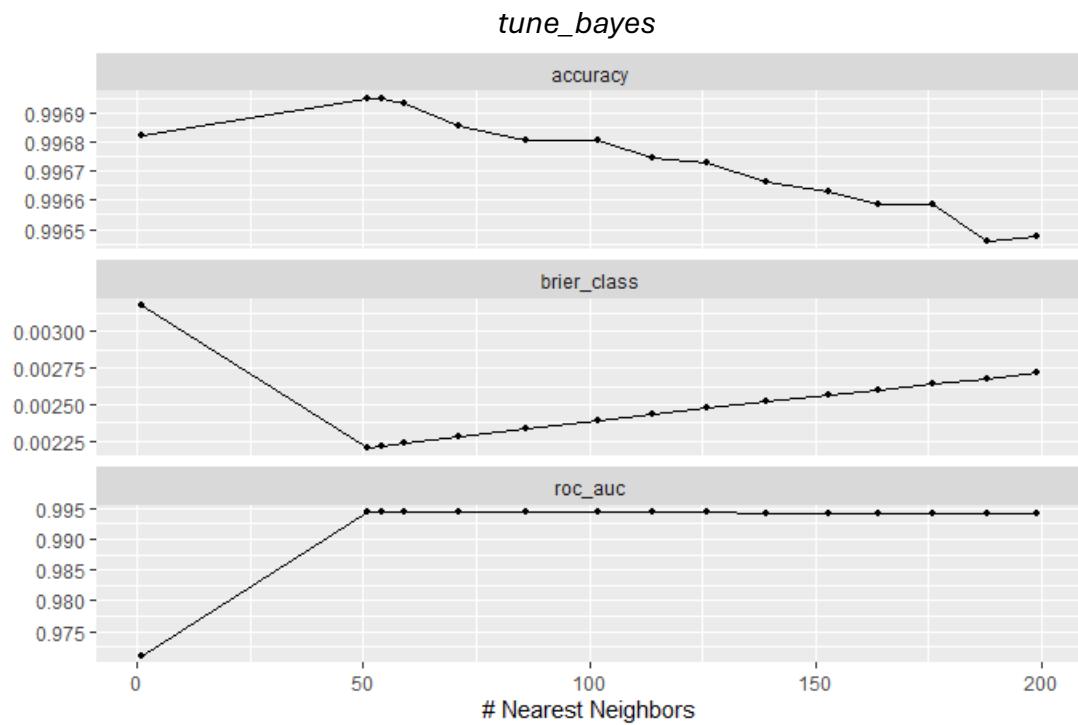
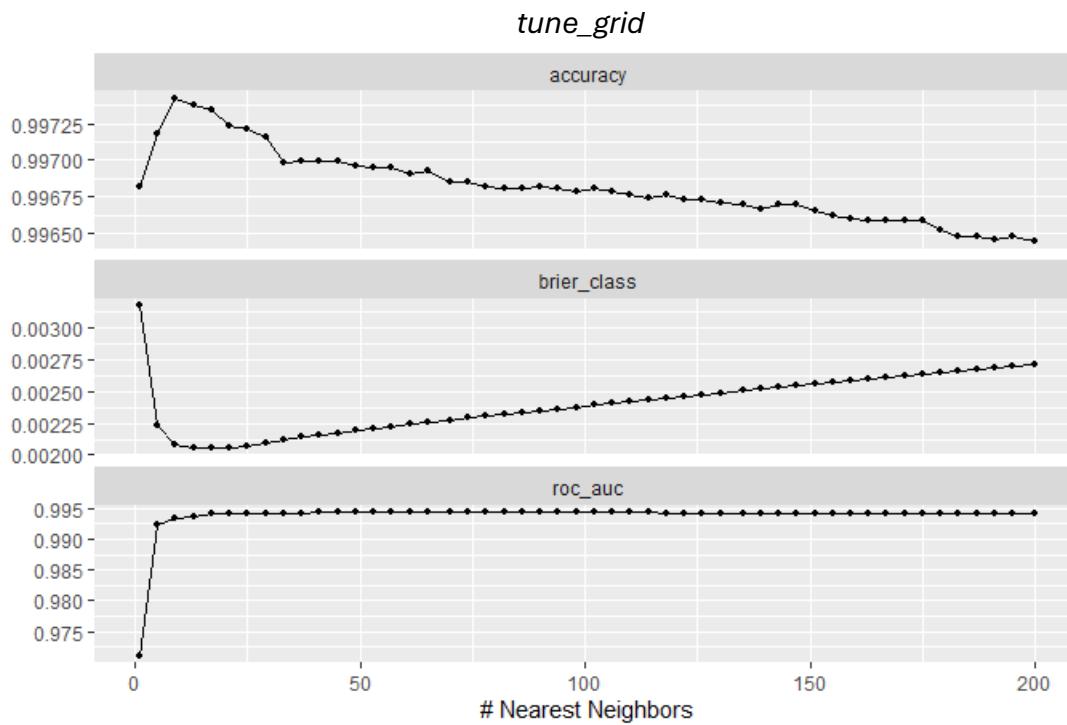


K-Nearest Neighbor Model_ full training set

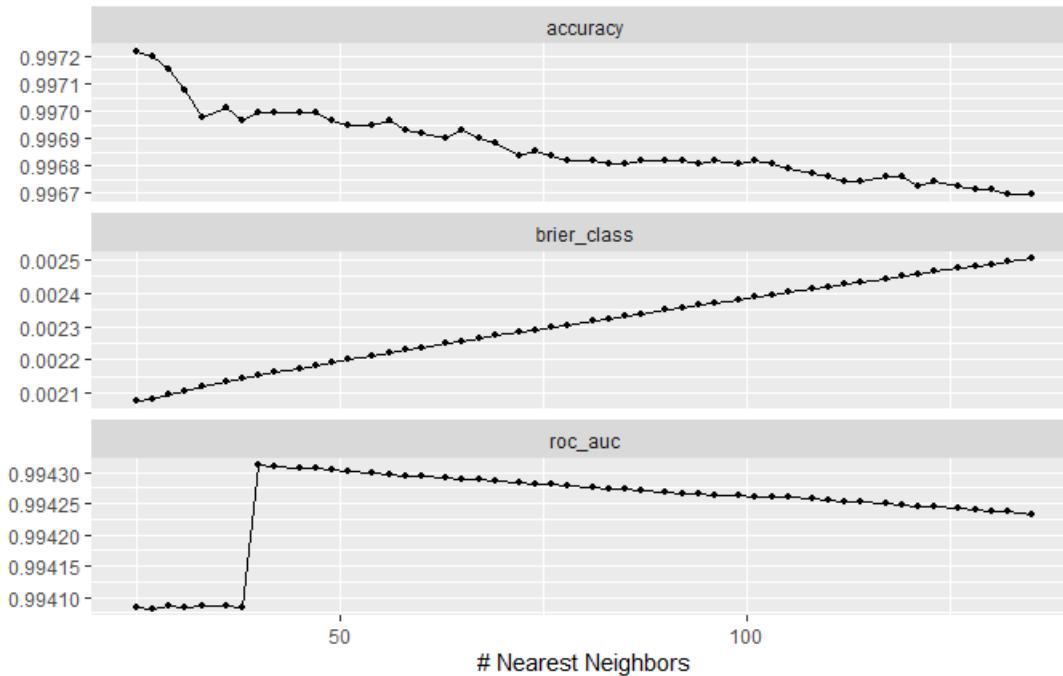
Initial tuning neighbors (1~200)



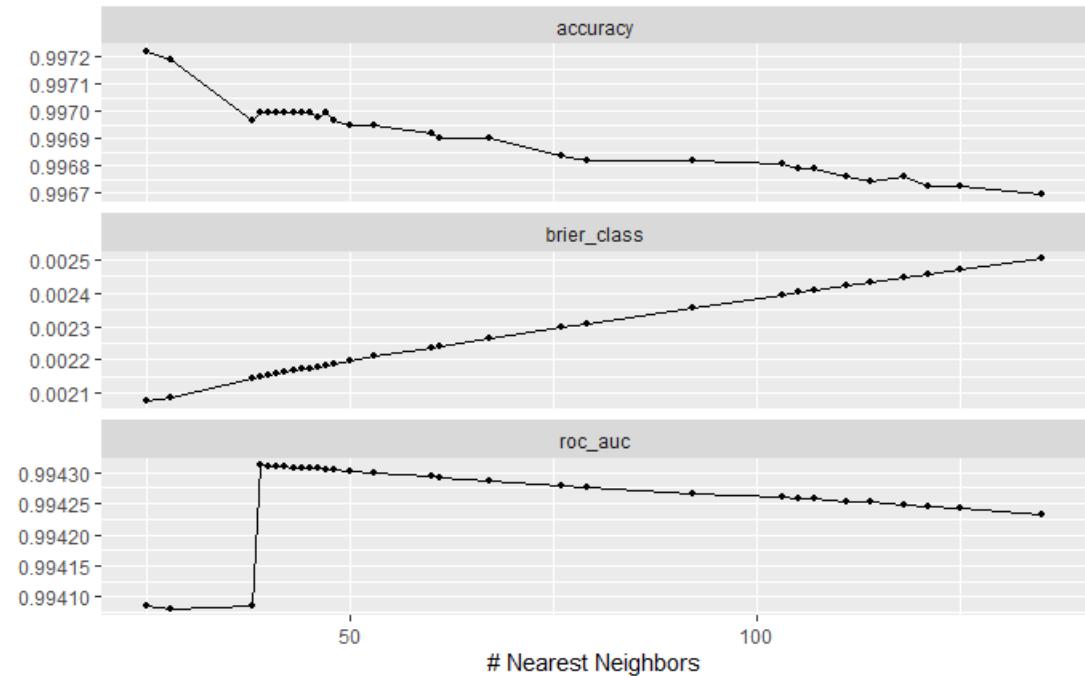
K-Nearest Neighbor Model_ full training set

