ECS 171 Final Report

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1 Abstract

In this project, we compared the effectiveness of several machine learning classifiers at determining forest cover types from cartographic variables. The classifiers we used were artificial neural networks, k nearest neighbors, and random forests. Our results showed that random forests more accurately predicted the correct forest cover type than any other classifier.

2 Introduction

For this project, we decided to use the *ForestCoverType* dataset from UCI's machine learning repository [11]. Determining forest cover type from purely cartographic variables is important in situations where it is unfeasible or impossible to obtain cover type data through empirical methods. Thus, being able to accurately estimate the cover type of an area is of great interest to forest scientists [1, 12]. At the same time, the dataset provides a large amount of well structured data (581012 samples with 54 attributes) upon which different machine learning techniques can be tested and compared, making it an attractive dataset for computer scientists [2, 3, 4, 5, 6, 7]. To give an idea of how the data looks, we present some figures that show the class distribution of the data, as well as a pairwise comparison of the features.

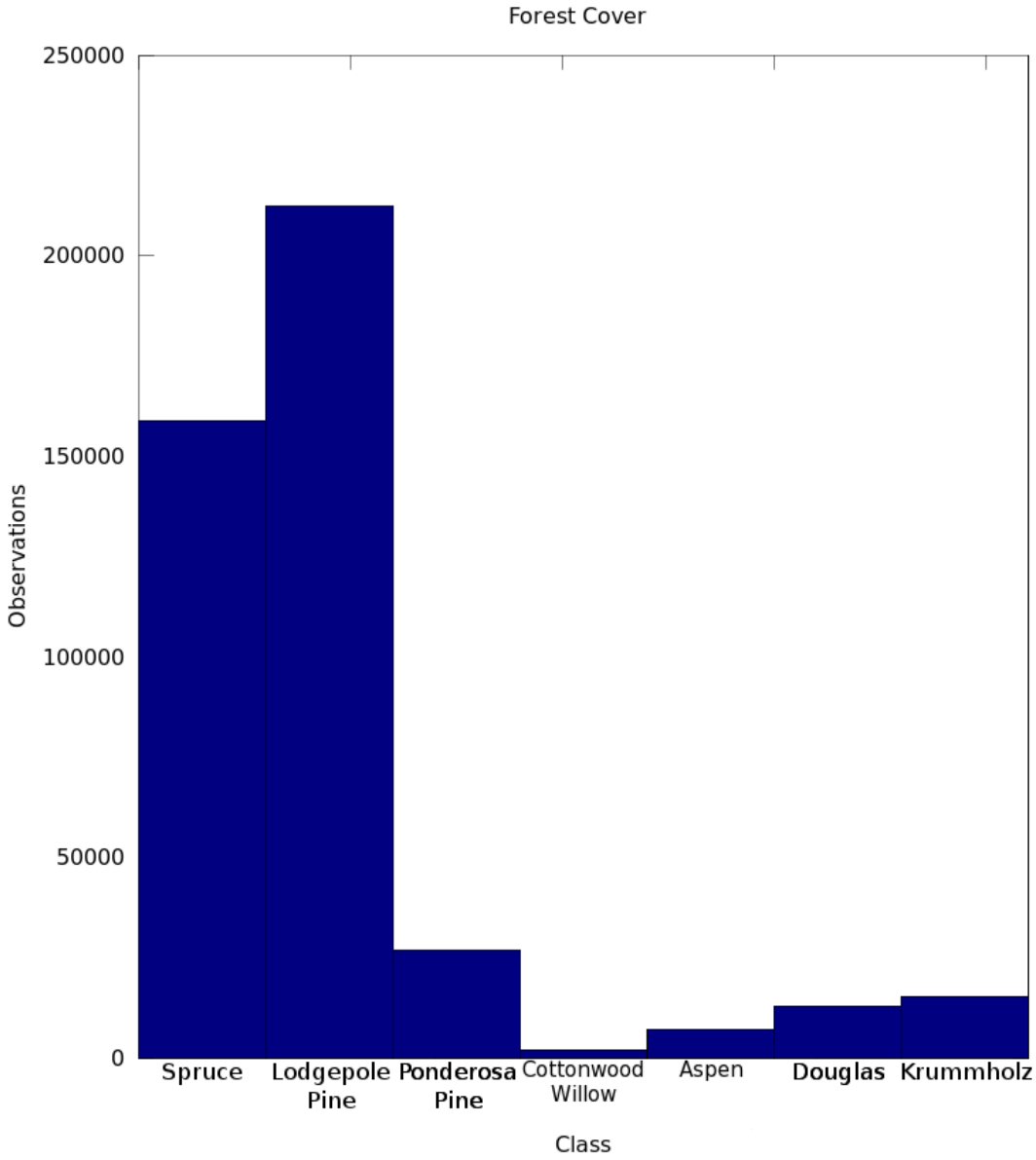


Figure 1: Histogram of class distribution. Note the heavy bias towards Spruce and Lodgepole Pine.

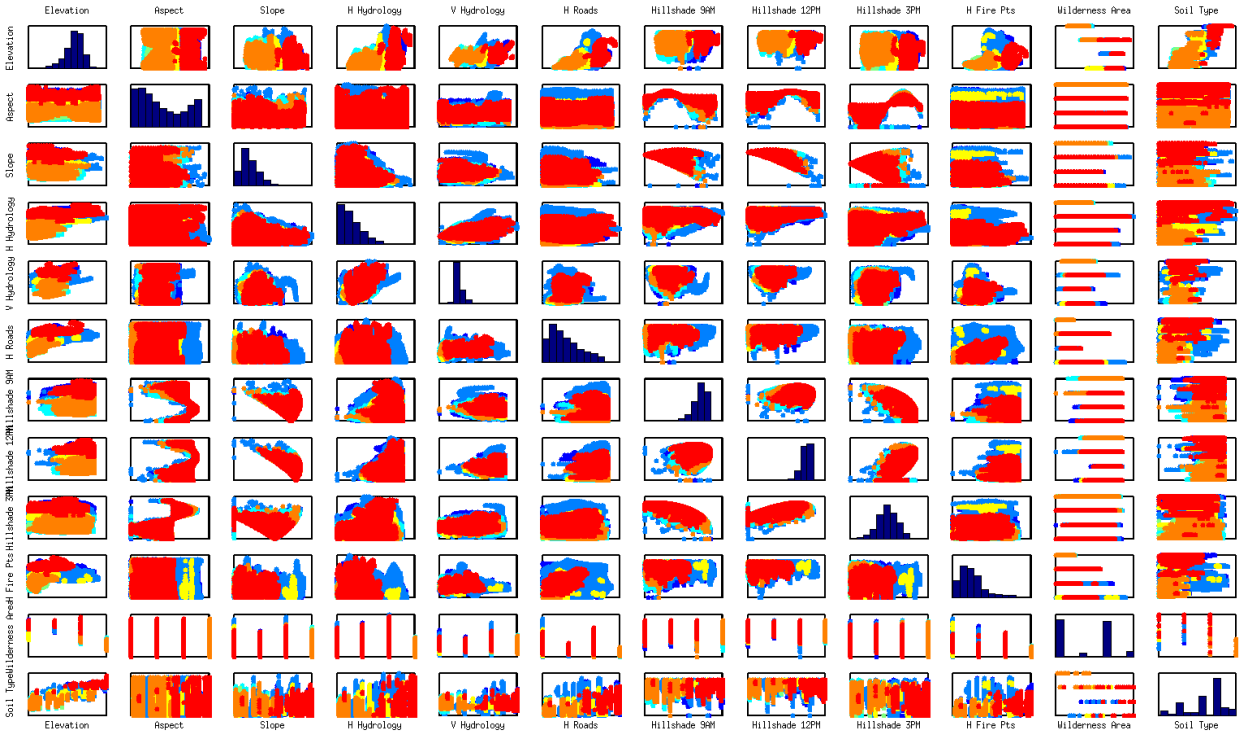


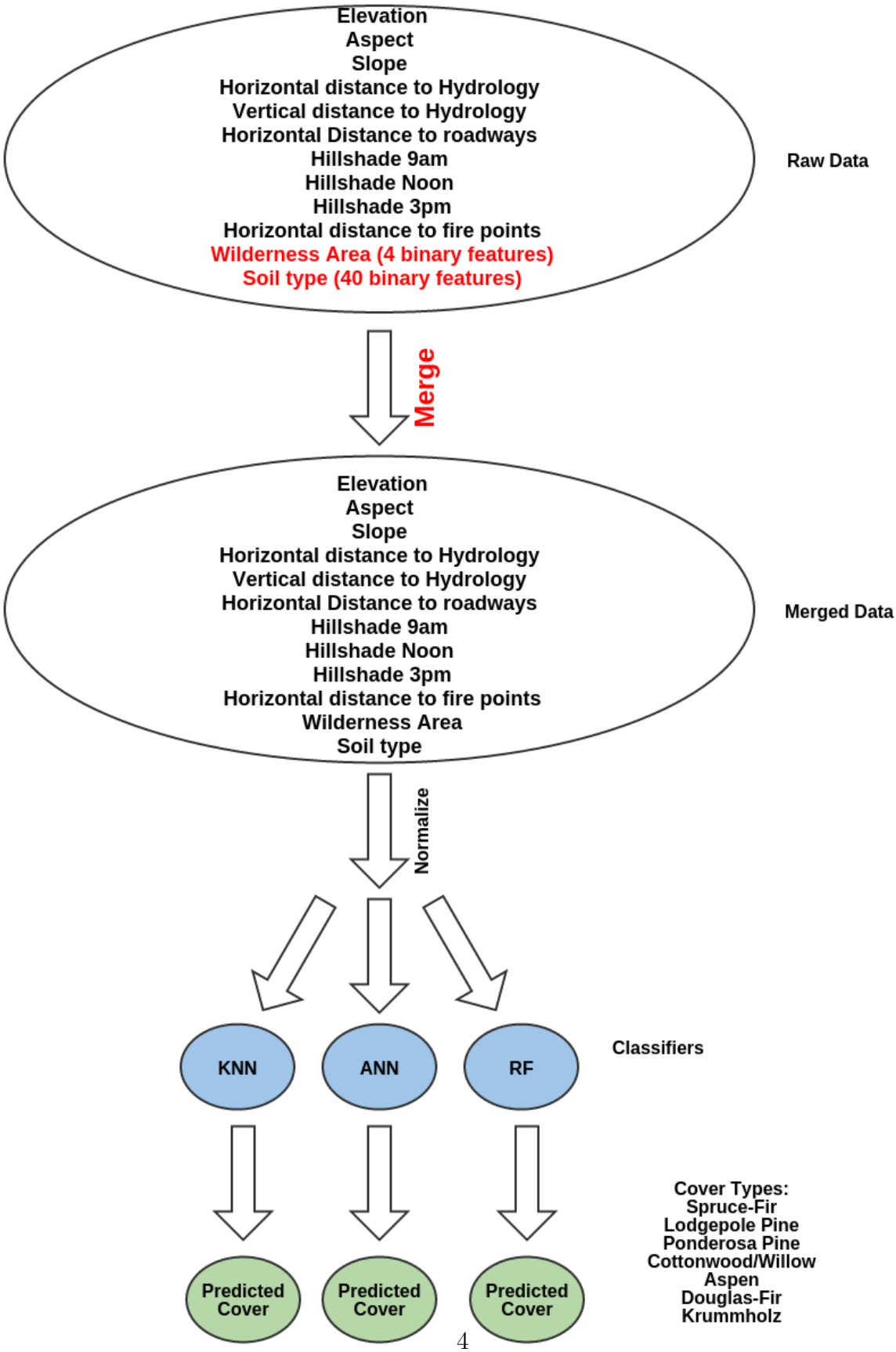
Figure 2: Pairwise comparison matrix of features. You may need to zoom in to see details.

