScaler	0.8	10	0.341010	0.199356
98	MinMaxScaler	0.8	5	0.326744	-0.105680

	Clusters Found	Noise Points
94	5	2398
95	4	2486
93	4	2265
101	2	1683
100	3	1578
92	5	2103
91	10	2013
90	30	1973
99	2	1521
98	5	1425

When using standard scale on my data and using PCA on my features I was able to print out an image that shows me the variance of data that is covered within the increment increase of PCA. When I used min_max it was a similar PCA variance to standard scaler.

Figure 8




```
PC1: 0.3947 (0.3947 cumulative)
PC2: 0.2696 (0.6643 cumulative)
PC3: 0.1976 (0.8619 cumulative)
PC4: 0.0898 (0.9516 cumulative)
PC5: 0.0064 (0.9580 cumulative)
PC6: 0.0042 (0.9623 cumulative)
PC7: 0.0014 (0.9637 cumulative)
PC8: 0.0009 (0.9646 cumulative)
PC9: 0.0007 (0.9654 cumulative)
PC10: 0.0007 (0.9660 cumulative)
```

I will be using PC3 and PC4 to test on my ARI and silhouette scores with just PCA without feature selection yet. PC4 seems to be the beginning of the peak where my cumulative does not increase too much after that.

When selecting min_max as my parameter to run for PC3 and PC3. I get PC3 with an ARI score of .714159 and silhouette score of .414627. For PC4 I get an ARI of .764595 with a silhouette score of .475295. Based on these results keeping all the features tends to outperform or be equal to keeping all features without PCA.

I will now try using feature selection and then PCA with that feature selection to see if I can increase my ARI and silhouette scores. I checked to see if any variance was 0 and there was not in the data.

Next, I used unscaling, min_max scaling and standard_scaling to see if feature selection will make a difference. I varied my cluster options to 5,6,7 and 8 and feature counts to 10,20,40,50 and 100.

When looking at my output I get .70, .80 or .90 ARI scores now with silhouette scores of .40 to .53 with the majority of all the parameters above. Just based on this I will be selecting Feature counts of 50 and 100 with PCA components of 2,3, and 4 as well as cluster of 5 and 6. I will print out figures and explain what gave me the best results.

Figure 9

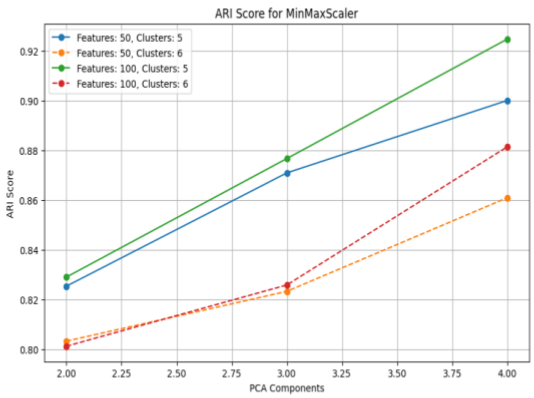
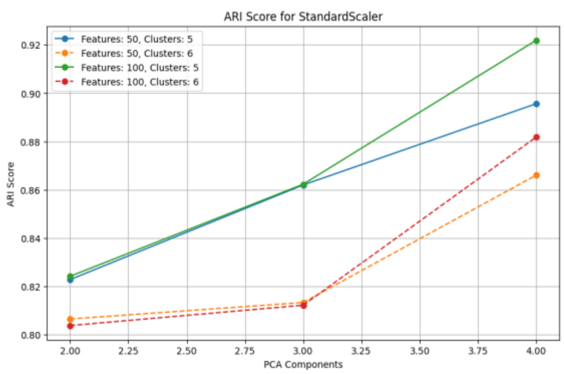


Figure 9



Just based on Figure 8 and Figure 9 my ARI scores have approved big time compared to what I have had so far with Feature Reduction with PCA components. I get an ARI score of .94 with Features 100, PCA 4, cluster 5 with min_max scaling. This will be what I will be going off of as my parameters when I start to select my classifier types.

Figure 10

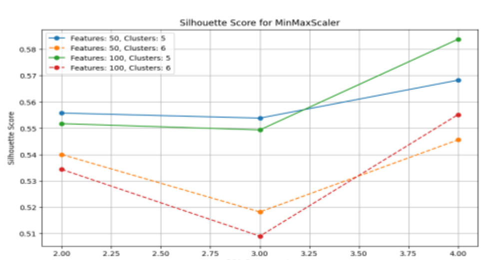
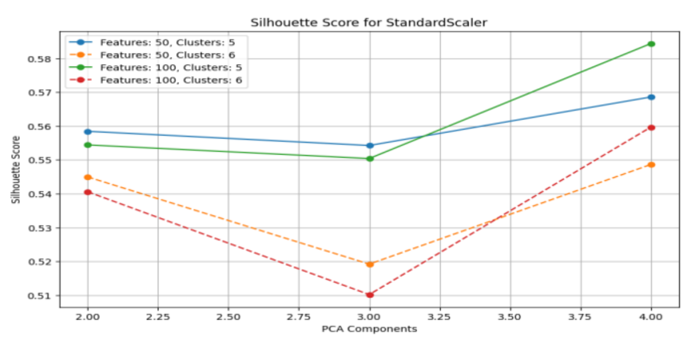
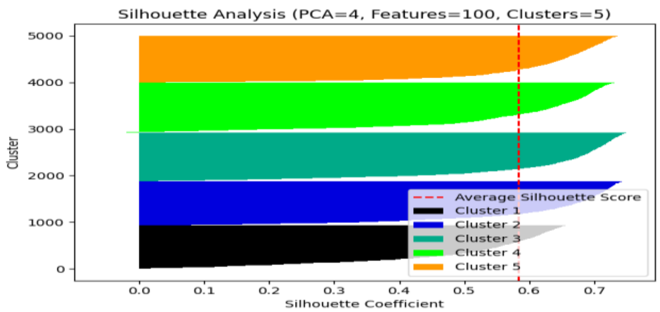