Second tuning neighbors (25~135)

tune_grid

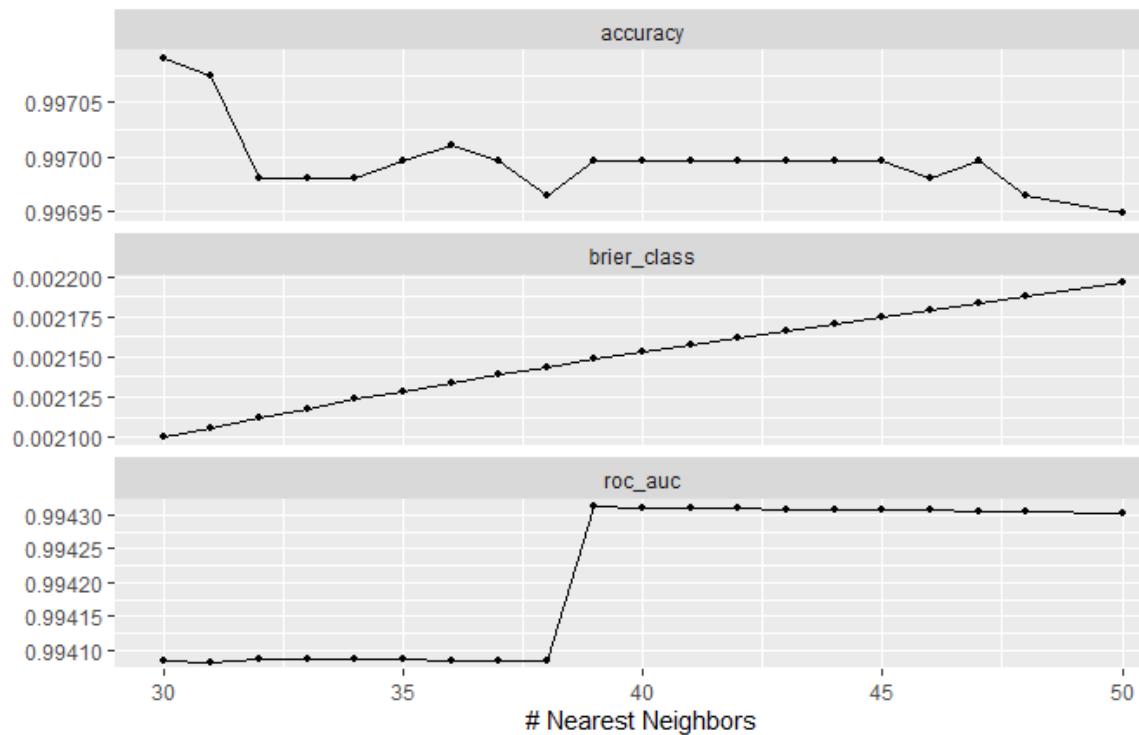


tune_bayes



K-Nearest Neighbor Model_ full training set

Final tuning neighbors (30~50)



A tibble: 3 × 7

neighbors	.metric	.estimator	mean	n	std_err	.config
39	roc_auc	binary	0.9943117	10	0.001139645	Preprocessor1_Model10
40	roc_auc	binary	0.9943110	10	0.001139833	Preprocessor1_Model11
41	roc_auc	binary	0.9943105	10	0.001139690	Preprocessor1_Model12

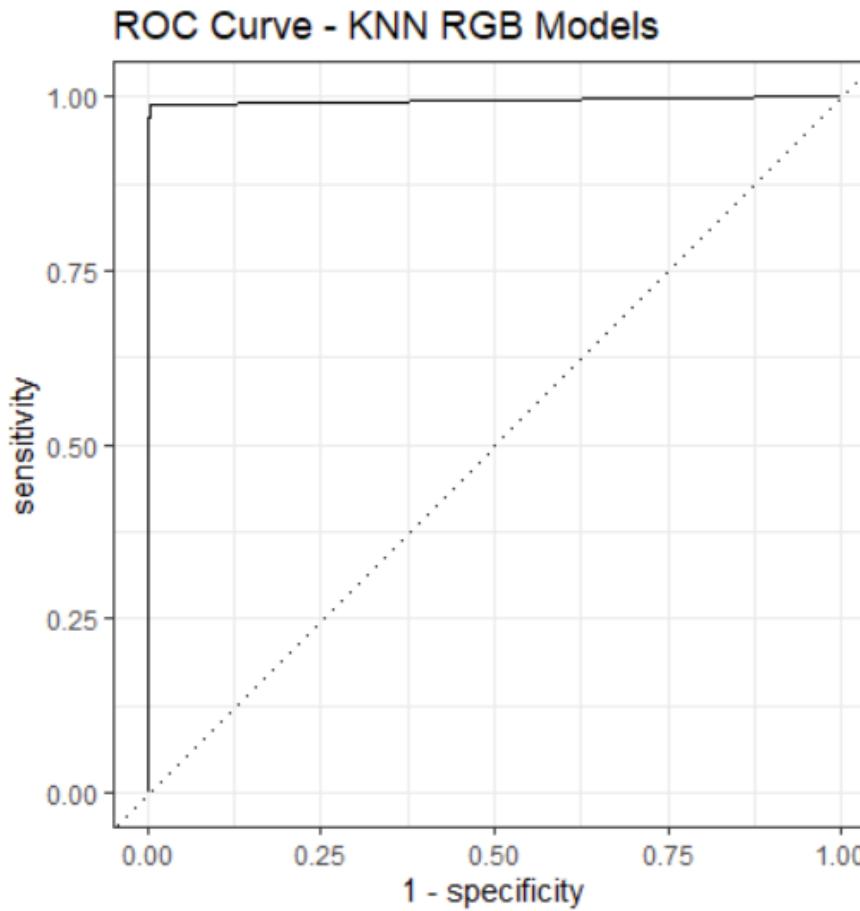
3 rows

K-Nearest Neighbor Model_ full training set

Fit the model with the optimal tuning parameter (neighbors=39) and estimate model performance with 10-fold cross validation

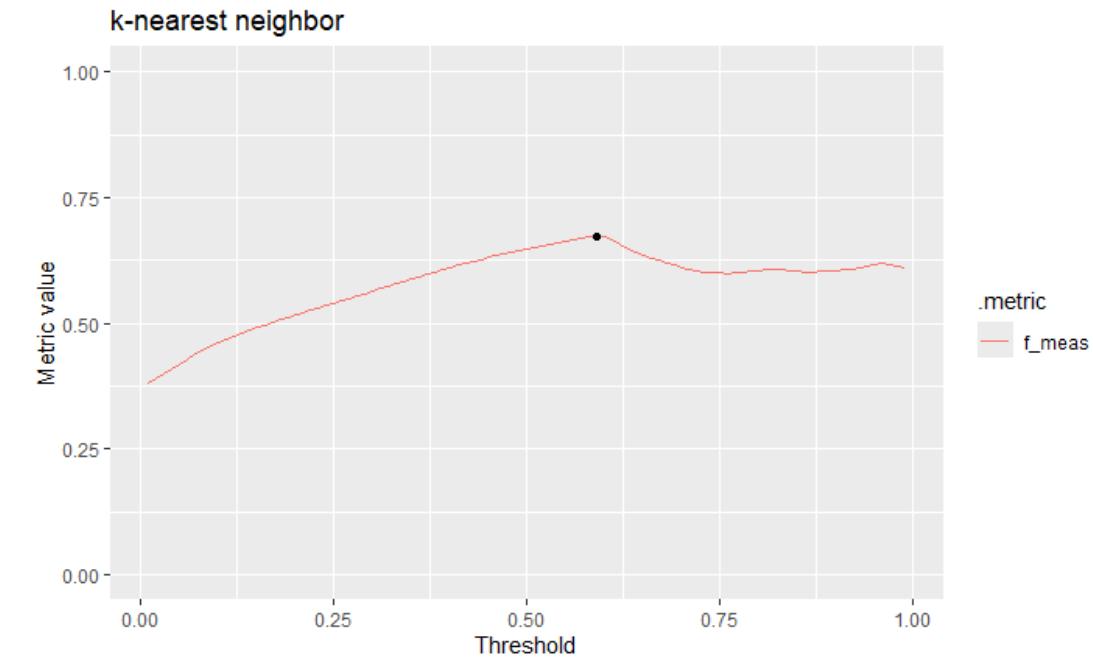
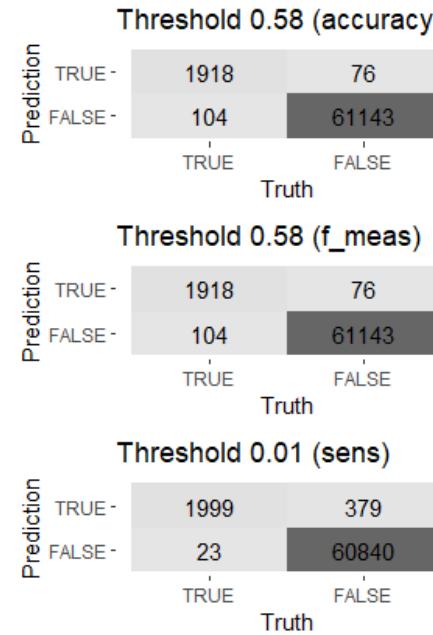
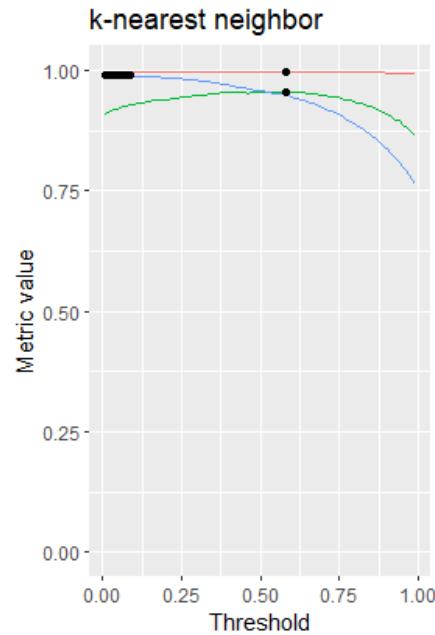
Cross-validation metrics for k-nearest neighbor models

model	accuracy	f_meas	precision	roc_auc
k-nearest neighbor	0.997	0.953	0.949	0.994



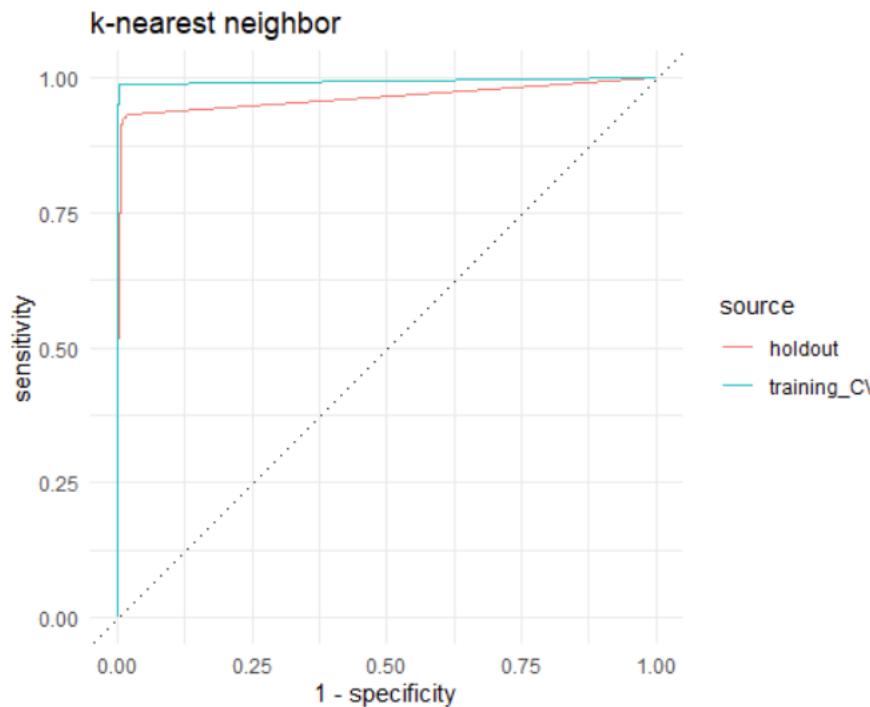
K-Nearest Neighbor Model_ full training set