Research on this particular dataset has compared Gaussian discriminant analysis with artificial neural networks (ANNs). Discriminant analysis achieved 58% classification accuracy and the ANN achieved 70% classification accuracy [1]. Blackard and Dean did not use cross validation when evaluating their classifiers, and when building their classifiers, they did not use advanced techniques such as feature selection or regularization. In this project, we improved upon their methods and provided more accurate metrics to evaluate these methods.

3 Methods

We used three different classifiers to determine forest cover type: artificial neural networks, k nearest neighbors, and random forests. The data contained 54 cartographic features from 581012 different 30 by 30 meter plots, along with the cover type for each plot which was determined from US Forest Service (USFS) Region 2 Resource Information System (RIS) data. Within these 54 features, 4 were boolean categorical variables describing the wilderness area, and 40 were boolean categorical variables describing the soil type. We merged the wilderness and soil type features, normalized the data, and then ran our classifiers.

Figure 3: A diagram of how we ran our classifiers.



3.1 Artificial Neural Networks

We used a deep learning toolbox in Octave to implement a feed forward back propagation ANN with L2 regularization and multiple activation functions [13]. ANNs with one hidden layer and two hidden layers were evaluated with 10-fold cross validation and the misclassification rate was used as the error. The settings were: learning rate = 1.5, L2 penalty = 0.0001, number epochs = 50. We selected the ANN with the lowest misclassification rate as our classifier and used it to create both ROC curves and PR curves. We created confusion matrices for each output node by iterating through threshold values. From this we plotted the ROC and PR curves. Finally, we took the predicted output for all our data through 10-fold crossvalidation and created a multiclass confusion matrix that details how classes were misclassified.

3.2 k Nearest Neighbors

The k-Nearest Neighbors (KNN) Algorithm involves classifying a given sample as a particular type, given the type of the k closest samples to it, as determined by some distance function [16]. Our initial approach was to use a standard Euclidean distance function, defined as follows [17]:

$$\sqrt{\sum_{k=1}^{n}(x_{jk} - x_{ik})^2}$$

We decided to begin with this naive approach to isolate failure points (essentially, if something were to work incorrectly, we could rule out the distance function as failure point). We debated creating a distance function tailored to the dataset by hand, or by simply trying many different possible distance functions. However, we decided to generate a distance function with the largest-margin nearest neighbors algorithm (more precisely, we generated a transformation matrix that was used to transform the data, and still used the Euclidean distance). Choosing the right value for k was also critical to the performance of the algorithm, so we decided to test a wide range of k values in order to determine what would work best.

LMNN (Largest Margin Nearest Neighbors) is a variant of KNN that can be implemented in two ways. One method is to learn a Mahalanobis distance function, which measures the distance (in standard deviations) from the center of a cluster of similarly typed samples. Another method, and the method our implementation used, is to learn a transformation matrix that, when applied to the dataset, yields higher correct classification rates [15]. It learns this matrix by iteratively applying small perturbations to the transformation matrix with the goal of maintaining a large distance between "impostors" (close neighbors that are of the wrong type) and the perimeters that surround groups of similarly-typed neighbors. LMNN is very helpful because it saves us the trouble of testing many different distance functions [18], or trying to derive a distance function by hand for each particular dataset.

3.3 Random Forests

For random forests, we used Liaw and Wiener's R port [8] of Breiman's random forest algorithm [9]. The algorithm takes several parameters which control its speed and performance, so we used empirical analysis to determine optimal values for these parameters. The

first of these was $mtry$, which controls the number of variables that are sampled at each split when building the decision trees. 7 was determined to be the optimal value, as increasing the value past 7 caused almost no change in error, but consumed far more system resources. The other parameter was $ntree$ which controls the number of trees to be generated in the forest. For the same reasons as $mtry$, 40 was found to be the optimal value.

To determine error, we used the OOB (out of bag) error [10]. We used this estimate because it is automatically generated by the algorithm while it runs, and because cross validation is not required when using OOB error, due to the way it is computed [9, 10], which saved us computation time. It has also been shown to be close to an optimal estimate of the generalization error[10].

4 Results

To compare the performance of the different classifiers we used ROC and PR curves, along with the AUC. To generate ROC and PR curves for our classifiers, we used a 7-way one versus all approach (as opposed to generating ROC and PR surfaces), as generating multiclass ROC and PR curves is computationally intensive [14], quite complex to implement, and generally difficult to do. This means that we split the response vector into 7 boolean response vectors and generated curves for each binary classifier trained with those vectors.

4.1 ANN Results

We found that the optimized tanh activation function outperformed the sigmoid function. ANNs with one hidden layer had decreasing error until there were about 30 hidden nodes. The one hidden layer structure did not achieve an accuracy higher than 79%. ANNs with two hidden layers did slightly better with the best achieving 80.3% accuracy.

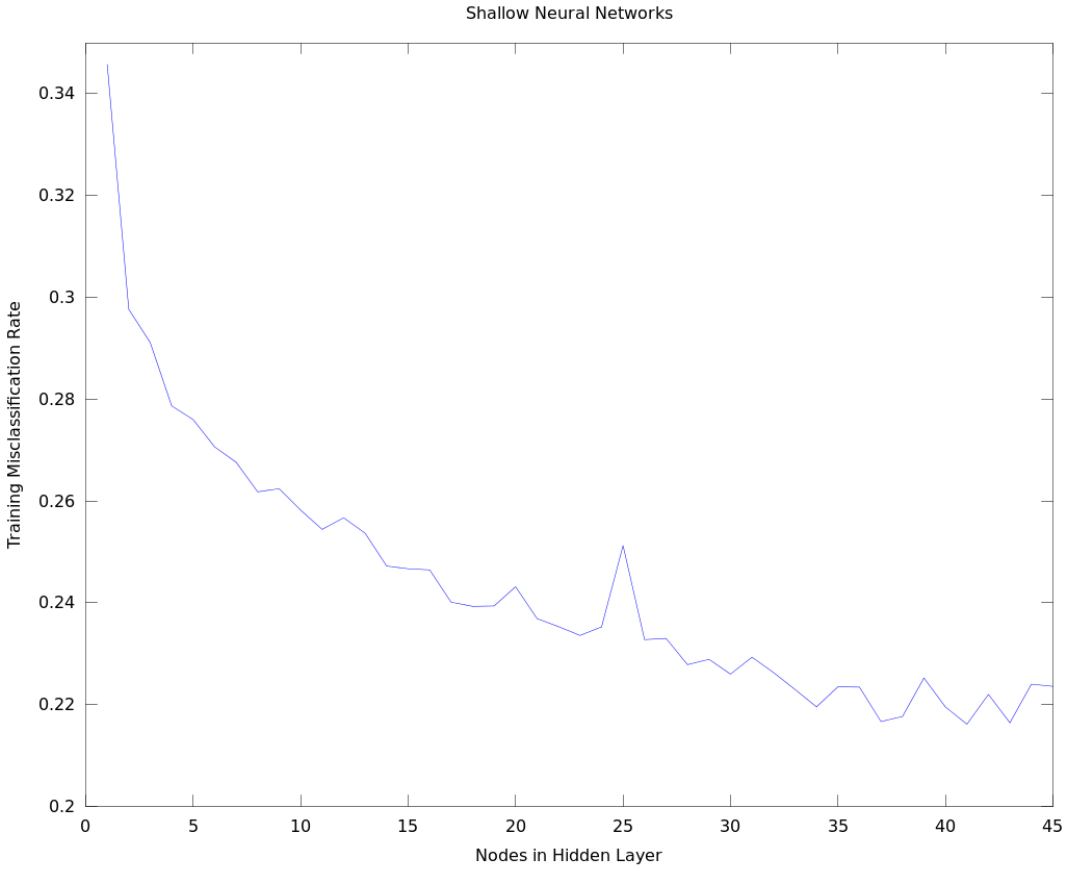


Figure 4: A graph of error vs. number of nodes in the hidden layer (one hidden layer).

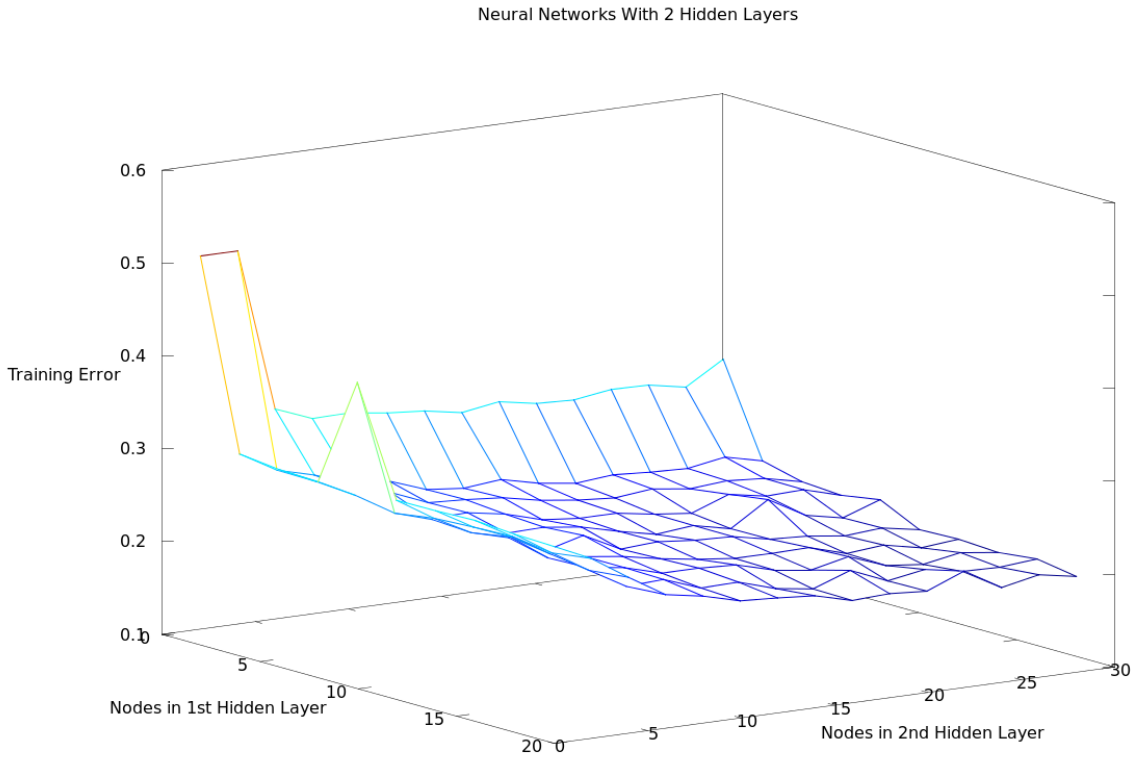


Figure 5: A graph of error vs. number of nodes in the hidden layer (two hidden layers).