Figure 11



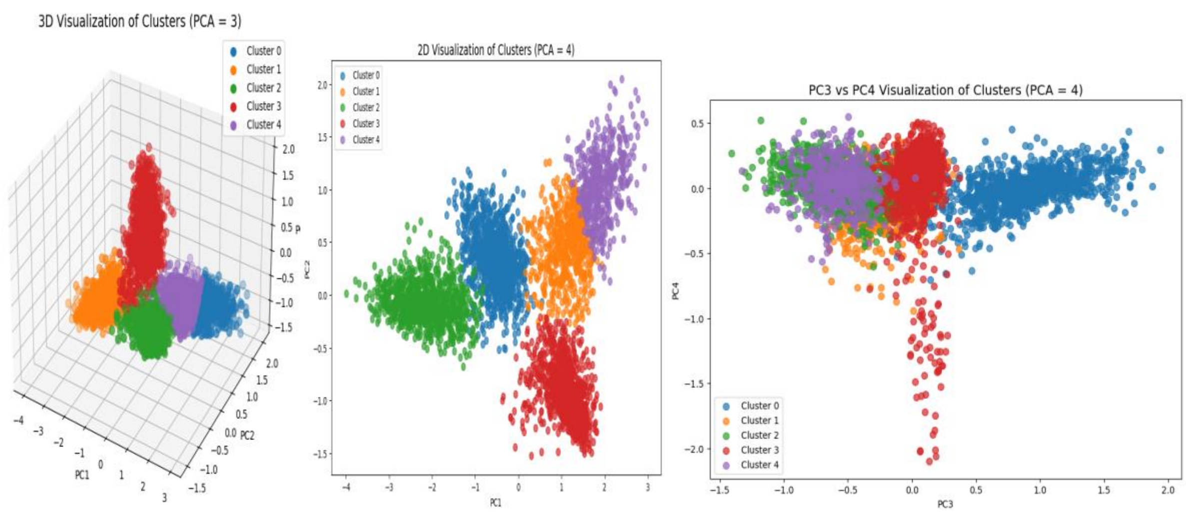
Even based on my silhouette scores I will still be picking features 100, PCA 4, Cluster 5 with Min_Max as my best parameter off the top when I start to pick my classifiers. Below in Figure 12 is my silhouette scores from my best parameters for my clusters. I get good cluster scores that range from .5 at the worse to .7 at the top.

Figure 12



I printed the visualization of PCA 3 and PC4 at 2d and 3d to get a feel of what kind of classifier types I might use.

Figure 13



Based on just looking at the visualization I will be Kernal SVM, Random Forest, Logistic Regression and KNN. However, I was given harder extra_hard_samples.csv file so now I will be training and testing that data with the parameters above.

Before training my SVM model, I selected 70 samples of each class from Extra_hard_samples.csv and combined them to my data.csv data. I made sure all the columns matched.

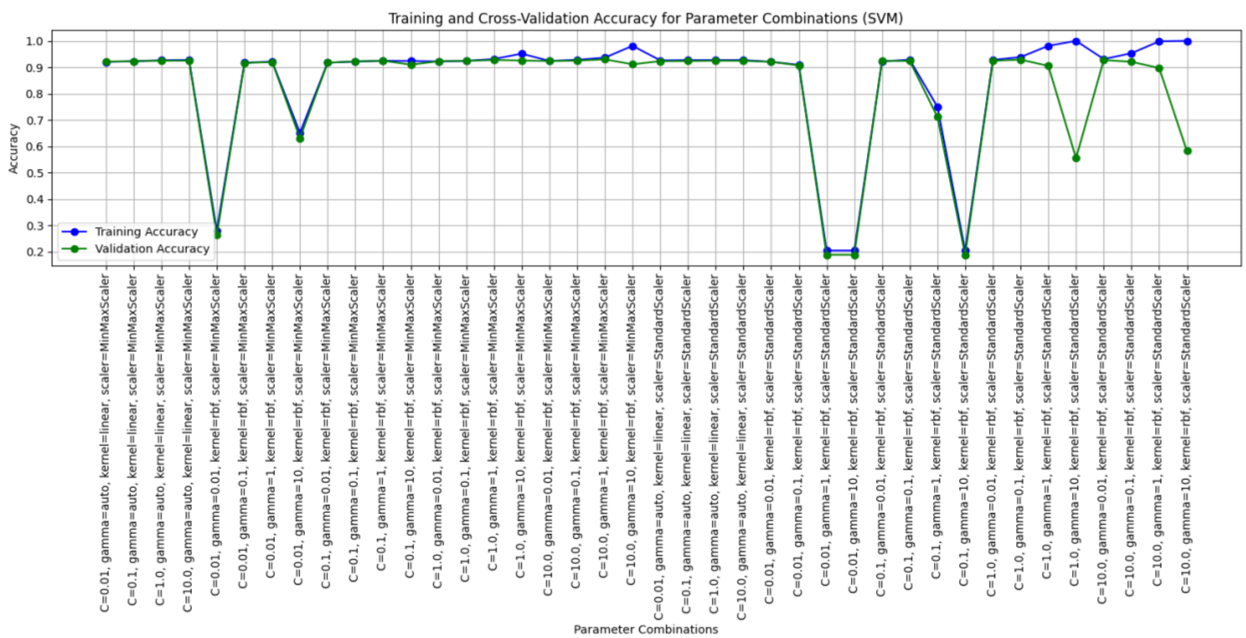
I will be doing an 80/20 split when training and testing my data. I will use PC4 with 100 top features based on MI scores. I got the best results in my preprocessing steps with the above features. When testing and training my data I will use both standard_scaler and min_max scaler.