Threshold scanning for both training (cross validation) and holdout data



K-Nearest Neighbor Model_ full training set

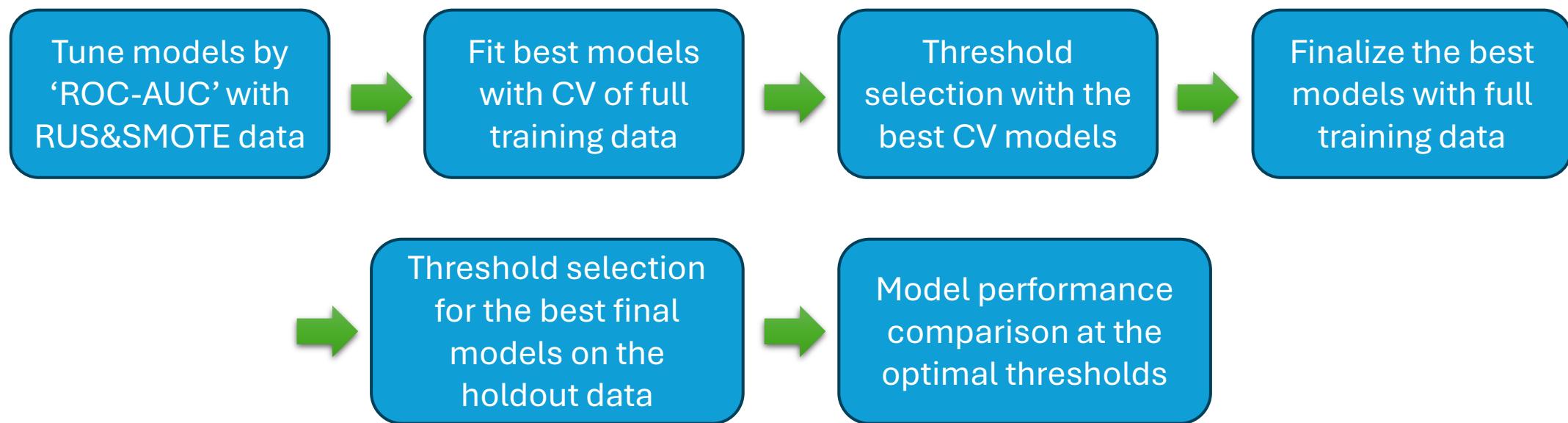
Comparison and performance of the tuned KNN model after threshold optimization



Performance metrics for tuned k-nearest neighbor model with optimal threshold

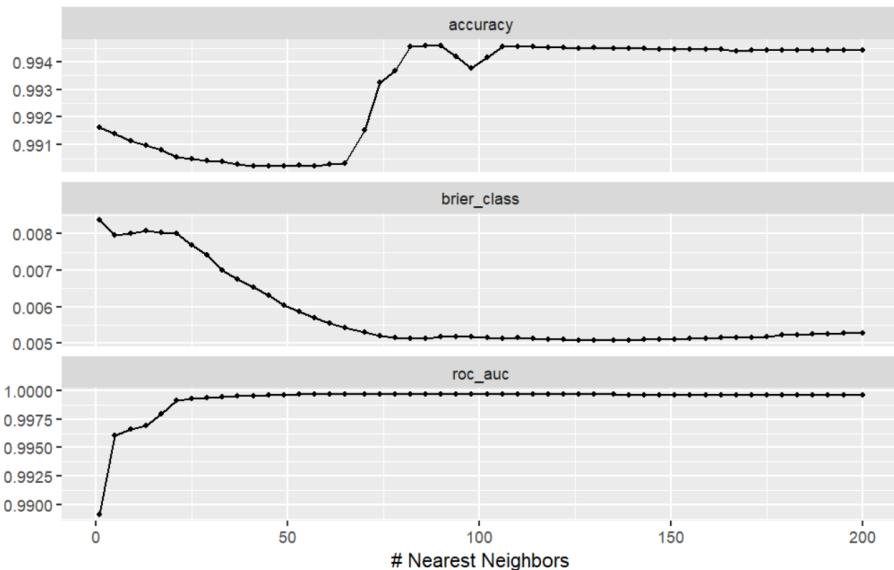
color_space	model	dataset	threshold	accuracy	kap	roc_auc	f_meas	sens
RGB	k-nearest neighbor	train	0.58	0.997	0.958	0.994	0.959	0.952
RGB	k-nearest neighbor	holdout	0.59	0.994	0.670	0.964	0.673	0.884

To lower the demand on computational resources for model tuning, we applied Random Under-sampling (RUS) combined with Synthetic Minority Over-sampling Technique (SMOTE) to pre-process the training data for model tuning and the following workflow for building KNN classifiers.

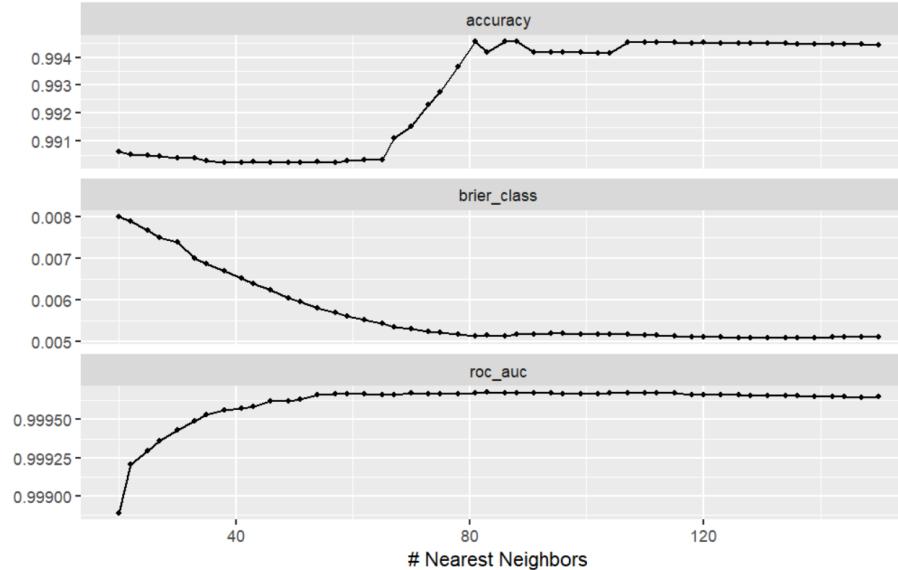


K-Nearest Neighbor Model_ RUS&SMOTE

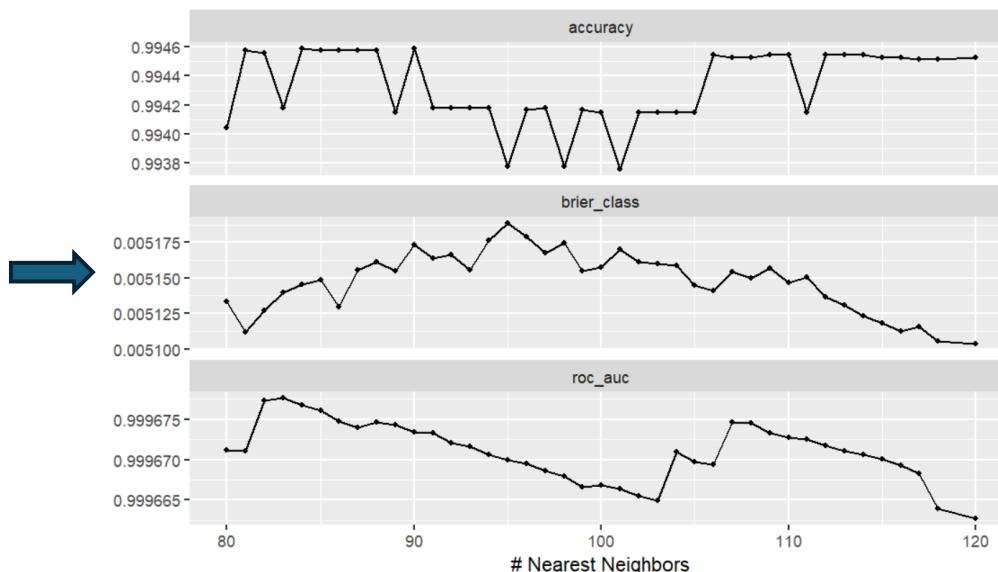
Initial tuning neighbors (1~200) *tune_grid*