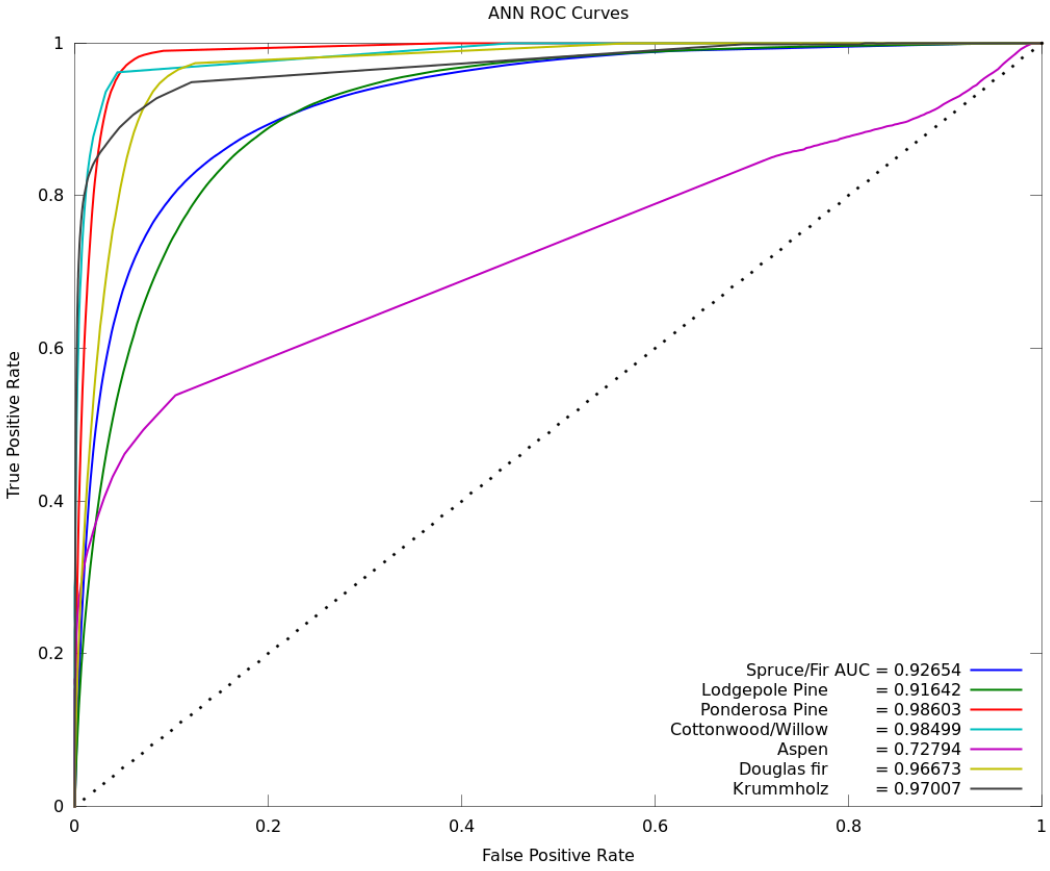


Figure 6: ROC curves for each class, with the AUC for each curve.

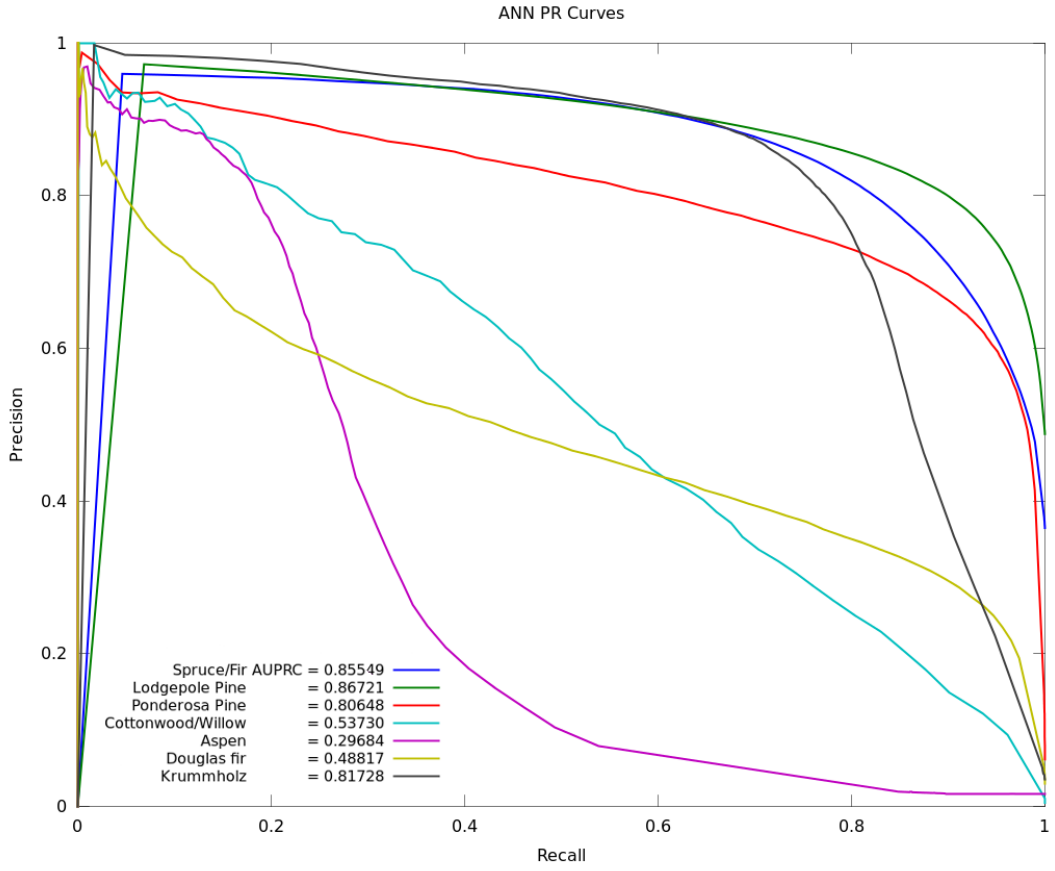


Figure 7: PR curves for each class, with the AUC for each curve.

The multiclass confusion matrix revealed that there was a lot of misclassificaiton between Spruce and Lodgepole pine. Cottonwood/Willow, Aspen, and Douglas-Fir were all misclassified the majority of the time.

	Observed	Observed	Observed	Observed	Observed	Observed	Observed
True Class	Sp.-Fir	L. Pine	P. Pine	C./Willow	Aspen	D.-Fir	Krum
Sp.-Fir	**166919**	42605	16	3	47	34	2216
L. Pine	28706	**250128**	2821	8	310	996	330
P. Pine	22	3140	**30817**	196	0	1579	0
C./W.	0	11	1671	**863**	0	202	0
Asp.	471	7176	288	0	**1529**	29	0
D.-Fir	124	4303	8558	110	1	**4271**	0
Krum.	5031	518	0	0	0	0	**14961**

4.2 KNN Results

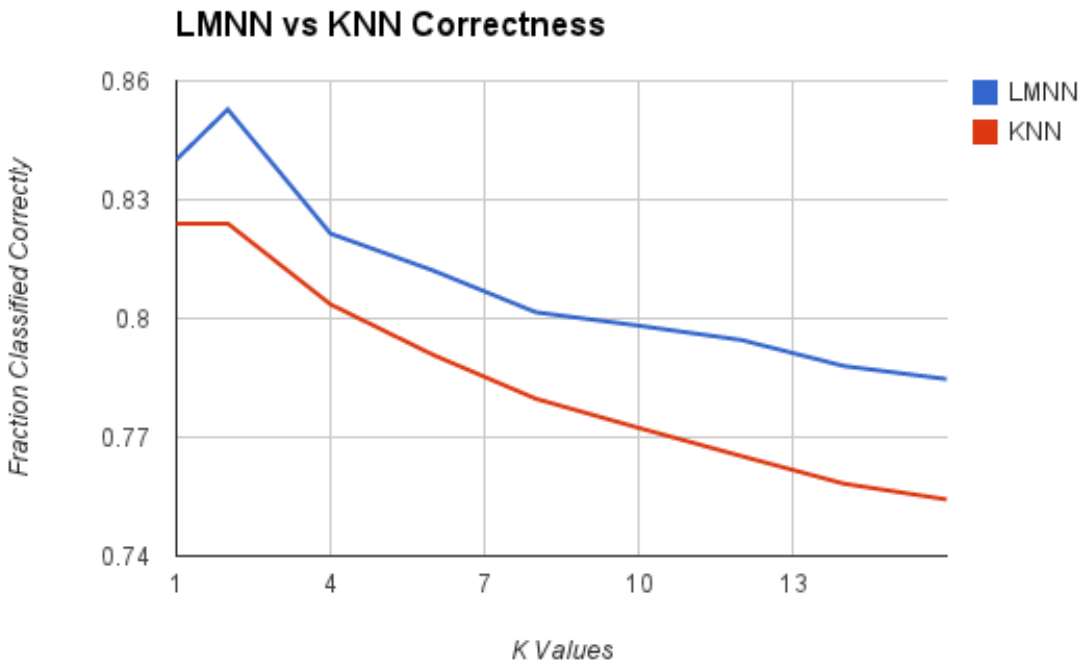


Figure 8: Graph of accuracy vs. K values.

LMNN was able to boost the correct classification percentage across all values of k. On average, we saw 2.46% better classification rates. Using LMNN, we came up with the following ROC and PR curves.