SVM

I will be using k-fold = 4 with parameters set at C_values = [0.01, 0.1, 1, 10], gamma_values = [0.01, 0.1, 1, 10], kernels = ['linear', 'rbf'] and scalers = { "MinMaxScaler": MinMaxScaler(), "StandardScaler": StandardScaler(}. I set top ranked features at 100 based on MI scores and PCA components set at 4.

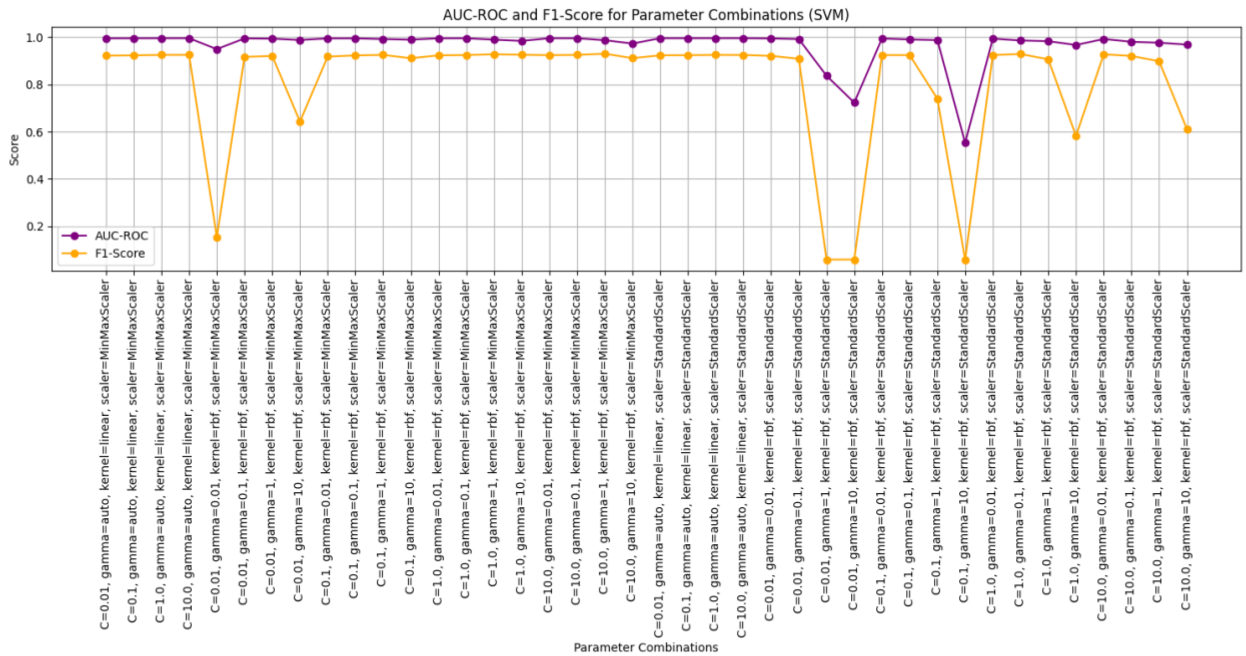
When running my results I will be outputting Average Train Accuracy, Average Cross Validation Accuracy, F1-Score, AUC-ROC and Time Taken.

Figure 14



When looking at figure 14, It appears that minmax appears to be more stable in average training accuracy and validation accuracy compared to Standard Scaler. Standard Scaler has higher training accuracy scores in comparison to min_max. However, validation scores appear to be similar. Linear kernel has better results on validation scores. Good generalization occurs unless its kernel is RBF with low C of .01. This is not always the case, but it does occur more often.