Second tuning neighbors (20~150) *tune_grid*



Final tuning neighbors (80~120) *tune_grid*

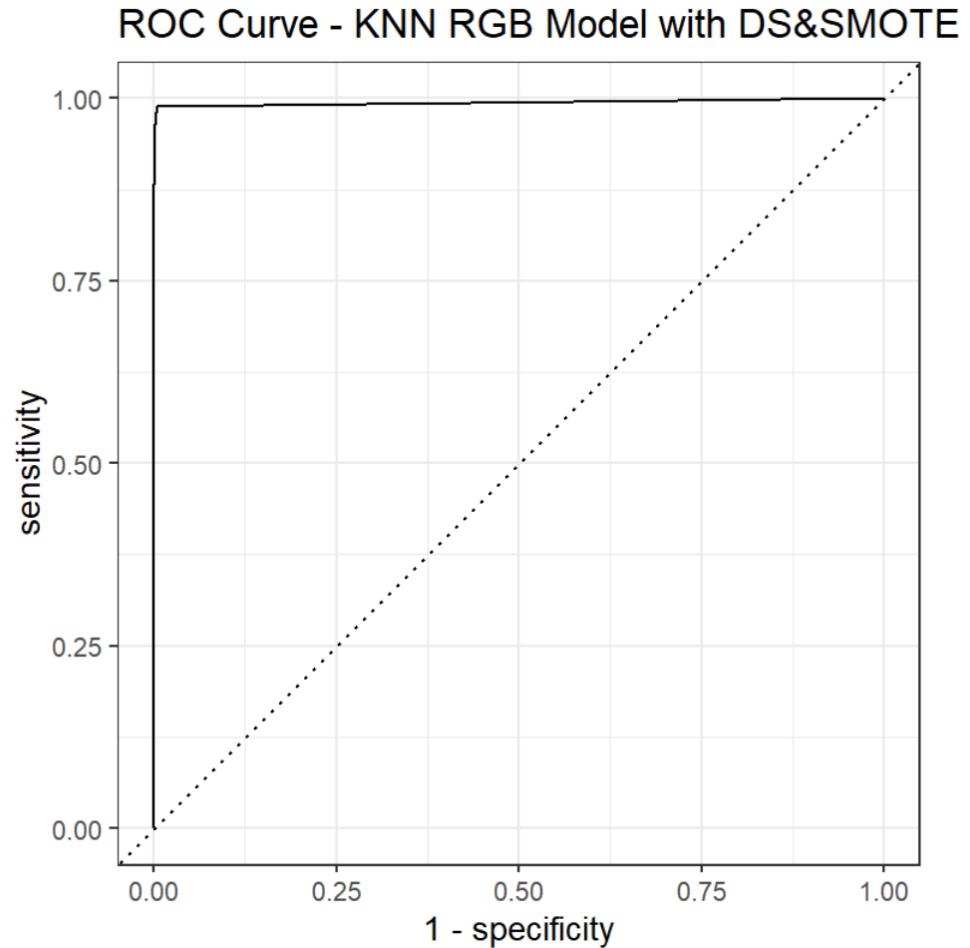


neighbors	.metric	.estimator	mean	n	std_err	.config
			<dbl>	<int>	<dbl>	<chr>
83	roc_auc	binary	0.9996776	10	3.057284e-05	Preprocessor1_Model04
82	roc_auc	binary	0.9996774	10	3.074929e-05	Preprocessor1_Model03
84	roc_auc	binary	0.9996767	10	3.077229e-05	Preprocessor1_Model05

K-Nearest Neighbor Model_ RUS&SMOTE

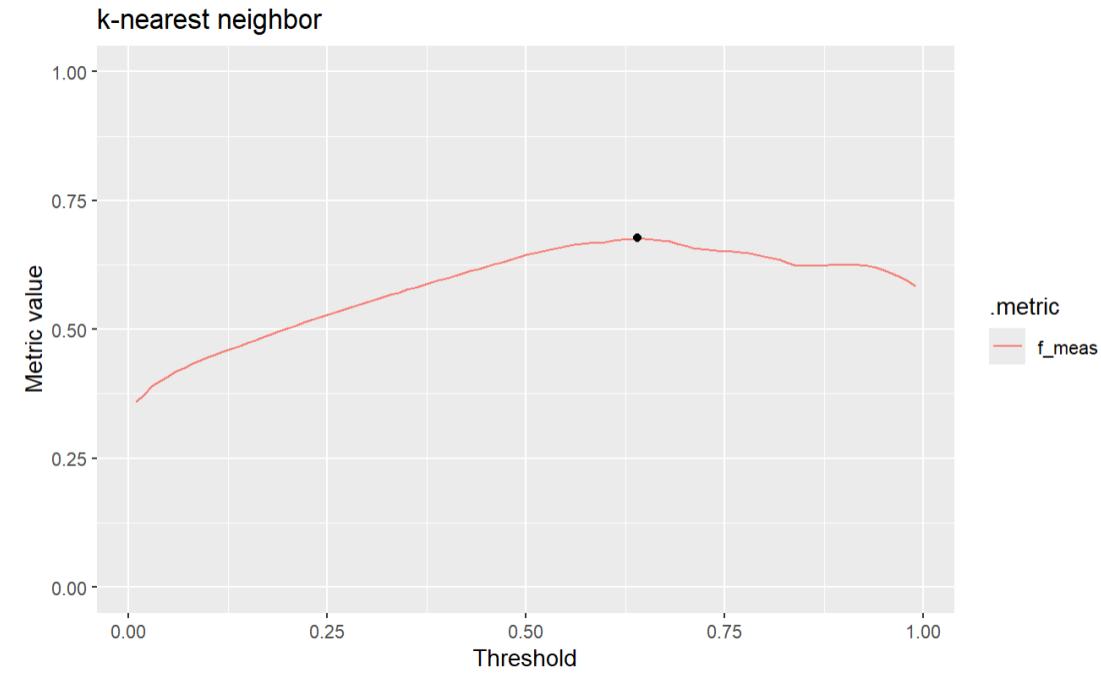
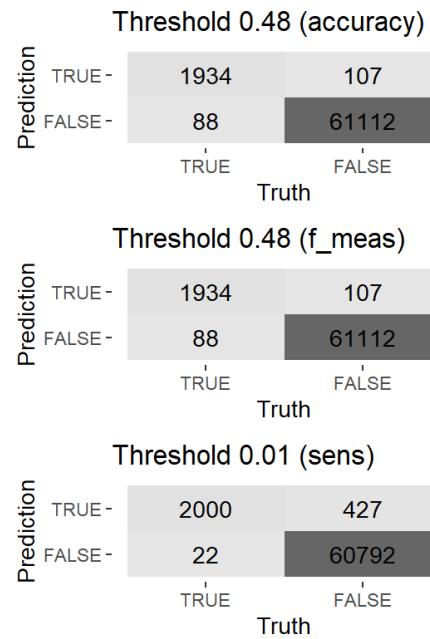
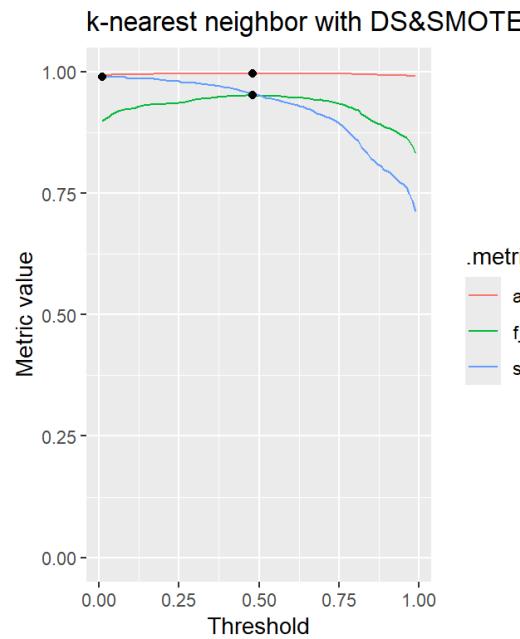
Fit the model with original workflow without down-sampling or SMOTE using the optimal tuning parameter (neighbors=83) and estimate model performance with 10-fold cross validation

Cross-validation metrics for KNN models by Down-sample&SMOTE				
model	accuracy	f_meas	precision	roc_auc
Tuned KNN DS&SMOTE Model	0.997	0.95	0.95	0.994



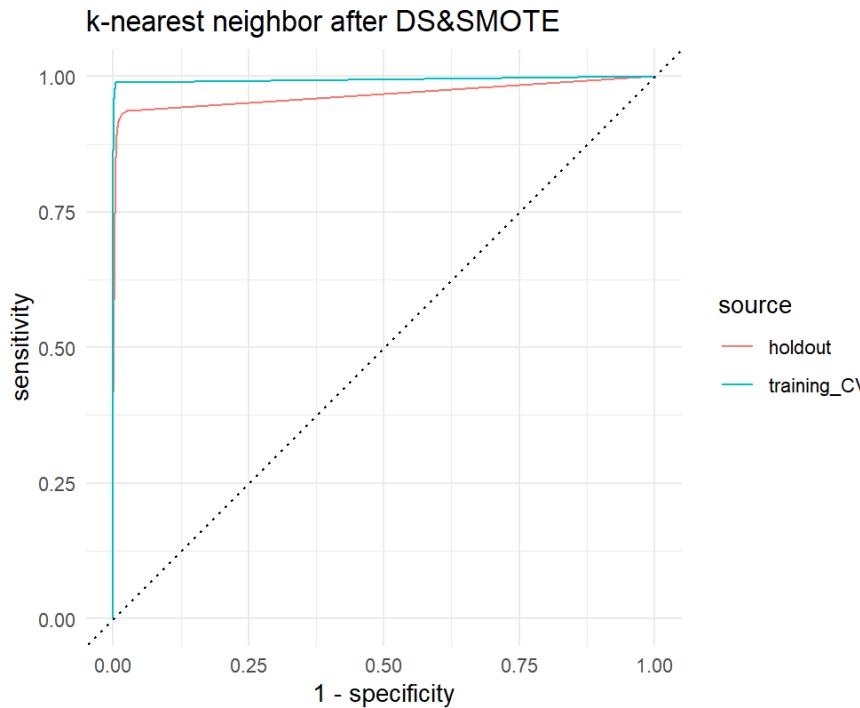
K-Nearest Neighbor Model_ RUS&SMOTE

Threshold scanning for both training (cross validation) and holdout data



K-Nearest Neighbor Model_ RUS&SMOTE

Comparison and performance of the tuned KNN model after threshold optimization



Performance metrics for tuned KNN model after DS&SMOTE with optimal threshold

color_space	model	dataset	threshold	accuracy	kap	roc_auc	f_meas	sens
RGB	k-nearest neighbor after DS&SMOTE	train	0.48	0.997	0.953	0.994	0.954	0.958
RGB	k-nearest neighbor after DS&SMOTE	holdout	0.64	0.995	0.674	0.966	0.677	0.796

Evaluation of Random Under-sampling (RUS) combined with Synthetic Minority Over-sampling Technique (SMOTE) on the KNN model performances.