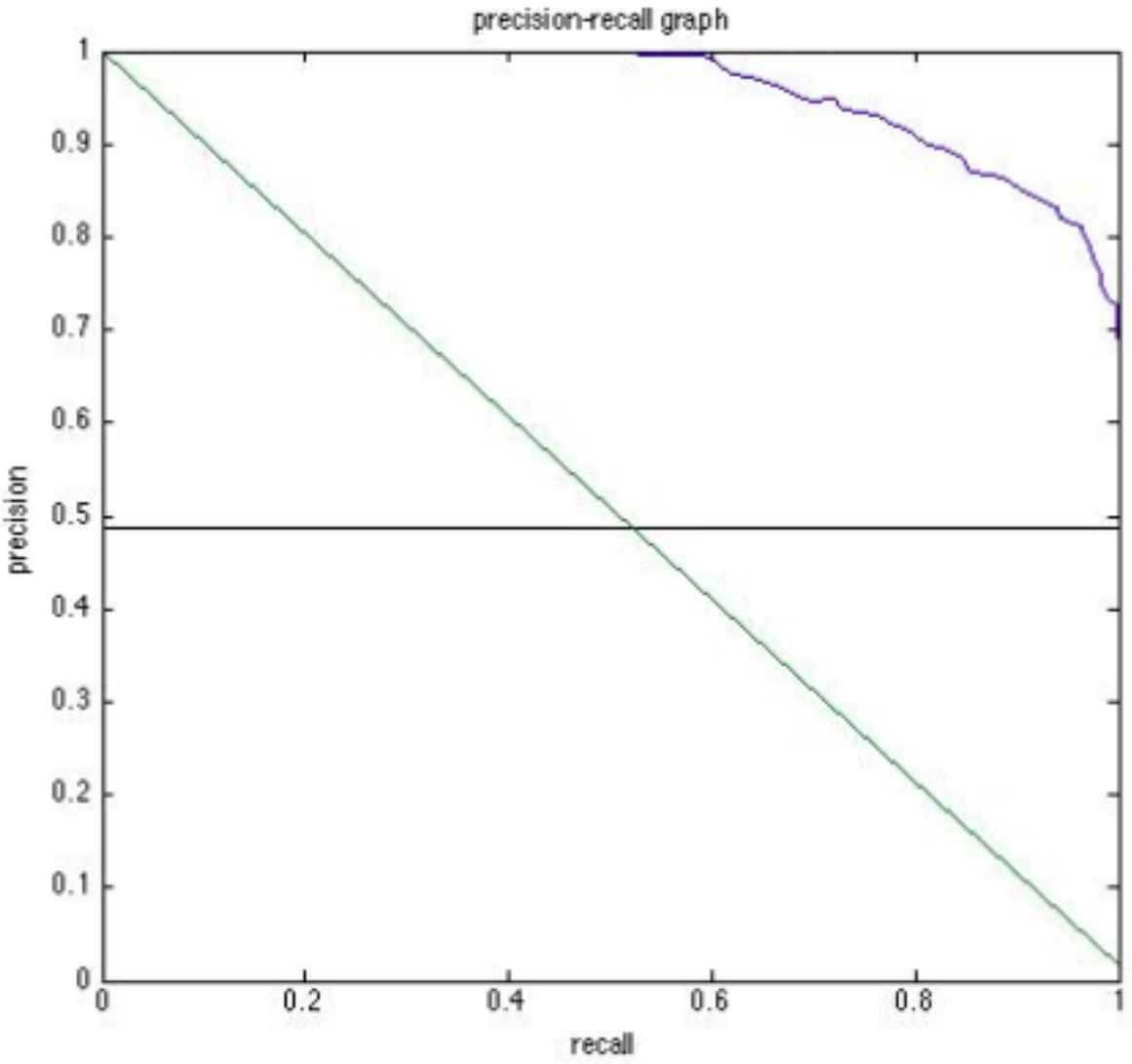


Figure 9: PR Curve for class Aspen

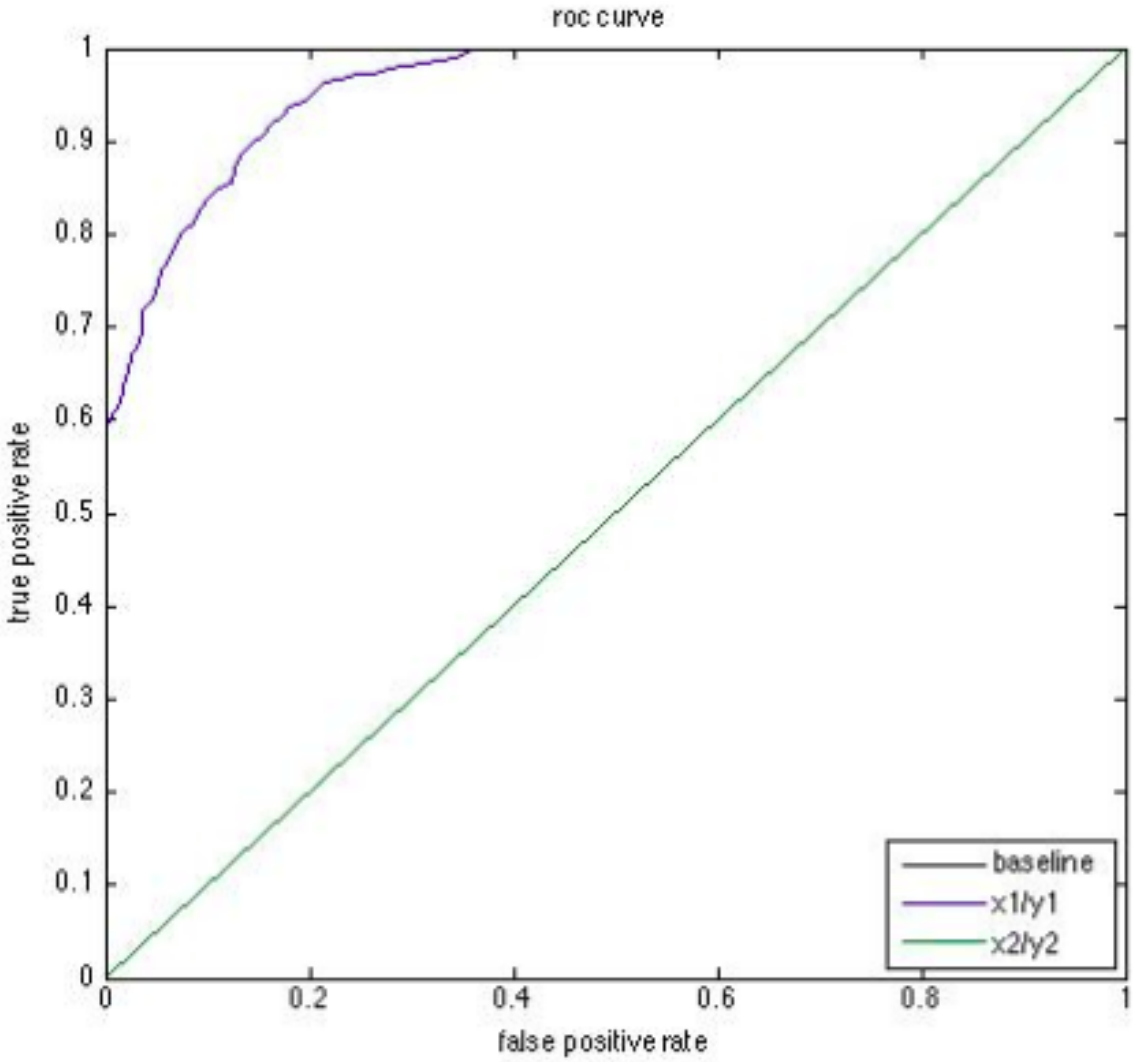


Figure 10: ROC Curve for class Aspen

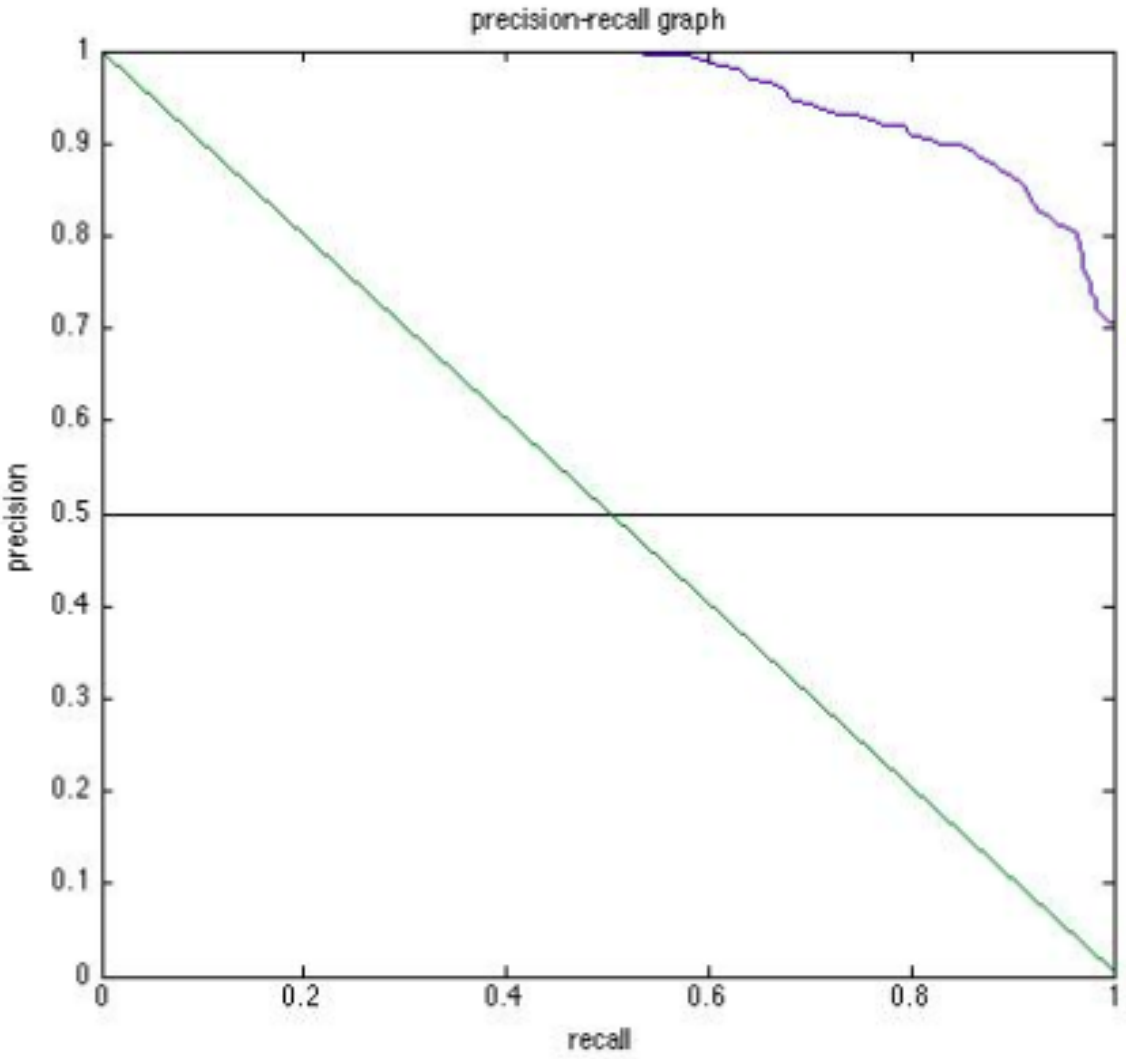


Figure 11: PR Curve for class Cottonwood

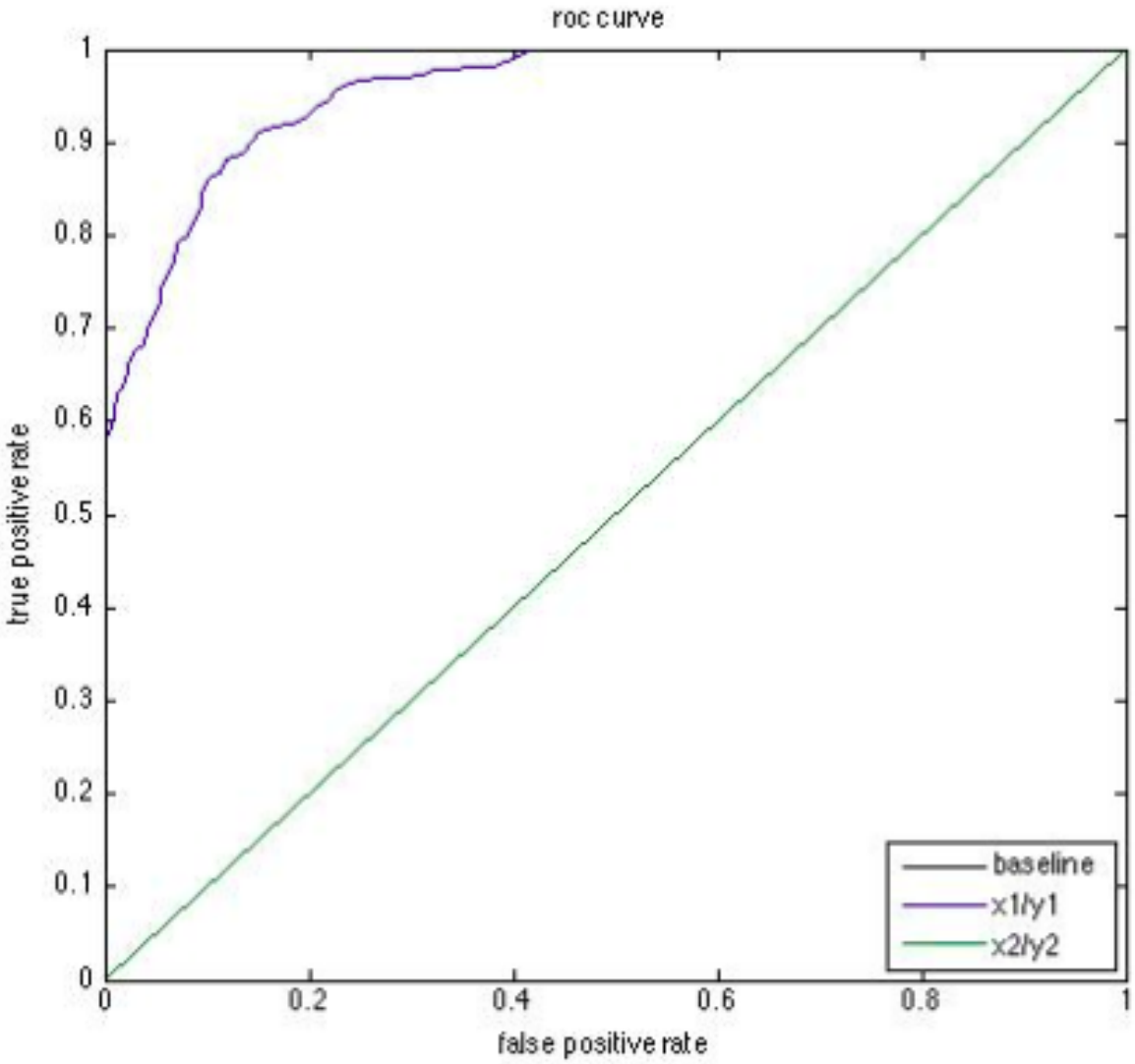


Figure 12: ROC Curve for class Cottonwood

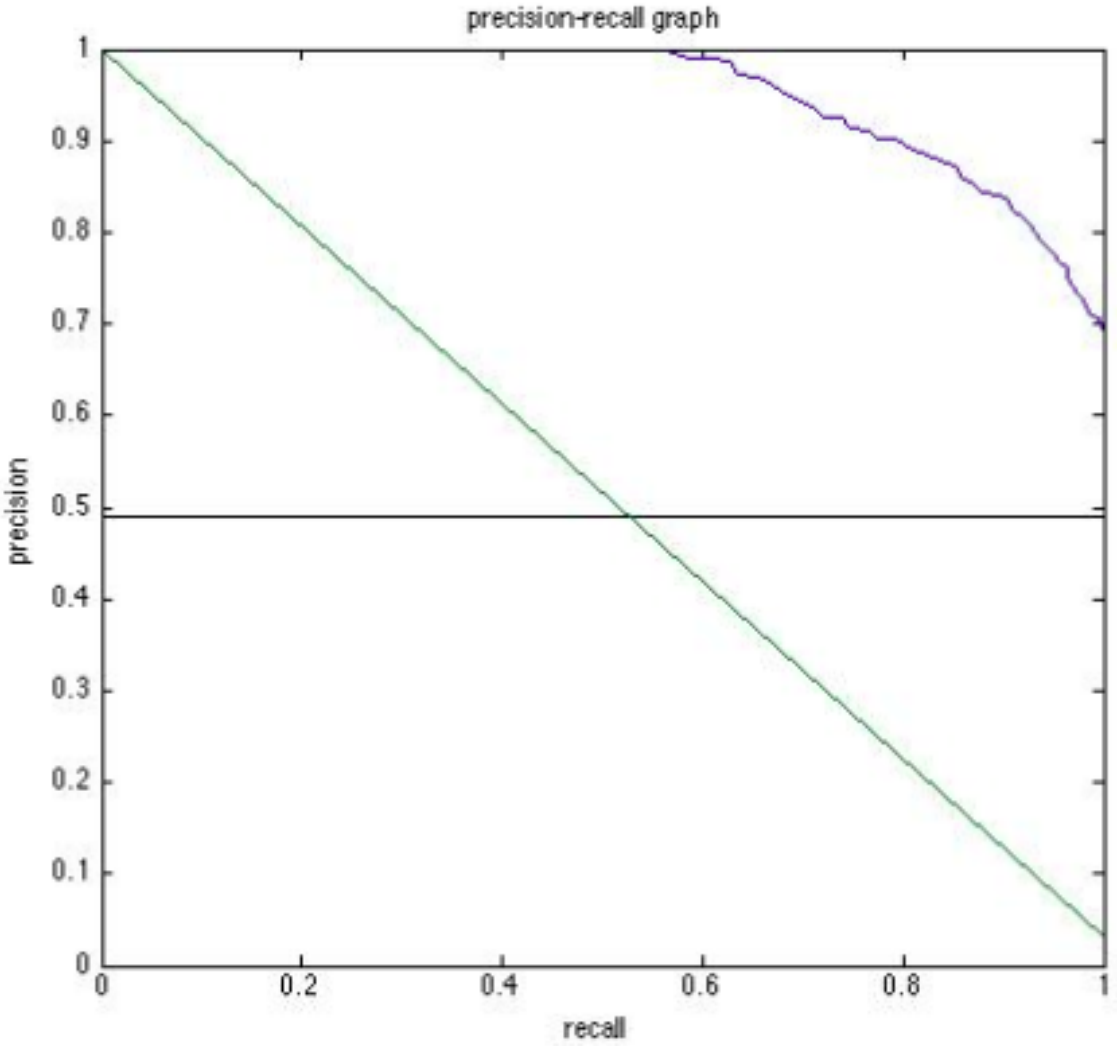


Figure 13: PR Curve for class Douglas Fir

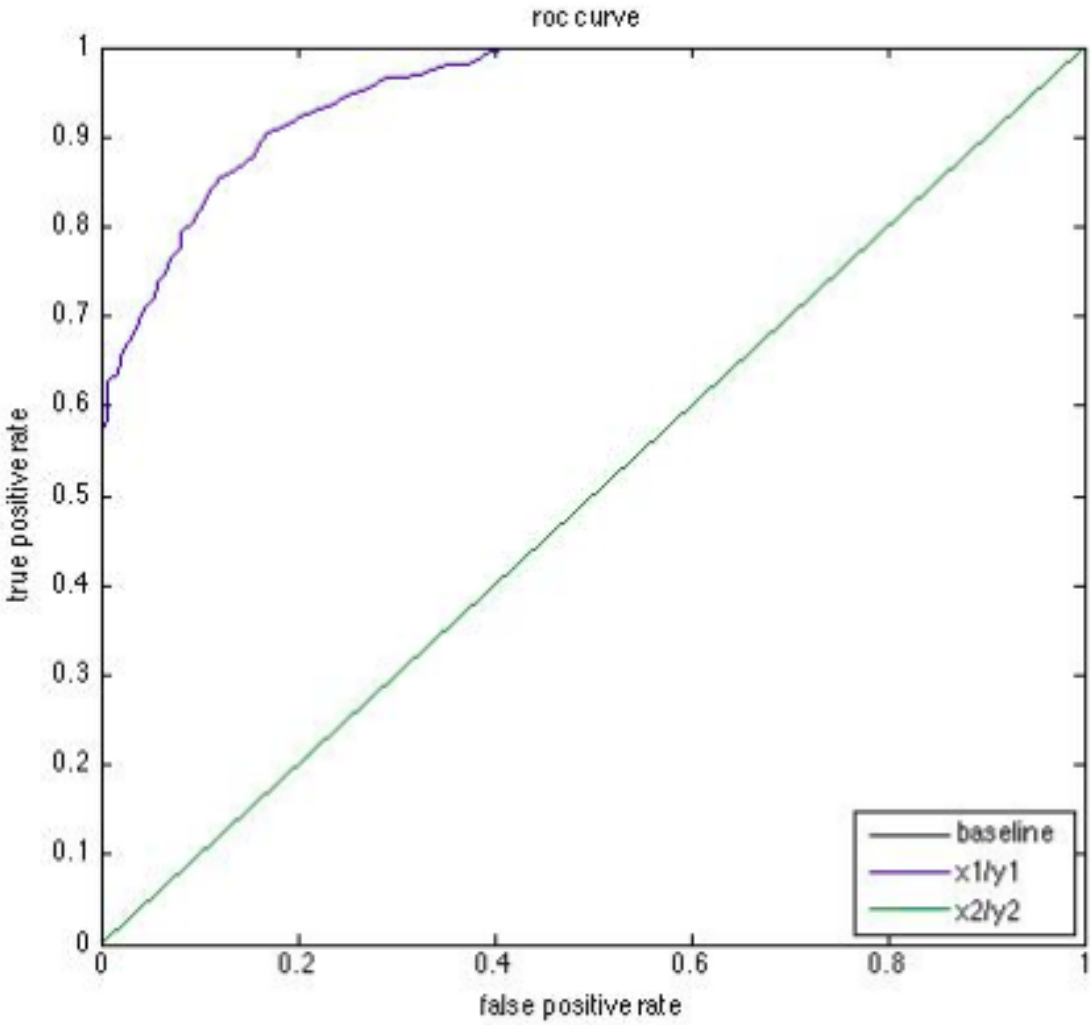


Figure 14: ROC Curve for class Douglas Fir

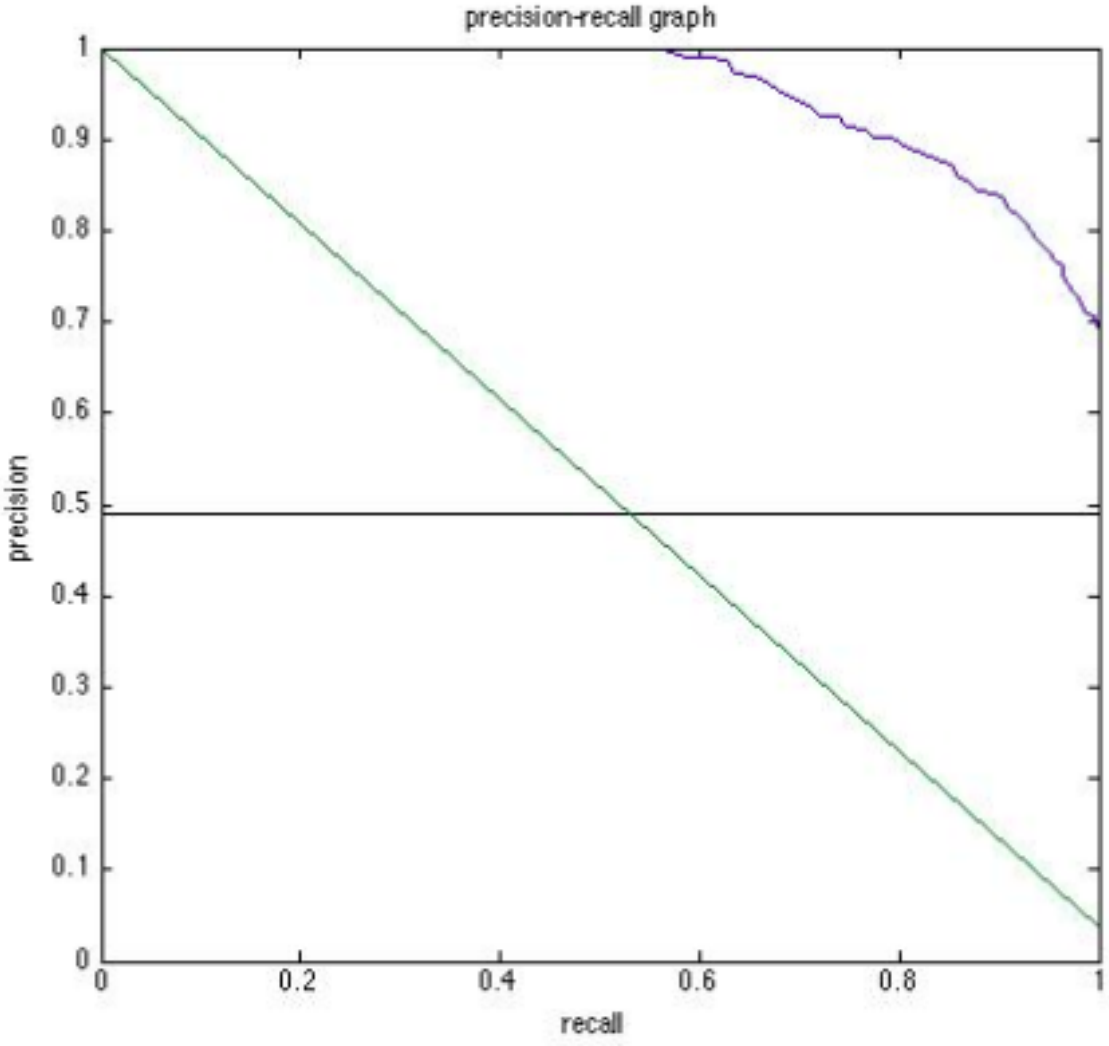


Figure 15: PR Curve for class Krummholz

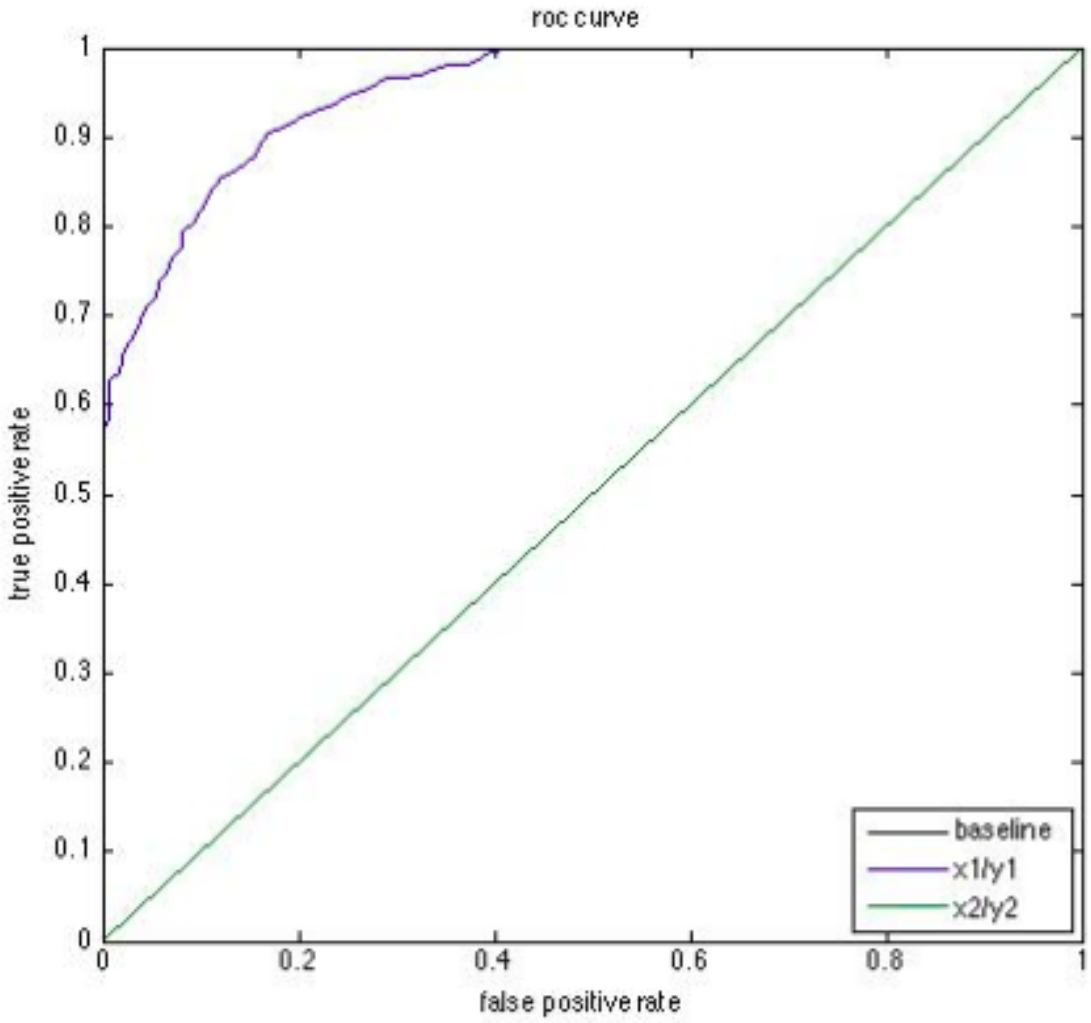


Figure 16: ROC Curve for class Krummholz

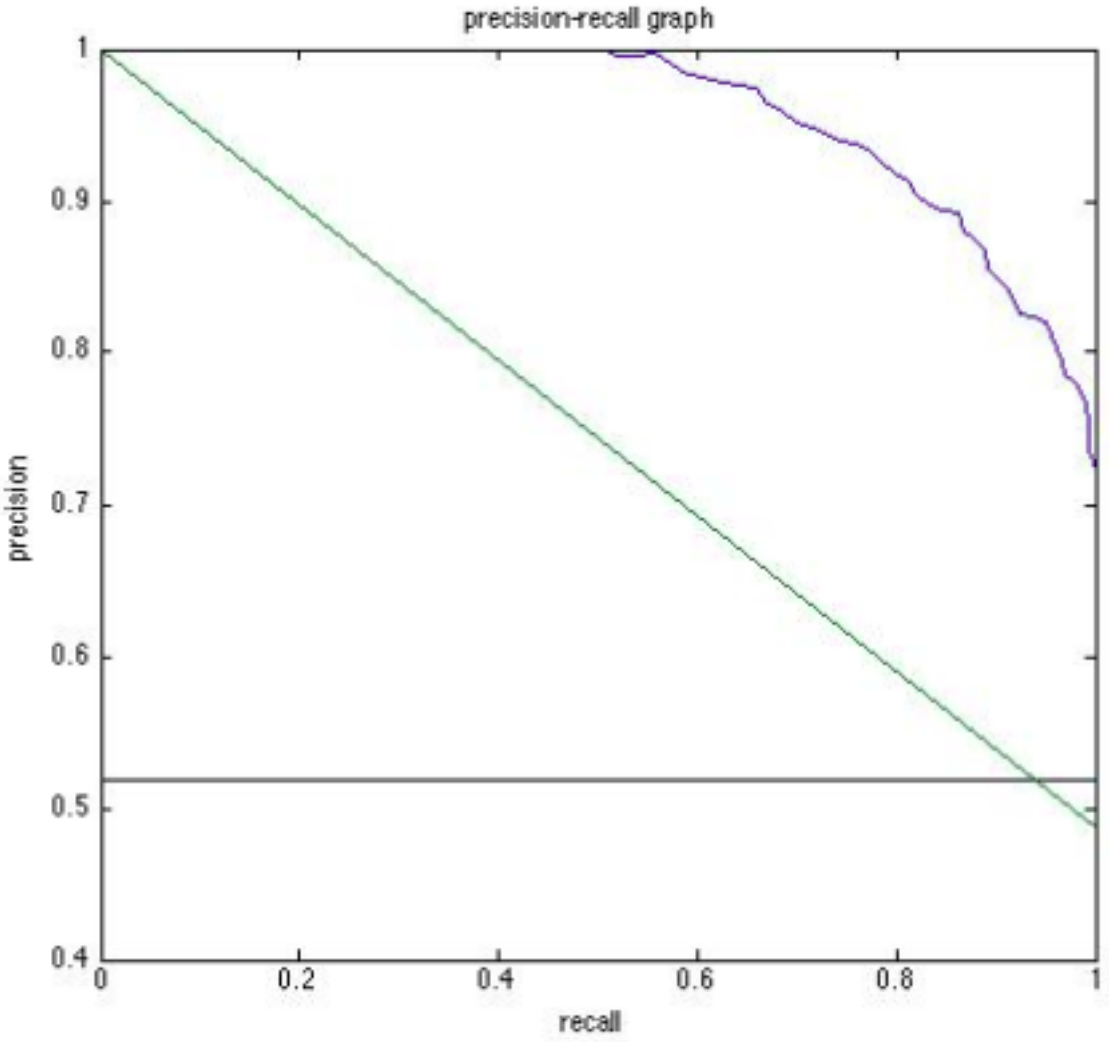


Figure 17: PR Curve for class Lodgepole Pine