Figure 15



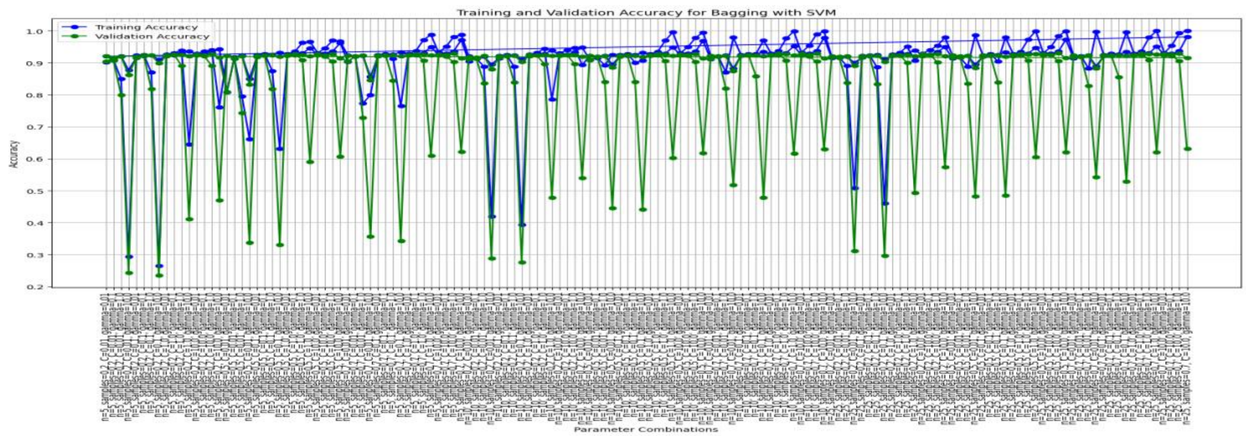
F1-Score is the measure between precision and recall which is very important which trying to balance these metrics importance. For AUC-ROC this is a good measure on how well your model can predict correctly. Based on observation in Figure 15 AUC-ROC will always be higher than F1-score. I also observe that Figure 15 when compared to Figure 14 shows me that usually when Training and Validation accuracy are high or low it correlates with AUC-ROC and F1- Score.

Based on my observation I will select C = 1.0, Gamma = Auto with Linear Kernal and Min_Max Scaler. High overall on all my parameters. However, I will try bagging to see if I can increase my scores.

For bagging SVM I will use the same parameters I had prior but now I will be adding bagging classifier with additional parameters. n_estimators = [5, 10, 25] and max_samples = [0.2, 0.5, 0.7].

Figure 16 will show output of all my parameters I ran when coming training and validation accuracy. When looking at this chart in Figure 16 it is really bunched together so I will separate them later. I also notice I get a lot higher training accuracy with bagging; I also get slightly higher validation accuracy. On the other side I get overfitting a lot more often with bagging which can happen with bagging.

Figure 16



When looking at figure 16, I did not notice anything unusual until I looked at min_max and standard_scaler differences. I observed that the accuracy and validation still correlate with AOC-ROC and F1-Scores, I also noticed that standard scaler did not do as well in generalization since it appeared too always overfit. Figure 17,18,19 show this.

Figure 17

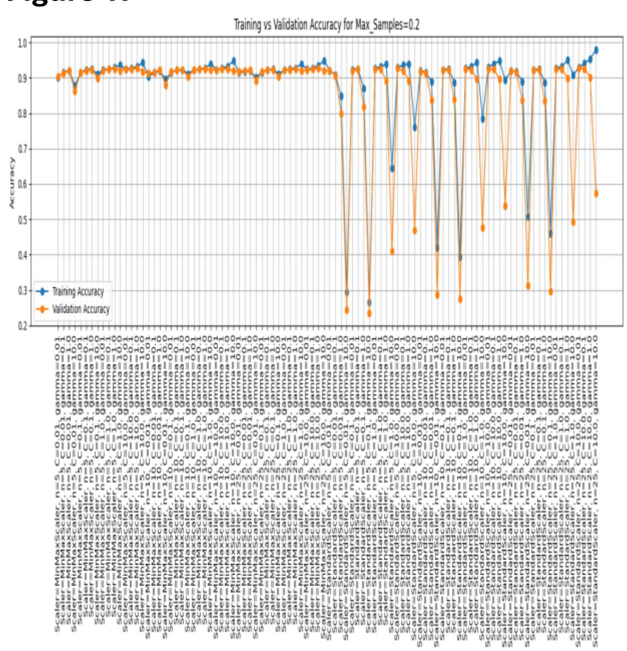


Figure 18

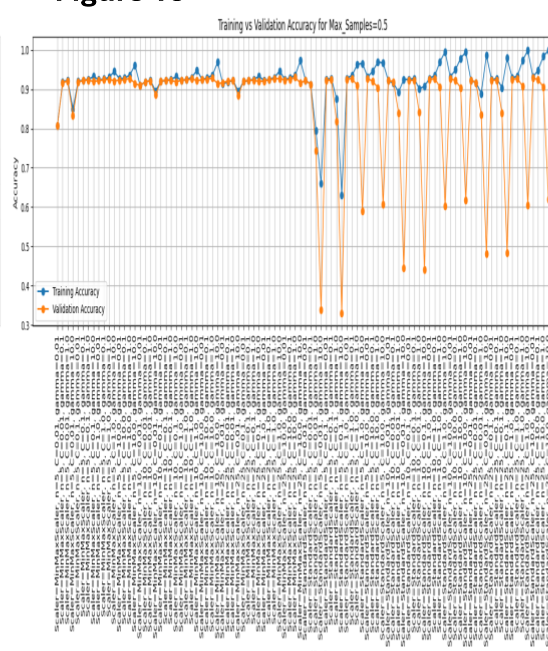
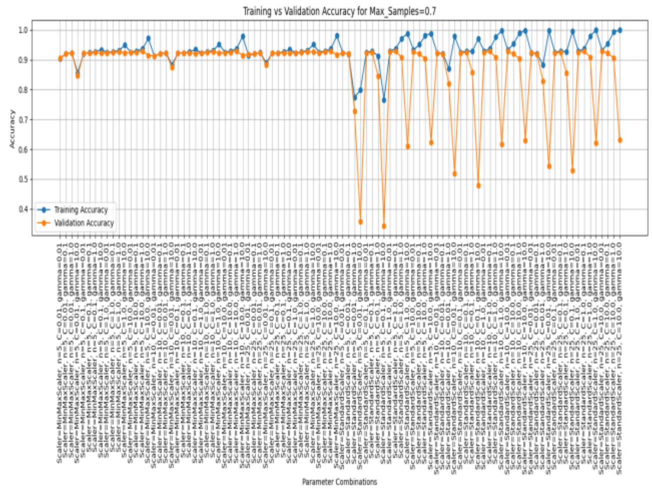