Performance metrics for tuned k-nearest neighbor model with optimal threshold

color_space	model	dataset	threshold	accuracy	kap	roc_auc	f_meas	sens
RGB	k-nearest neighbor	train		0.58	0.997	0.958	0.994	0.959
RGB	k-nearest neighbor	holdout		0.59	0.994	0.670	0.964	0.673

Performance metrics for tuned KNN model after DS&SMOTE with optimal threshold

color_space	model	dataset	threshold	accuracy	kap	roc_auc	f_meas	sens
RGB	k-nearest neighbor after DS&SMOTE	train		0.48	0.997	0.953	0.994	0.954
RGB	k-nearest neighbor after DS&SMOTE	holdout		0.64	0.995	0.674	0.966	0.677

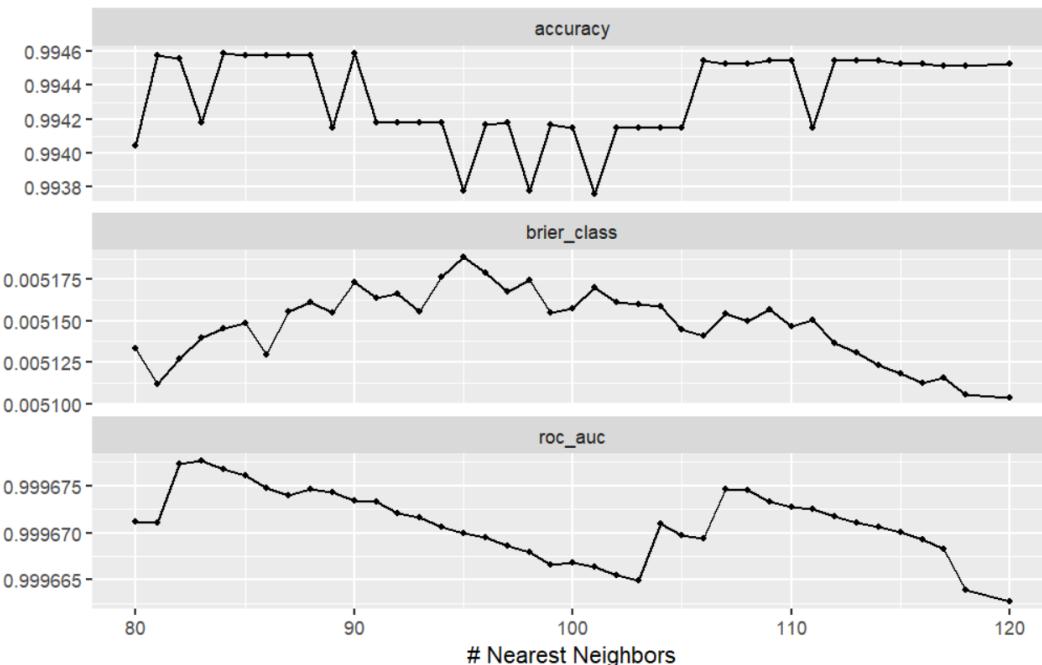
The strategy of Random Under-sampling (RUS) combined with Synthetic Minority Over-sampling Technique (SMOTE) even improved model performance a little on the holdout data.

Based on the result, the same hybrid pre-processing method (RUS&SMOTE) was applied to the tuning (only tuning) of all the models built here and after.

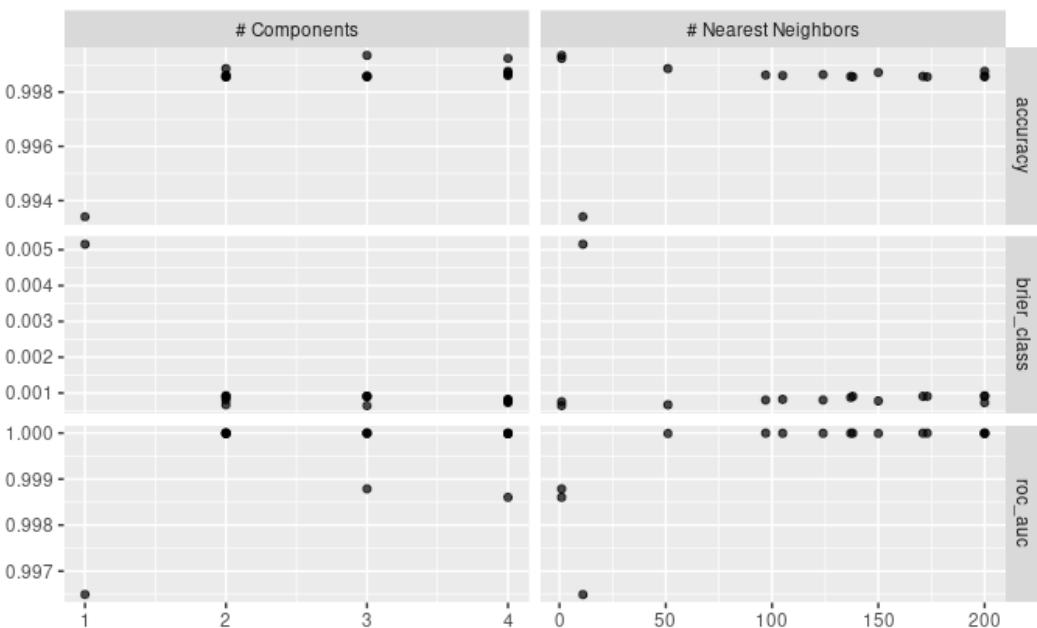
K-Nearest Neighbor Model - RGB vs. Engineered Features

Comparison between the RGB feature space and engineered full feature space for KNN models

RGB

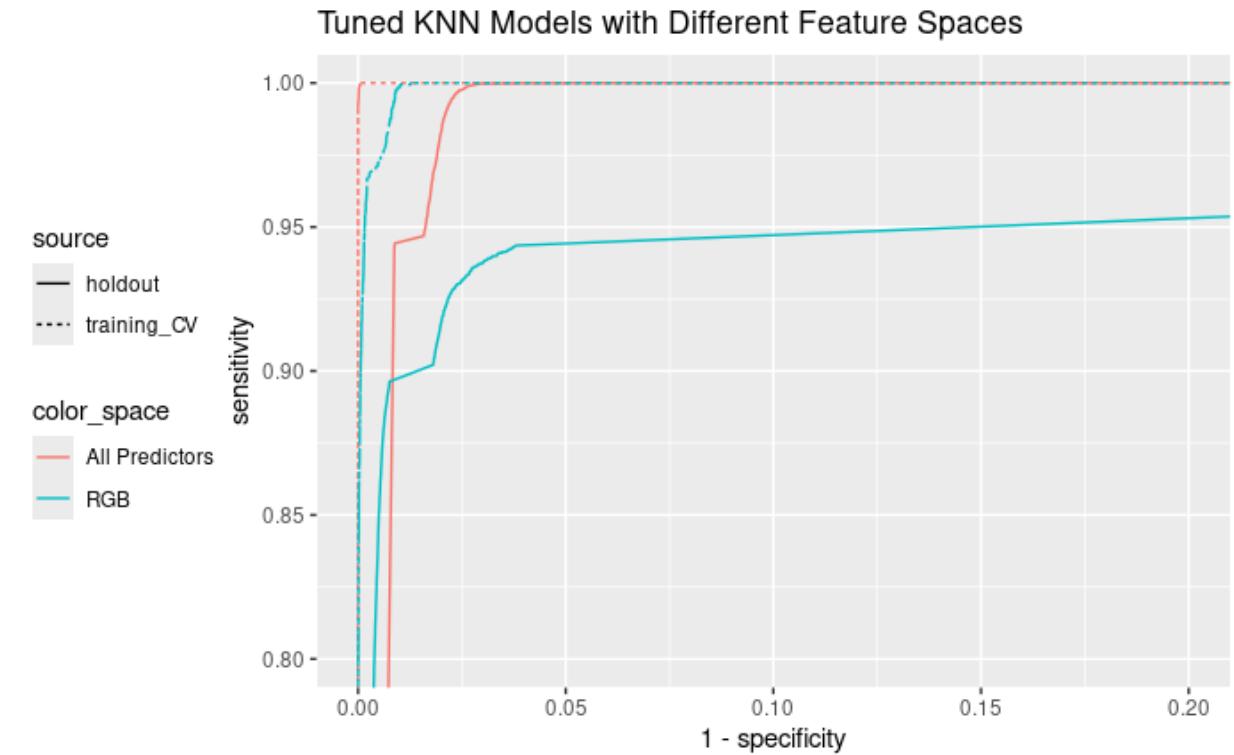
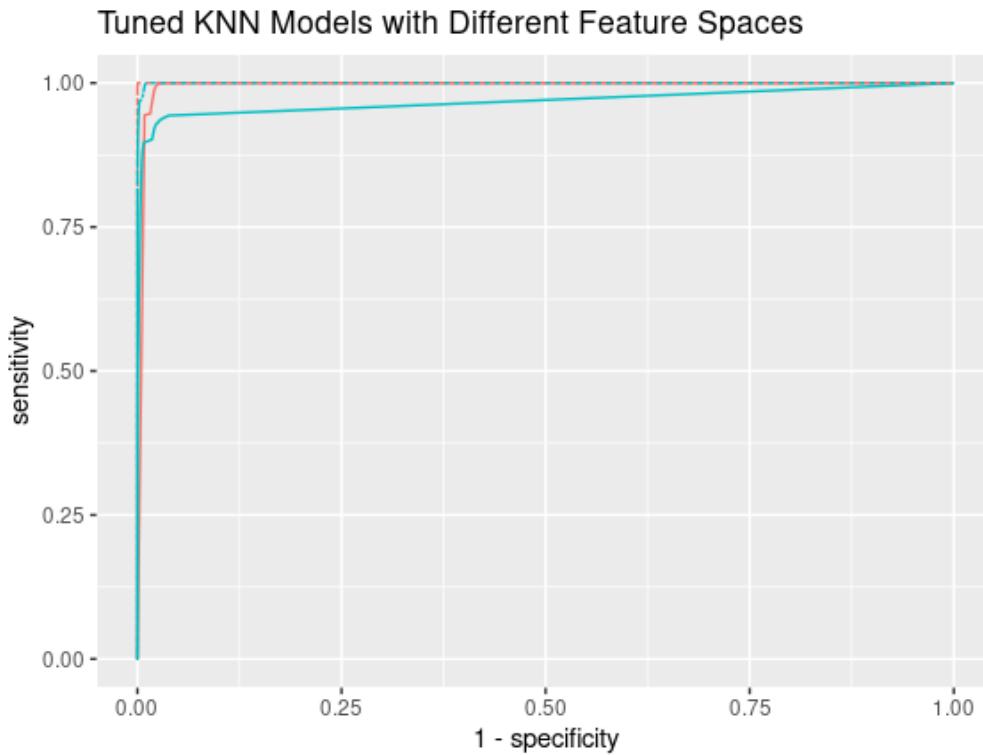


All Engineered Features + PCA



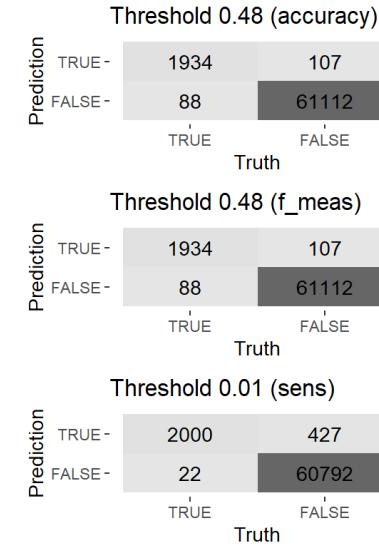
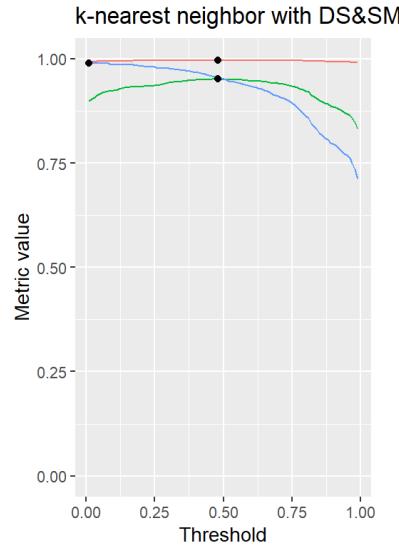
neighbors	.metric	.estimator	mean	n	std_err
173	roc_auc	binary	0.9999974	10	1.349389e-06
200	roc_auc	binary	0.9999974	10	1.196654e-06
137	roc_auc	binary	0.9999974	10	1.310655e-06