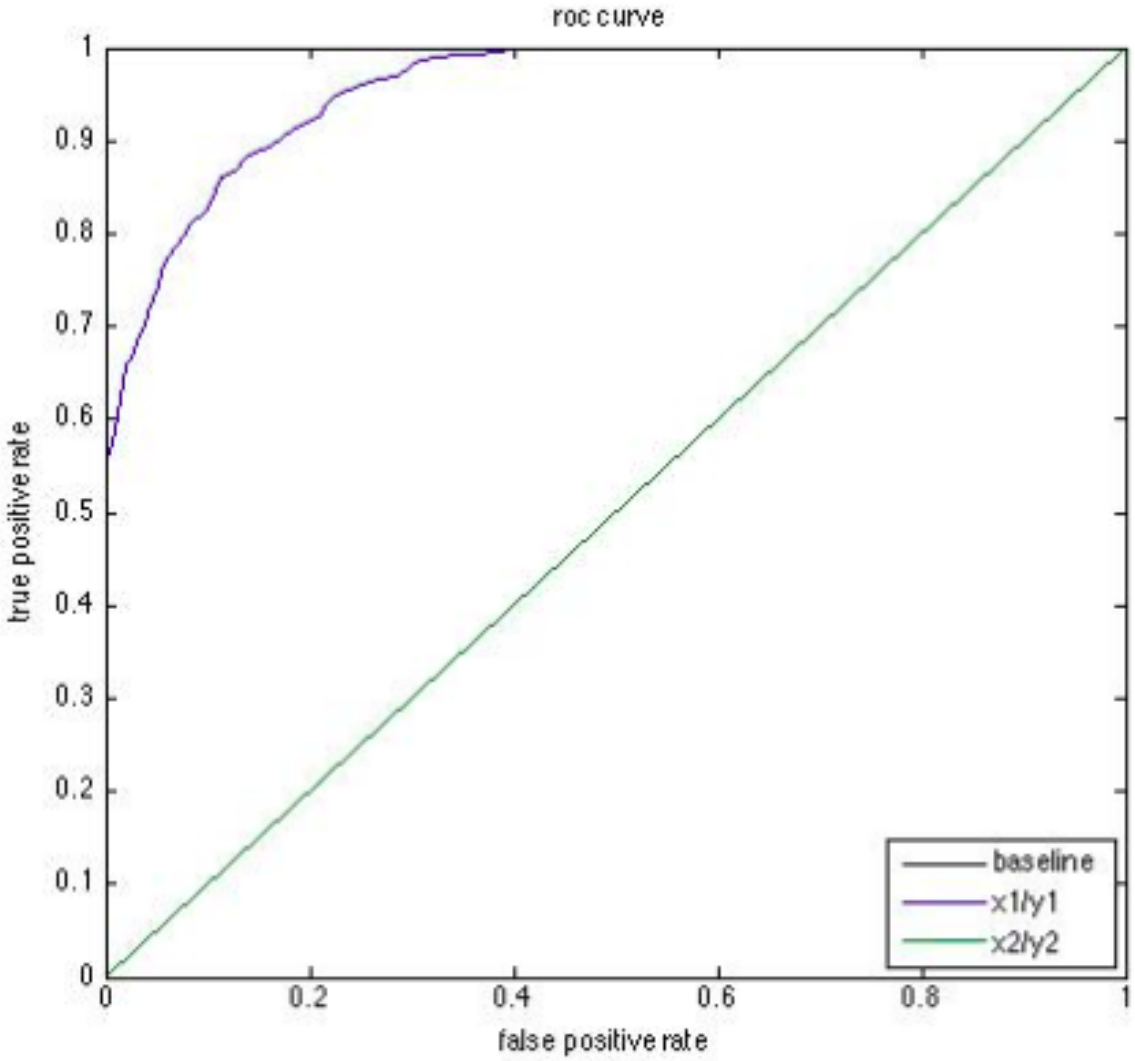


Figure 18: ROC Curve for class Lodgepole Pine

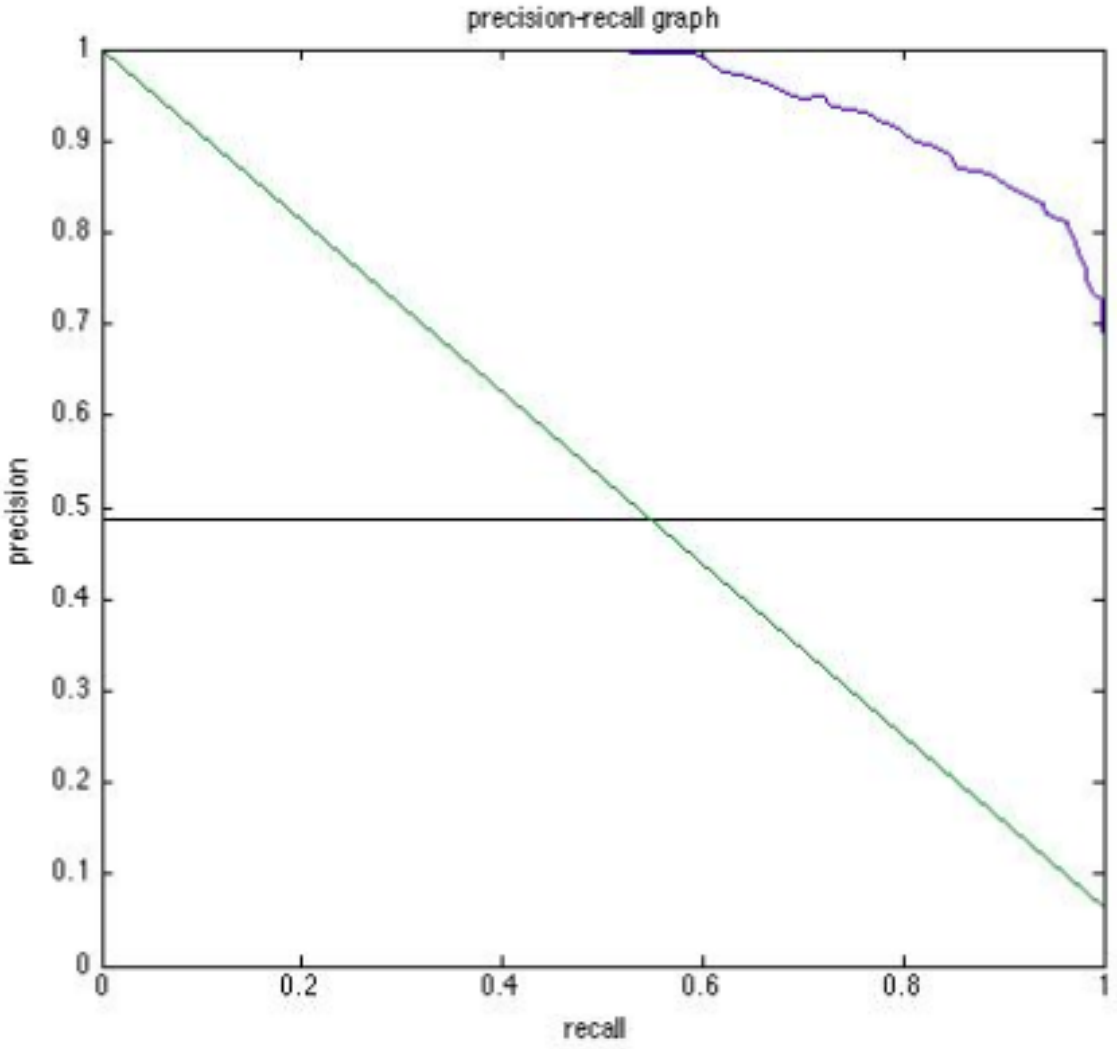


Figure 19: PR Curve for class Ponderosa Pine

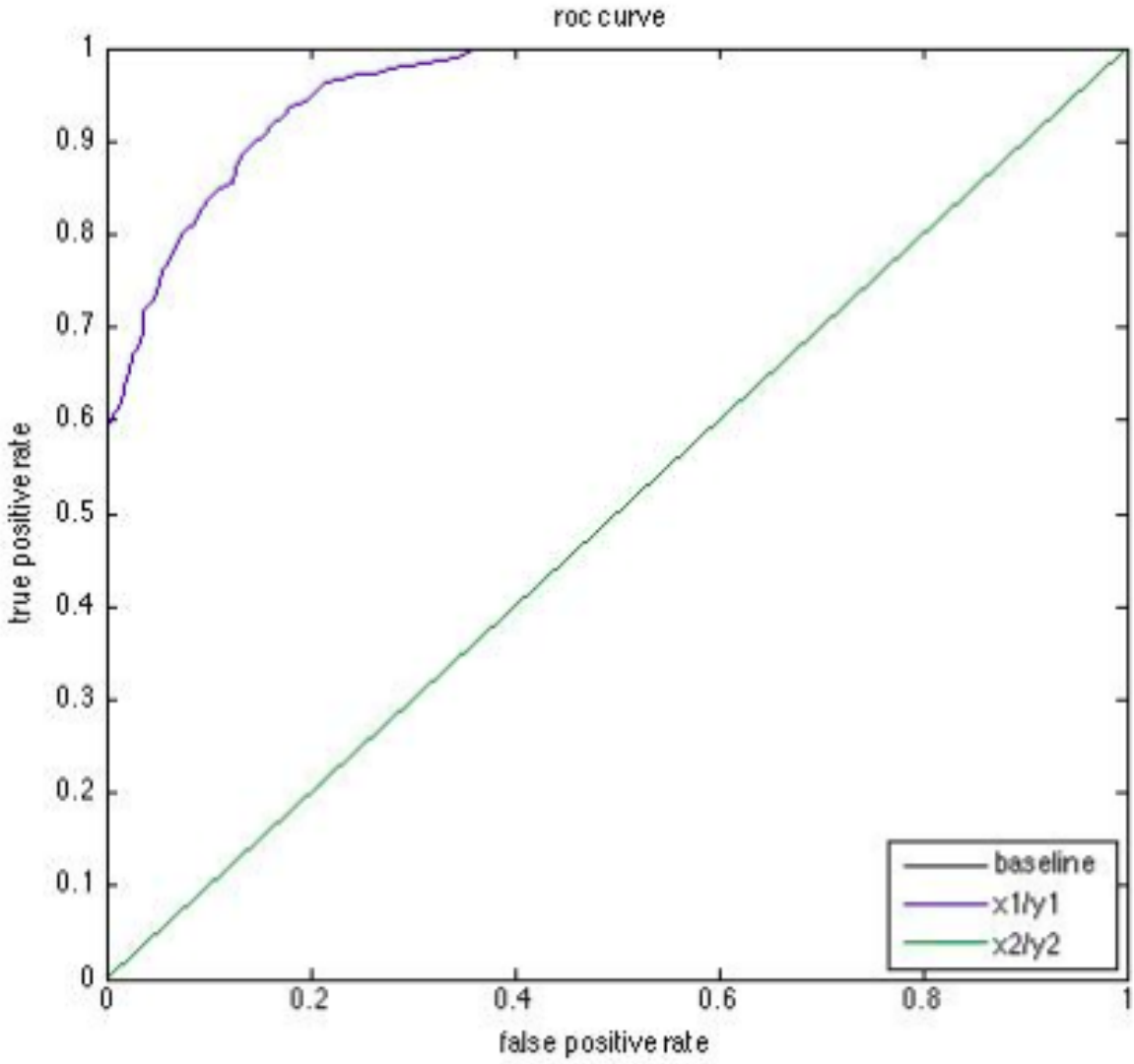


Figure 20: ROC Curve for class Ponderosa Pine

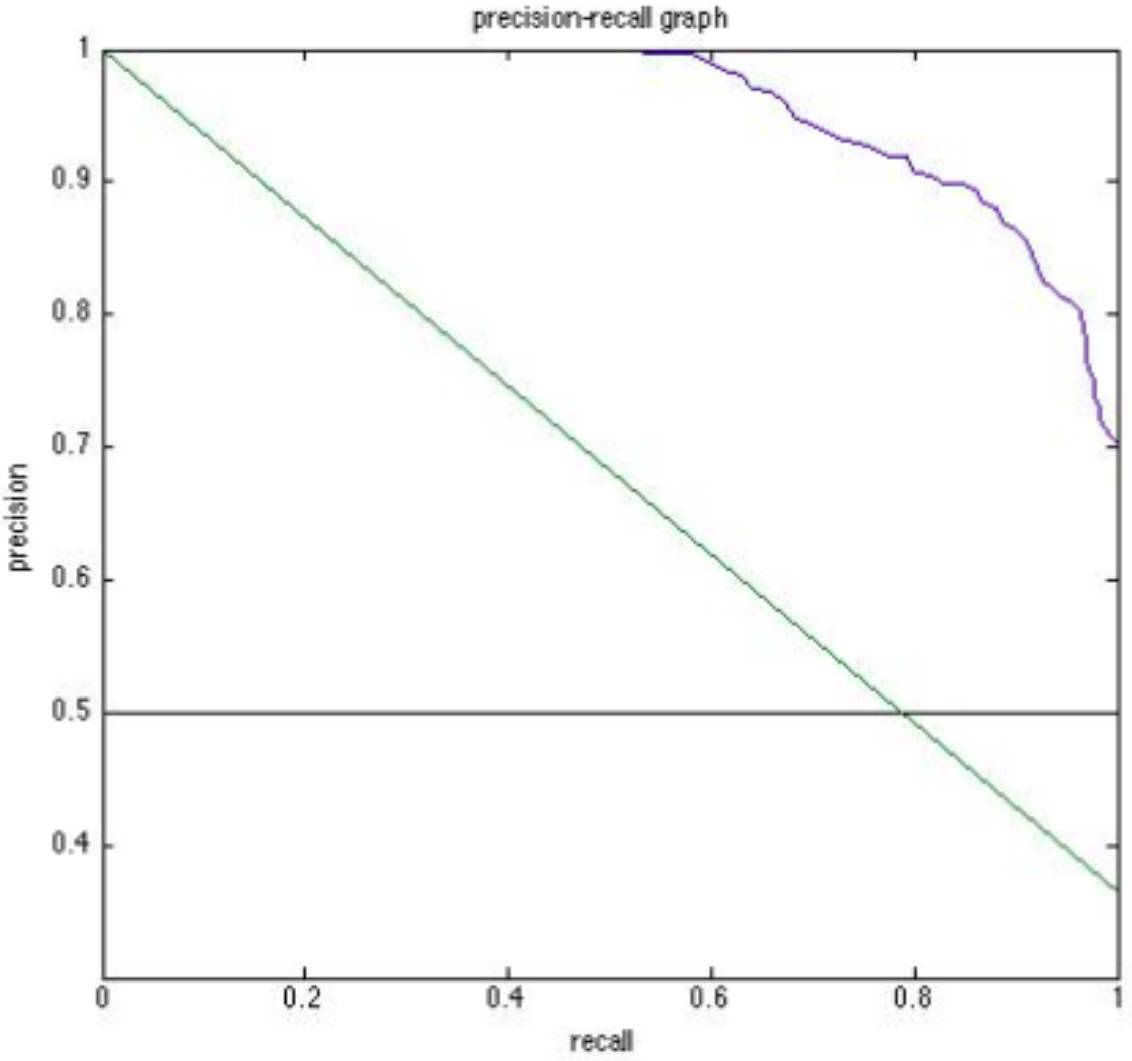


Figure 21: PR Curve for class Spruce Fir

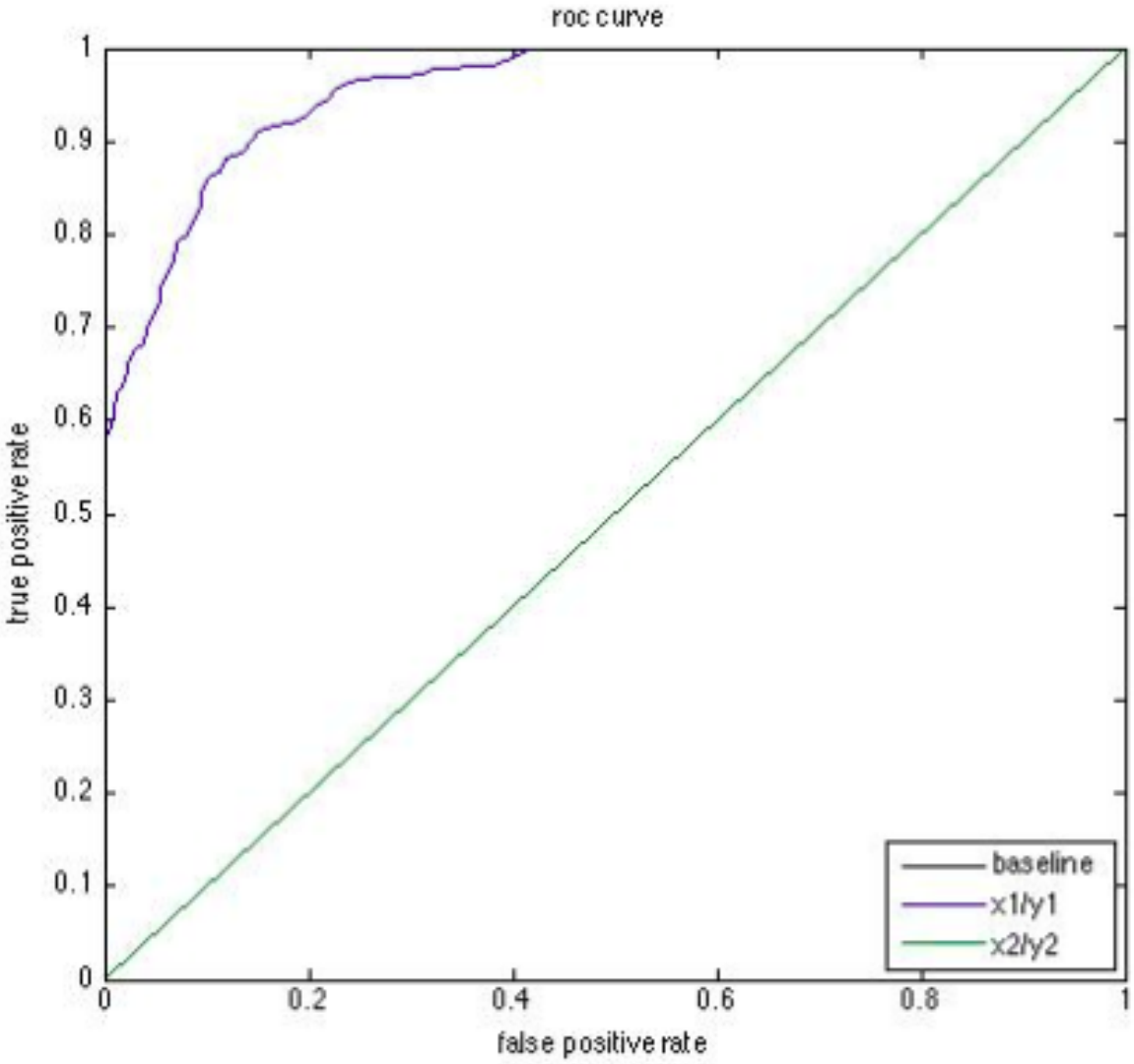


Figure 22: ROC Curve for class Spruce Fir

Cover Type	AUC
Aspen	.892
Cottonwood	.877
Douglas Fir	.885
Krummholz	.888
Lodgepole Pine	.891
Ponderosa Pine	.883
Spruce Fir	.873

Figure 23: AUC for each class.

4.3 RF Results

We used the ROCR library [19] to generate ROC and PR curves for random forests.