Figure 19



Just based on my results, I will not use bagging since it was like not using bagging. My validation accuracy was around 92 to 93 percent which is what I had without bagging. I could get higher training accuracy, but I like my training and validation accuracy to be closer to each other. I will be selecting no bagging with the parameters shown here. C = 1.0, Gamma = Auto with Linear Kernal and Min_Max Scaler.

KNN

For KNN I used the parameters as stated below.

```
k_values = [1, 3, 5, 7, 10, 13, 16, 20, 25, 30, 50]
weights = ['uniform', 'distance']
metrics = ['euclidean', 'manhattan']
scalers = {
   "MinMaxScaler": MinMaxScaler(),
   "StandardScaler": StandardScaler()
}
```

I kept the feature count and PCA the same as SVM as well as the k-fold=4. Figures 20, 21,22,23 will visualize my min_max and standard scaler training/validation accuracy, AUC-ROC, F1 Scores.

Figure 20

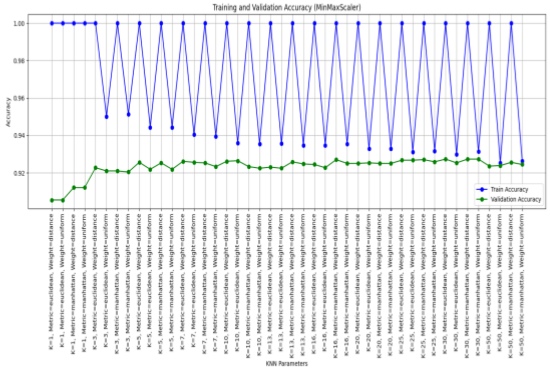


Figure 21

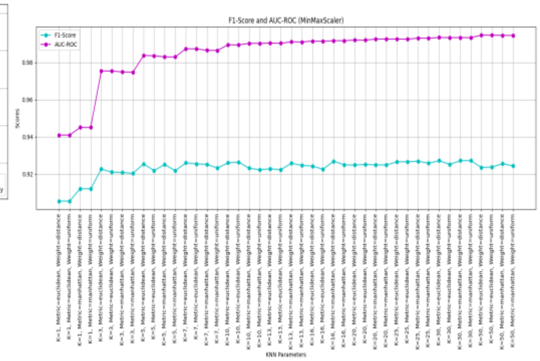


Figure 22

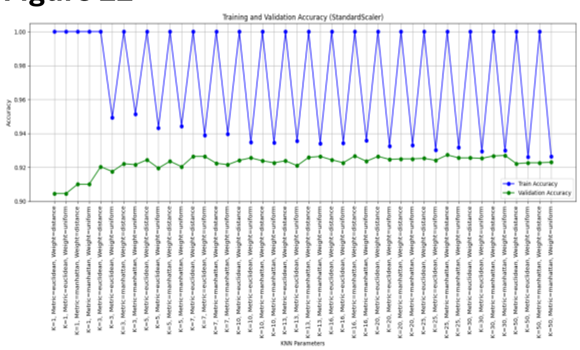
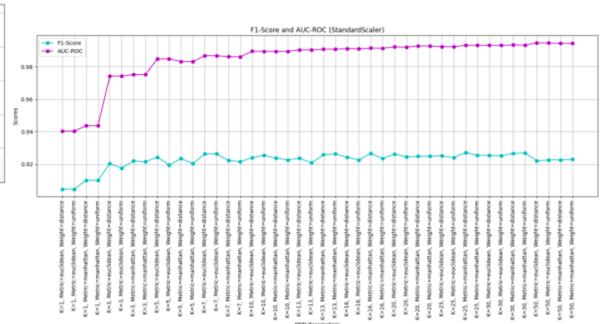


Figure 23



For figures 20-23, I have K parameter set up with its unique parameters as well. Its seperated by min_max and standard scaler. While looking at all these features, both standard scaler and min_max performed similiar. I have overfitting when all normalization have a weight that is distance. Uniform performs better on generalization. I will select K = 7 with min_max scaler, with metric of manhattan and weight as uniform. Even on AUC-ROC and F1-Scores I appear to stabilize at K=7.

Random Forest

I will continue using the same parameters as before with k-fold, PCA and feature selection. However, with Random Forest Classifier I will use N_estimators set at 2,3,5,7,10,25,50,100 and Max_depths set at 2,3,4,5,10,20. Normalization will be the same as before with min_max and standard_scaler.