Comparison between the RGB feature space and engineered full feature space for KNN models

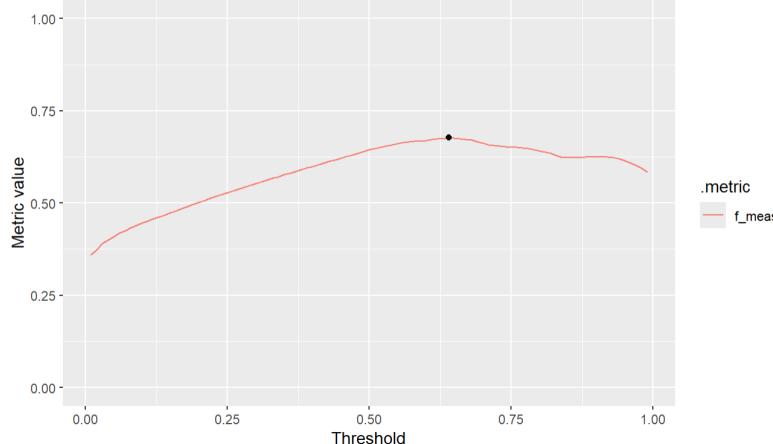


Comparison between the RGB feature space and engineered full feature space for KNN models

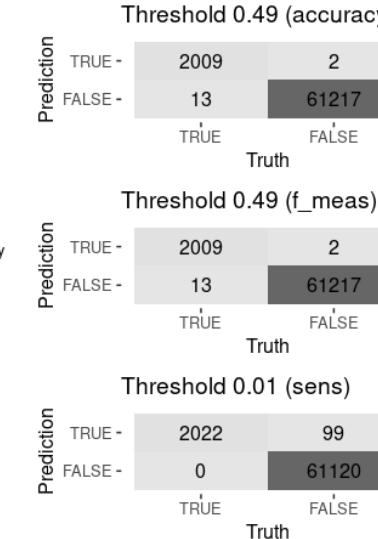
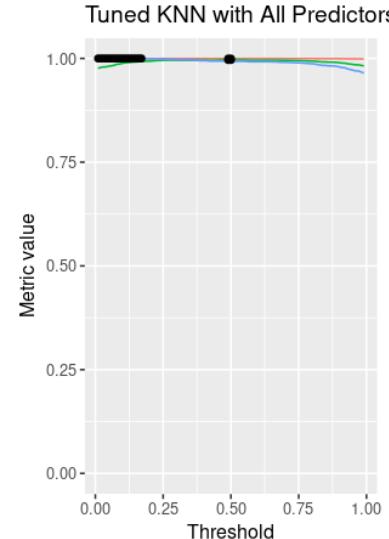
RGB



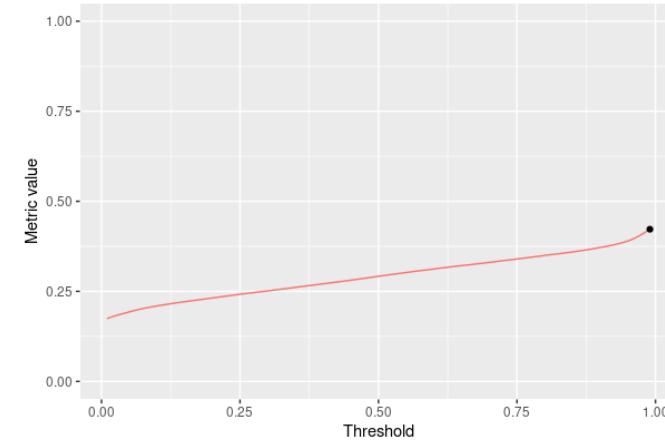
k-nearest neighbor



All Engineered Features + PCA



KNN All Features



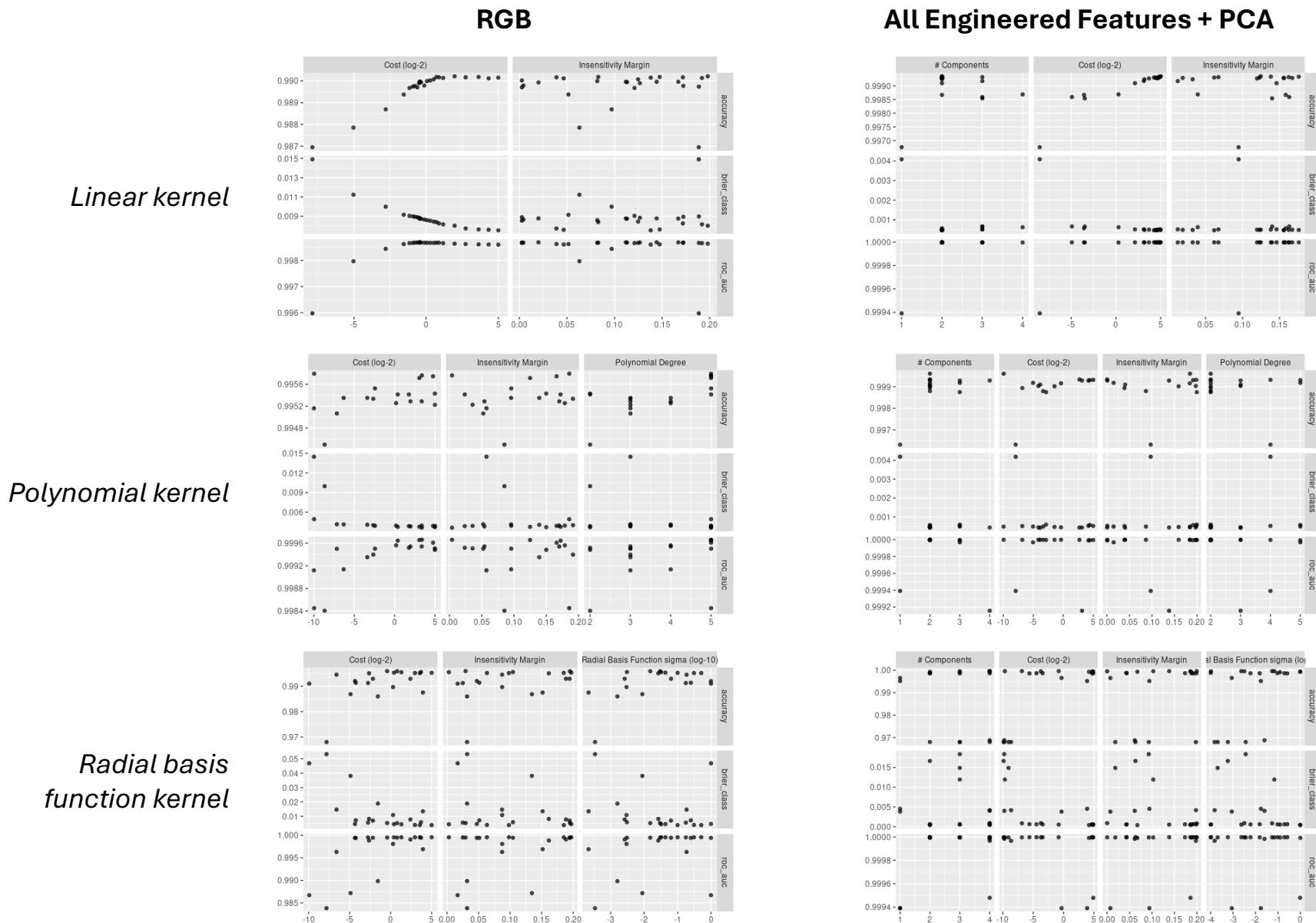
Comparison between the RGB feature space and engineered full feature space for KNN models

Performance metrics for tuned KNN model at optimal thresholds

color_space	model	dataset	threshold	accuracy	kap	f_meas	roc_auc
RGB	k-nearest neighbor	train	0.49	0.997	0.952	0.954	1.000
RGB	k-nearest neighbor	holdout	0.64	0.995	0.682	0.685	0.968

Build SVM classifiers

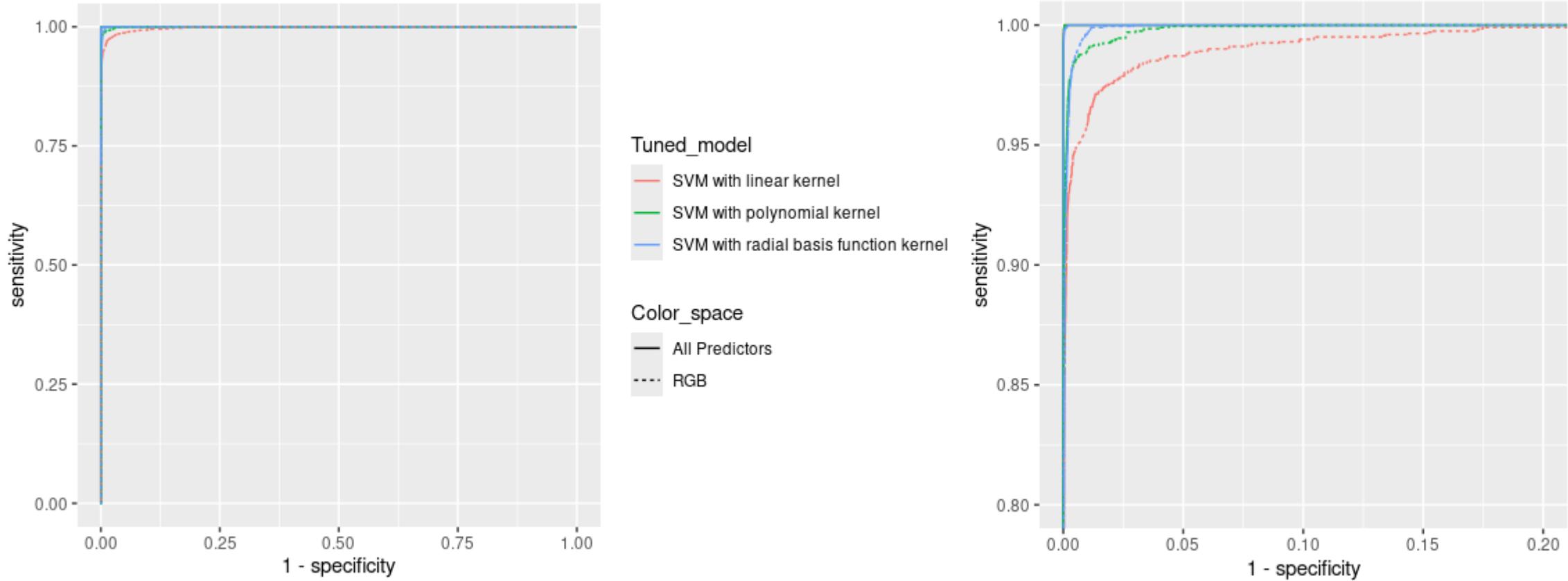
Build and Tune the SVM Models in Different Feature Spaces