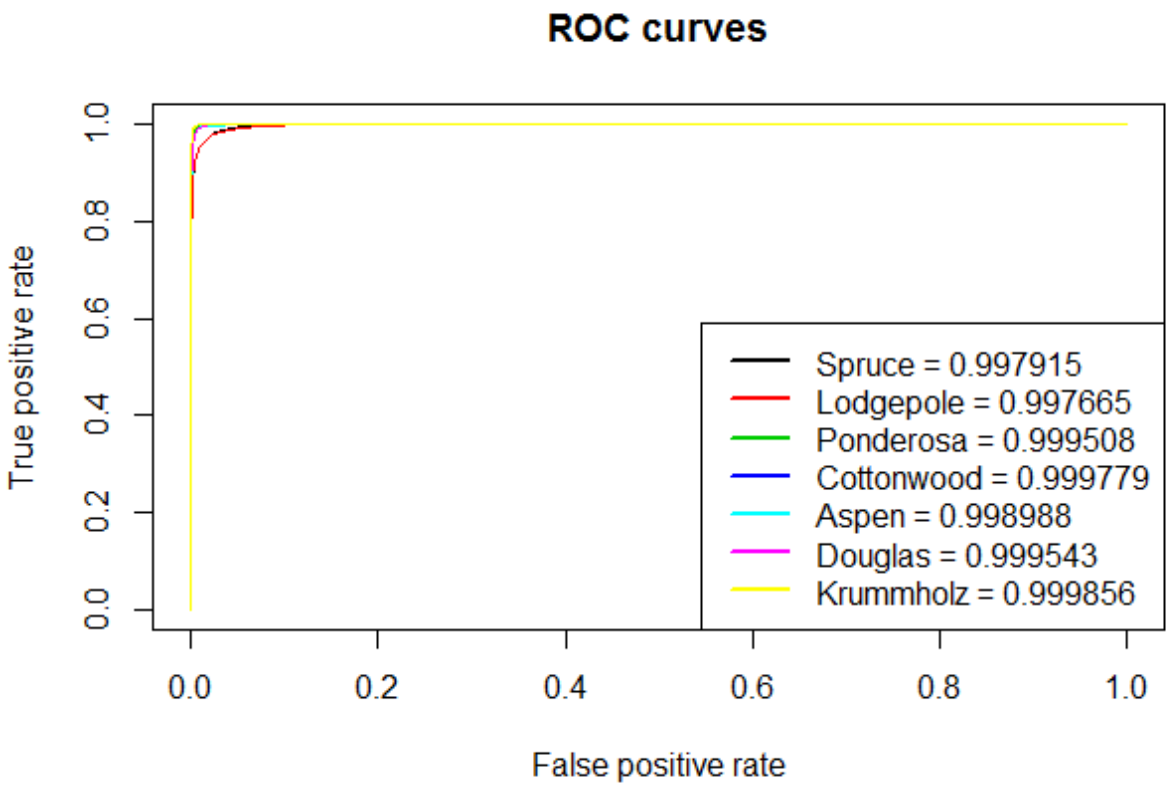


Figure 24: ROC curves for each class, with the AUC for each curve.

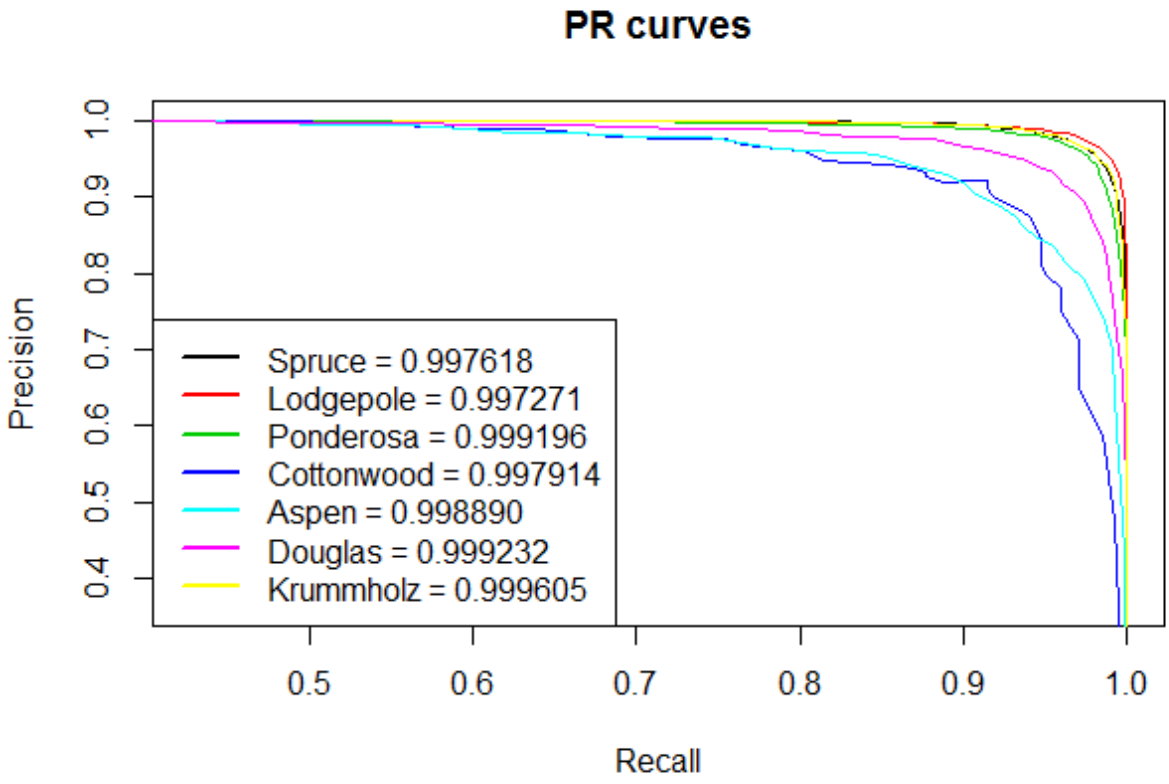


Figure 25: PR curves for each class, with the AUC for each curve.

5 Discussion

When weighting the importance of the AUC of a class by its representation in the data set, we get the following values for the average AUC:

Classifier	Average AUC
ANN	0.92503
KNN	0.88328
RF	0.99803

Figure 26: Average AUC for each classifier.

We're not quite sure why one classifier performed better or worse than another, but it could have to do with the bias present in the data. For example, ANNs had trouble correctly classifying underrepresented classes, such as Aspen. Regardless of the reasons why though, random forests outperformed ANN and KNN by 7.9% and 13.0% respectively, making it the clear winner.

6 Conclusion

In this project we used 3 different classifiers to predict forest cover type based on cartographic variables: artificial neural networks, k nearest neighbors, and random forests. We determined that random forests outperformed the other 2 classifiers. In the future, we may try to examine the performance of these classifiers on other datasets and then compare those results to those given here, or we may use different classifiers on the cover type dataset to see if we can improve our classification accuracy.

7 Contributions

Hilal Alsibai wrote ANN code and generated the feature comparison matrix. Alex Kot generated the ANN figures and tables, worked on the introduction, and worked on the ANN related writing. Pei Guo worked on ANN feature selection and worked on the ANN related writing.

Jesse Dyer wrote / gathered most of the code for the LMNN and KNN implementations. Ian Woods generated figures, ran computations, and wrote the report. Miguel Covarrubias ran computations and generated all ROC and PR curves.

Aaun Abbas and Raymond Lau wrote all of the code that was related to random forests. Christopher Chen wrote all parts of the report that were related to random forests, as well as some of the more general parts of the report. He also organized the team and took care of general logistics.

References

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