Figure 24

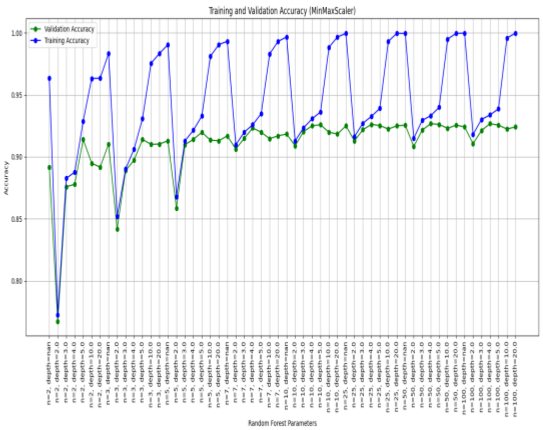


Figure 25

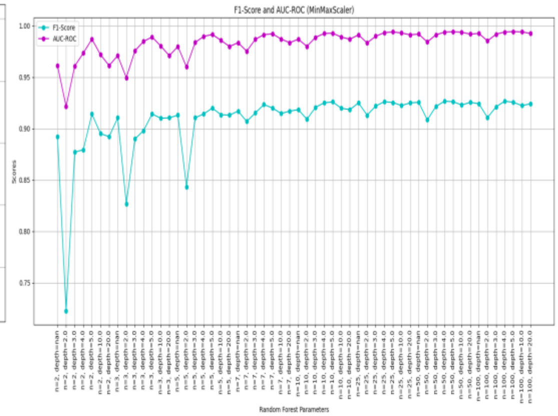


Figure 26

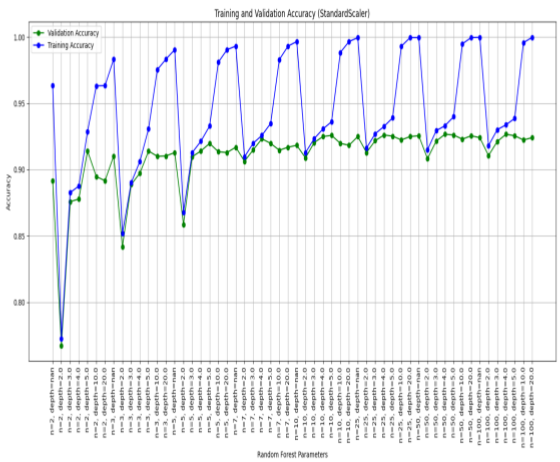
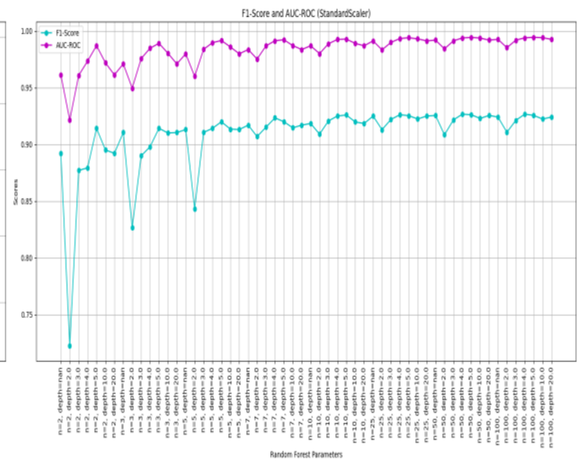


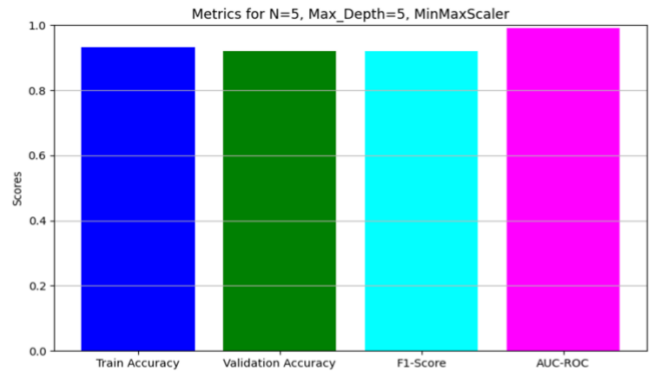
Figure 27



Just based on observation from the figures 24-27, Min_max and standard_scaler once again have similar results. I tend to overfit a lot more often than my previous two classifiers. More often than naught, when my max depth is 10 and above, I get overfitting. This would make sense since I am able to fit more into my training model which improves my training accuracy but is not able to perform as well to cross validation compared to its training. I will be using min_max since it performs as well as standard_scaler. N_Estimator = 3 is where I start to stabilize on all my generalization as well as my AUC-ROC and F1-Scores. Since this is where I don't really have any huge improvements after this. I will stick with N_Estimator = 3. With N= 5 and max_depth = 5, I get my best results on all metrics. Figure 28 visualizes this. I will select these parameters moving forward for Random Forest.