Cross-validation Performance of the SVM Models Build in Different Feature Spaces

		Cross-validation performance metrics				
		model	accuracy	f_meas	precision	roc_auc
RGB	SVM with linear kernel		0.995	0.915	0.976	0.998
	SVM with polynomial kernel		0.997	0.955	0.959	1.000
	SVM with radial basis function kernel		0.997	0.947	0.950	1.000
Cross-validation performance metrics for SVM models with all feature space						
All Engineered Features + PCA		model	accuracy	f_meas	precision	roc_auc
All Engineered Features + PCA	SVM with linear kernel		1.000	0.995	0.997	1
	SVM with polynomial kernel		1.000	0.996	0.998	1
	SVM with radial basis function kernel		0.999	0.991	1.000	1

ROC curve of all SVM models with training CV



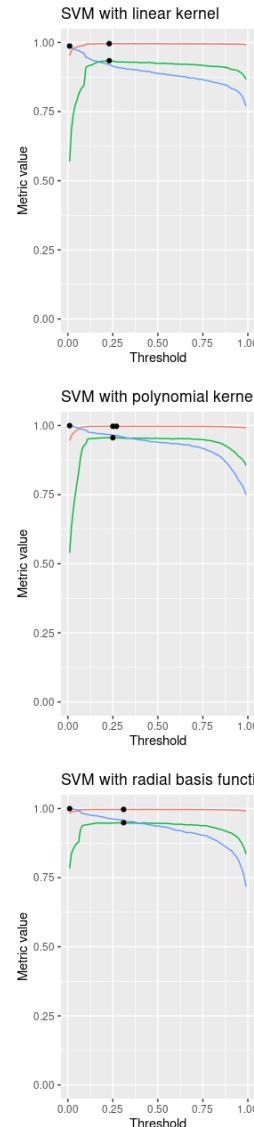
Threshold Selection for the SVM Models Build in Different Feature Spaces (with cross-validation)

RGB

Linear kernel

Polynomial kernel

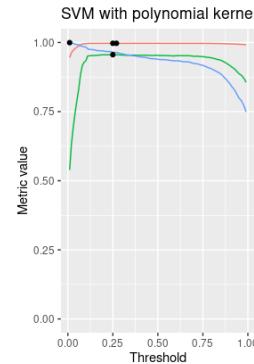
Radial basis function kernel



Threshold 0.23 (accuracy)			
Prediction	TRUE	1859	99
	FALSE	163	61120
	Truth	TRUE	FALSE

Threshold 0.23 (f_meas)			
Prediction	TRUE	1859	99
	FALSE	163	61120
	Truth	TRUE	FALSE

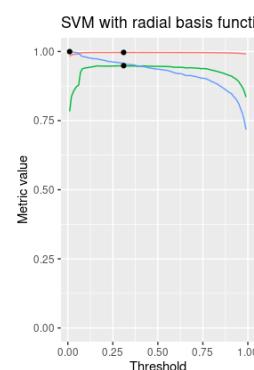
Threshold 0.01 (sens)			
Prediction	TRUE	1996	2988
	FALSE	26	58231
	Truth	TRUE	FALSE



Threshold 0.25 (accuracy)			
Prediction	TRUE	1952	110
	FALSE	70	61109
	Truth	TRUE	FALSE

Threshold 0.25 (f_meas)			
Prediction	TRUE	1952	110
	FALSE	70	61109
	Truth	TRUE	FALSE

Threshold 0.01 (sens)			
Prediction	TRUE	2021	3451
	FALSE	1	57768
	Truth	TRUE	FALSE

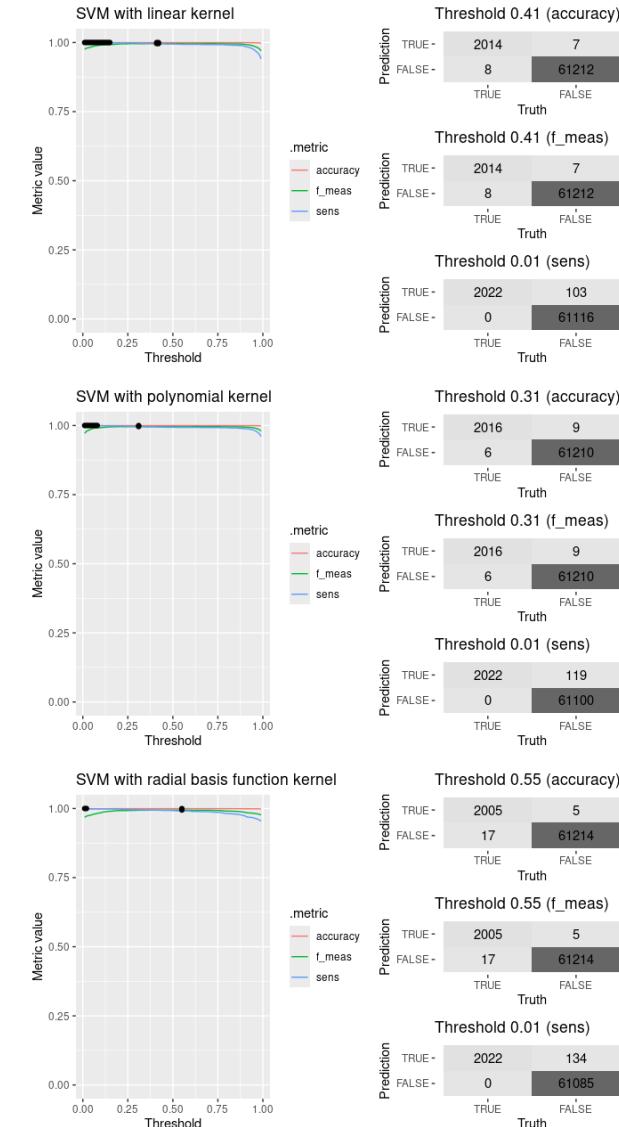


Threshold 0.31 (accuracy)			
Prediction	TRUE	1935	122
	FALSE	87	61097
	Truth	TRUE	FALSE

Threshold 0.31 (f_meas)			
Prediction	TRUE	1935	122
	FALSE	87	61097
	Truth	TRUE	FALSE

Threshold 0.01 (sens)			
Prediction	TRUE	2021	1116
	FALSE	1	60103
	Truth	TRUE	FALSE

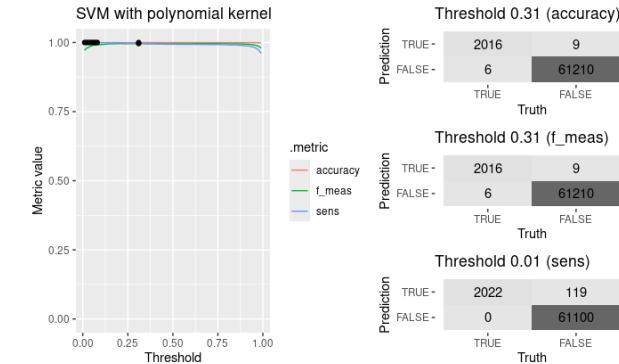
All Engineered Features + PCA



Threshold 0.41 (accuracy)			
Prediction	TRUE	2014	7
	FALSE	8	61212
	Truth	TRUE	FALSE

Threshold 0.41 (f_meas)			
Prediction	TRUE	2014	7
	FALSE	8	61212
	Truth	TRUE	FALSE

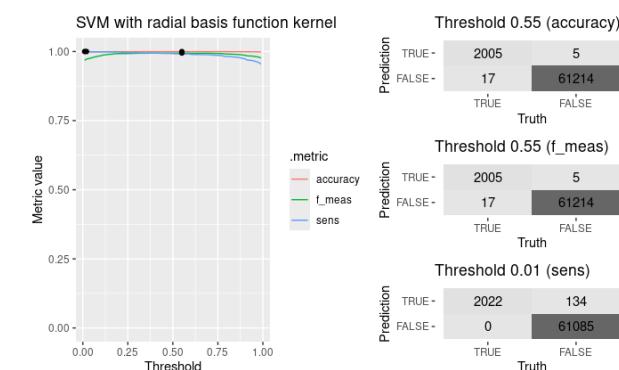
Threshold 0.01 (sens)			
Prediction	TRUE	2022	103
	FALSE	0	61116
	Truth	TRUE	FALSE



Threshold 0.31 (accuracy)			
Prediction	TRUE	2016	9
	FALSE	6	61210
	Truth	TRUE	FALSE

Threshold 0.31 (f_meas)			
Prediction	TRUE	2016	9
	FALSE	6	61210
	Truth	TRUE	FALSE

Threshold 0.01 (sens)			
Prediction	TRUE	2022	119
	FALSE	0	61100
	Truth	TRUE	FALSE



Threshold 0.55 (accuracy)			
Prediction	TRUE	2005	5
	FALSE	17	61214
	Truth	TRUE	FALSE