Figure 28

	Train Accuracy	Validation Accuracy	F1-Score	AUC-ROC
18	0.93295	0.919828	0.919889	0.991504



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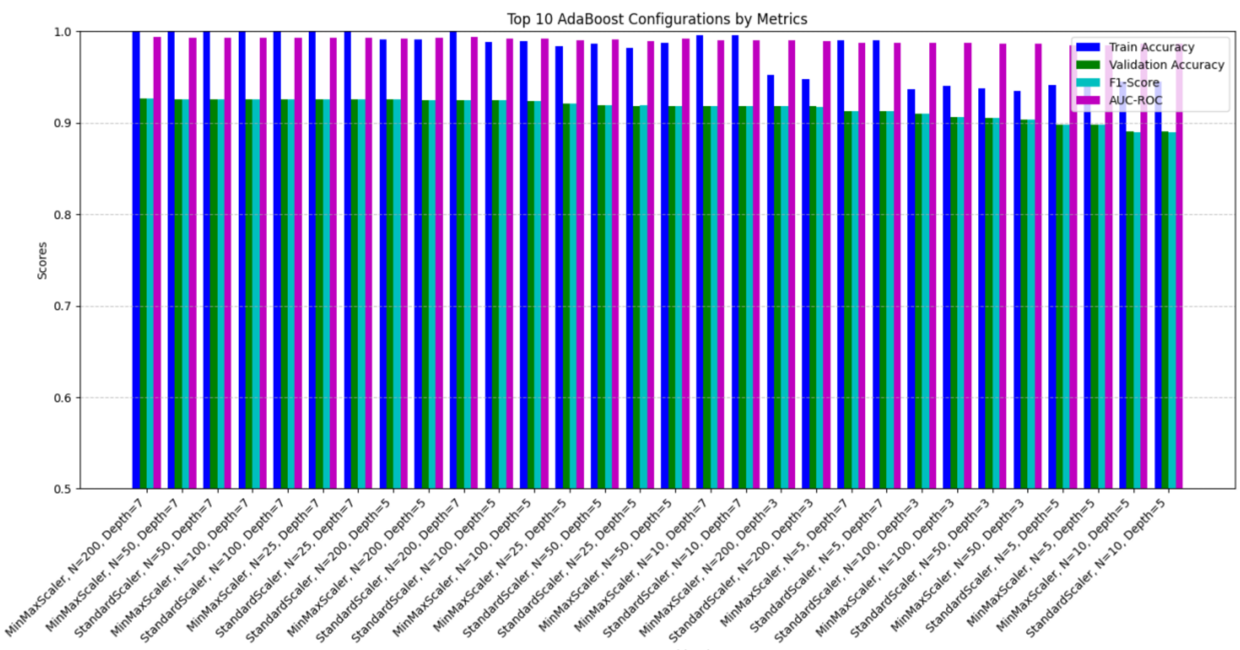
ADA Boost

Follow the same parameters as my other classifiers except I ran Ada boost with the parameters as listed here. n_estimators_values = [5, 10, 25, 50, 100, 200] max_depth_values = [1, 3, 5, 7] and min_max and standard scaler. Figure 29 visualizes my top 30 configurations based on training accuracy.

Figure 29



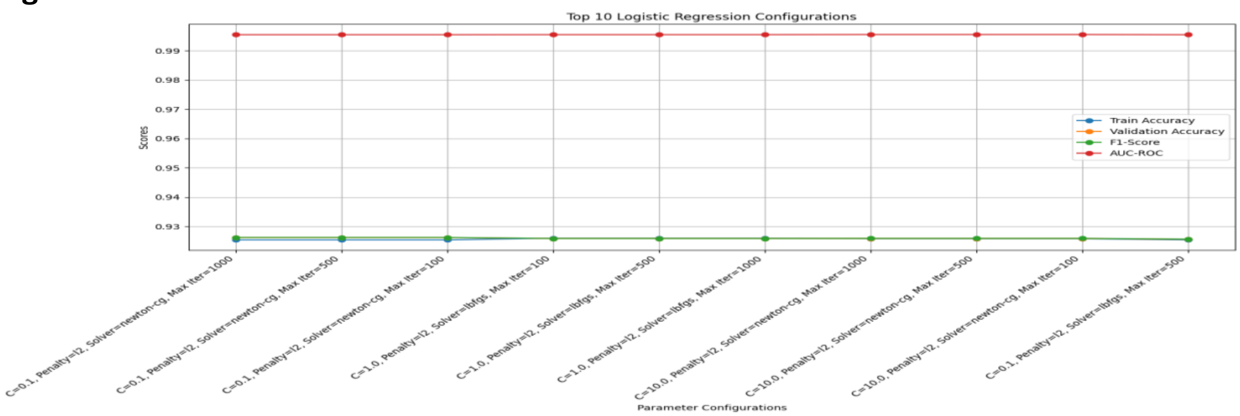
I have overfitting in much of my chart above, however, n = 200, depth = 3 with min_max gets me best results.

Logistic regression

I had set my parameters for c = .01, .1, 1, 10, 100, regularization type as L1, L2, Solvers as lbfgs, newton-cg and max_iteration as 100,500,1000. Min_max and standard_scaler is still applied as well as PCA=4, k-fold=4 and Feature selection = 100 based on MI scores.

I will display the top ten parameters based on training accuracy. However, when displaying all my parameters output, I have overfitting. Figure 30 shows my top ten results which is the same as all my other parameters not shown here. Just based on Figure 30 I will select c= .1, penalty = l2, solver= newtown-cg, max)_iter = 1000 with min_max. However, no parameter that I selected stood out over another.

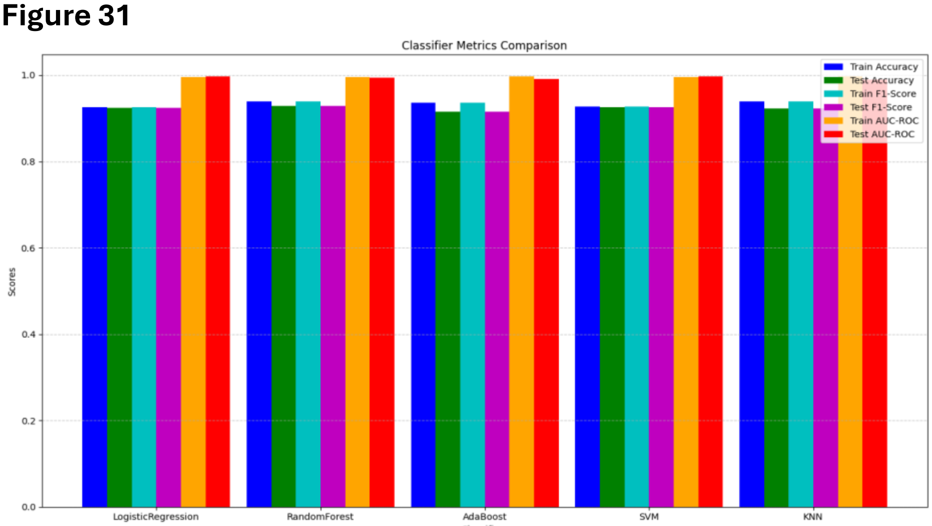
Figure 30



Testing my models with best parameters in each classifier type with pipeline

I will train my models with my training data now and be testing on my 20 percent testing data. Best parameters will be measures against each other. Figure 31 and Figure 32 visualize how my models performed.

Figure 31



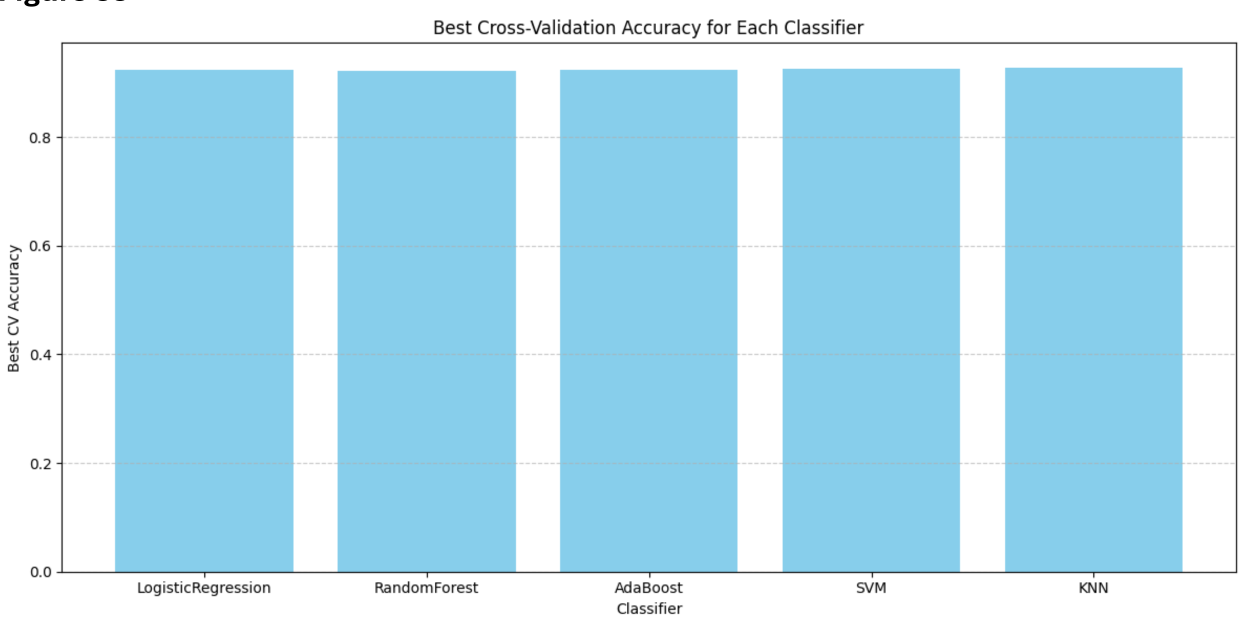
In figure 31 all my models performed similar, however, SVM was able generalize better on testing accuracy by .05 of a percent. In figure 32, Adaboost and SVM took longer to train due to complexity but it’s so short when the highest measure is 1.3 seconds and the shortest is .03. Test time for all models were similar with the highest (AdaBoost) being .03.

Figure 32

Grid Search

When running grid search on every single parameter that I had above for my cross-validation process, I was able to print out best cross validation accuracy for each classifier. When looking at the parameters that grid search selected there were all different from mine but that makes sense since the parameters were all close to each other.

Figure 33



I will be using SVM with c = 1.0, gamma = auto, linear kernal on my test dataset with 30 samples. PCA 4 and 100 features with min_max scaling will be preprocessed again. Video Link: https://youtu.be/2ZTPdyex3BI