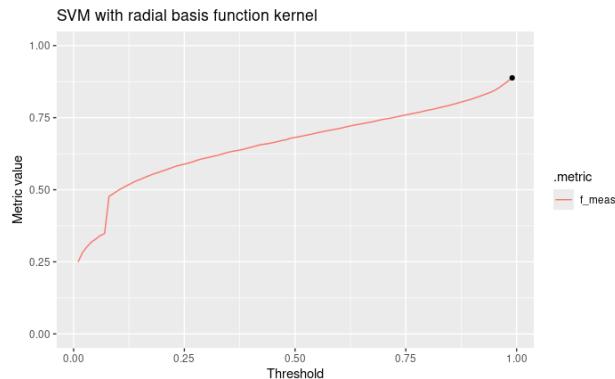
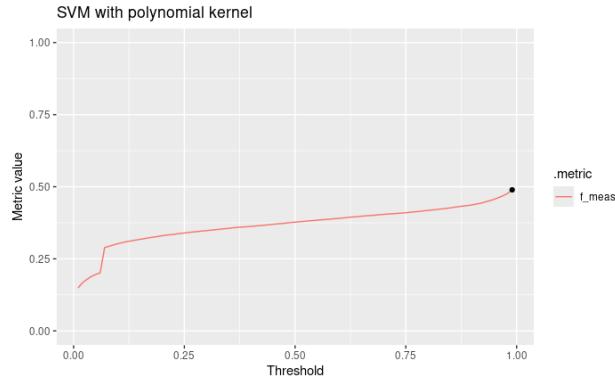
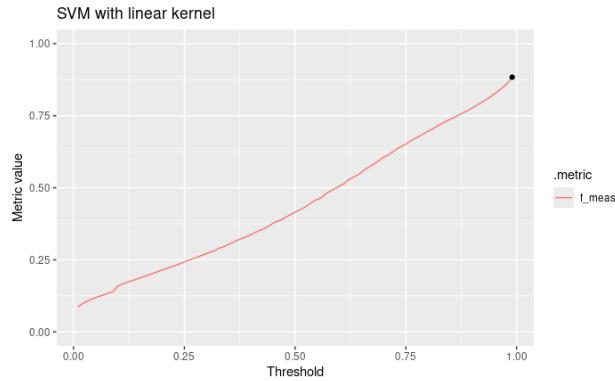
Threshold 0.55 (f_meas)			
Prediction	TRUE	2005	5
	FALSE	17	61214
	Truth	TRUE	FALSE

Threshold 0.01 (sens)			
Prediction	TRUE	2022	134
	FALSE	0	61085
	Truth	TRUE	FALSE

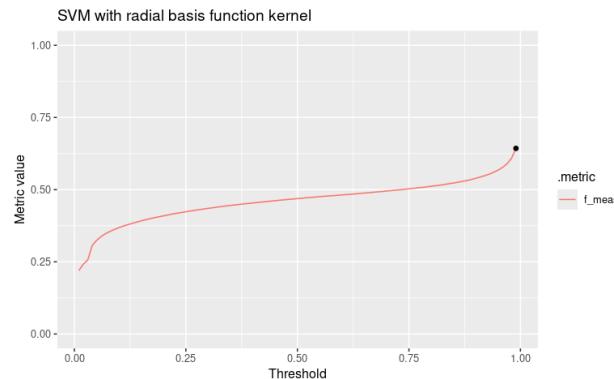
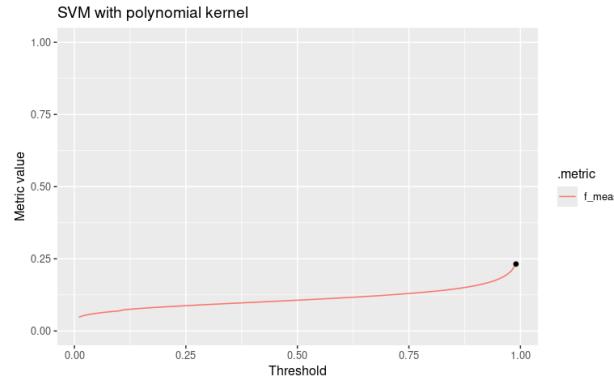
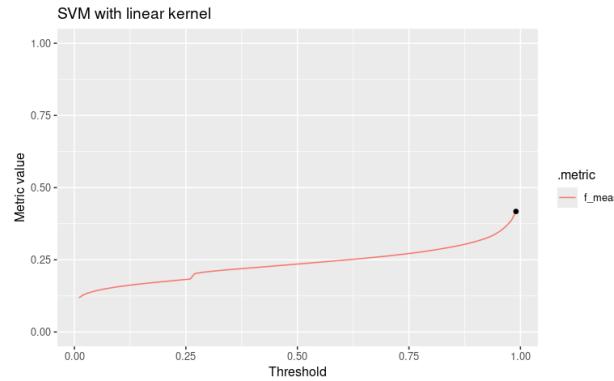
Threshold Selection for the SVM Models Build in Different Feature Spaces (with holdout data)

RGB

Linear kernel



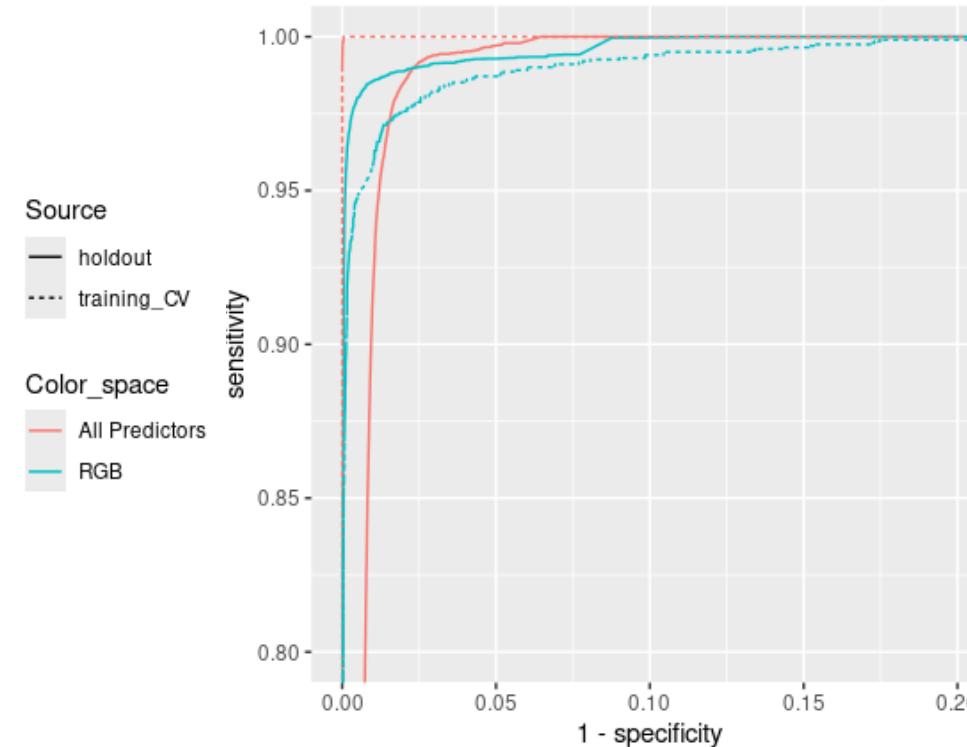
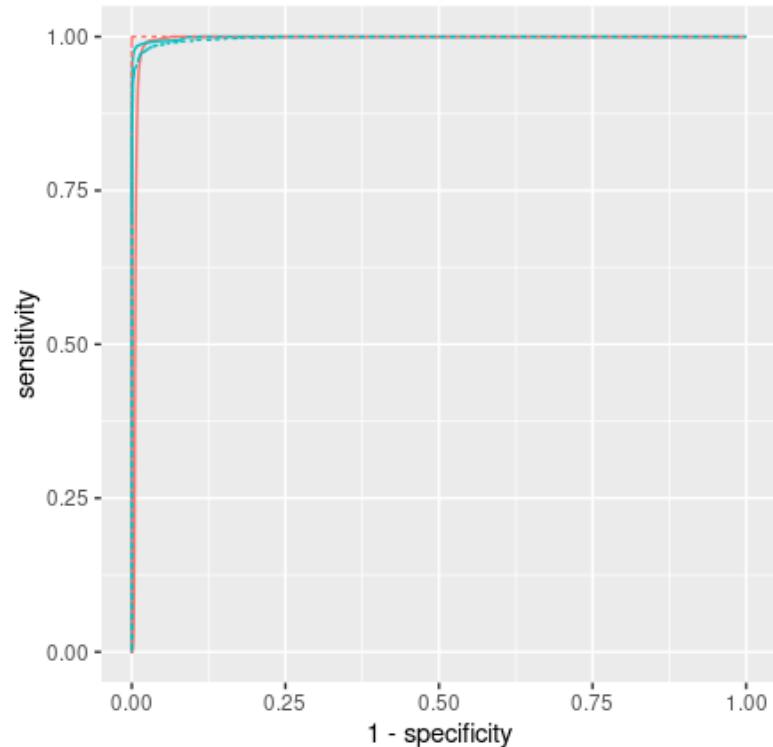
All Engineered Features + PCA



*Radial basis
function kernel*

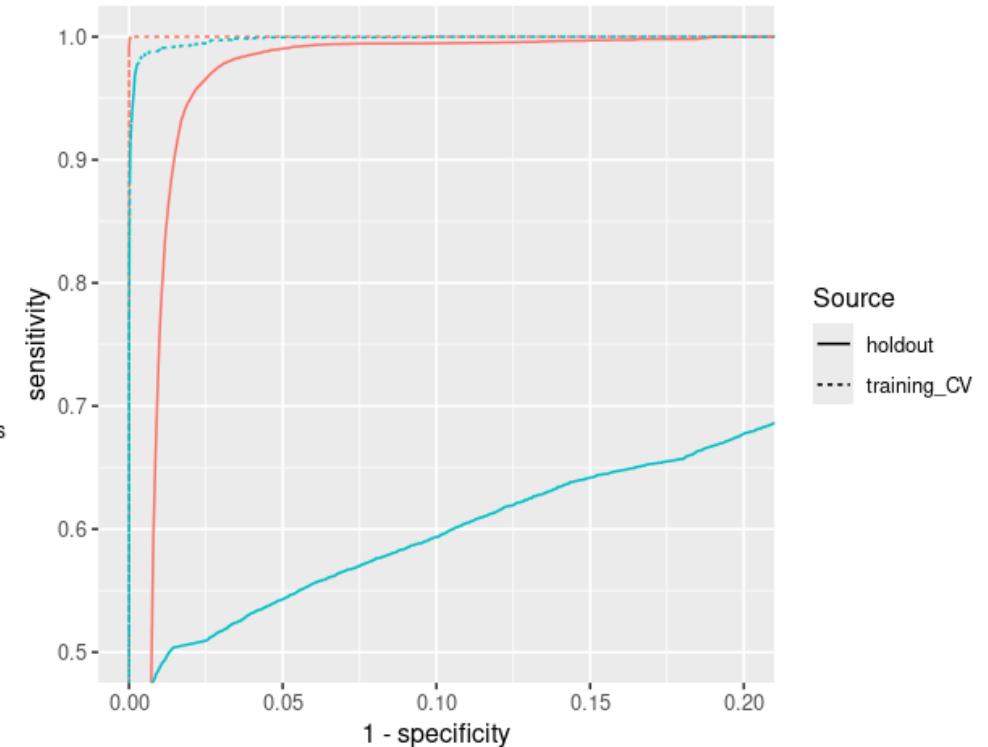
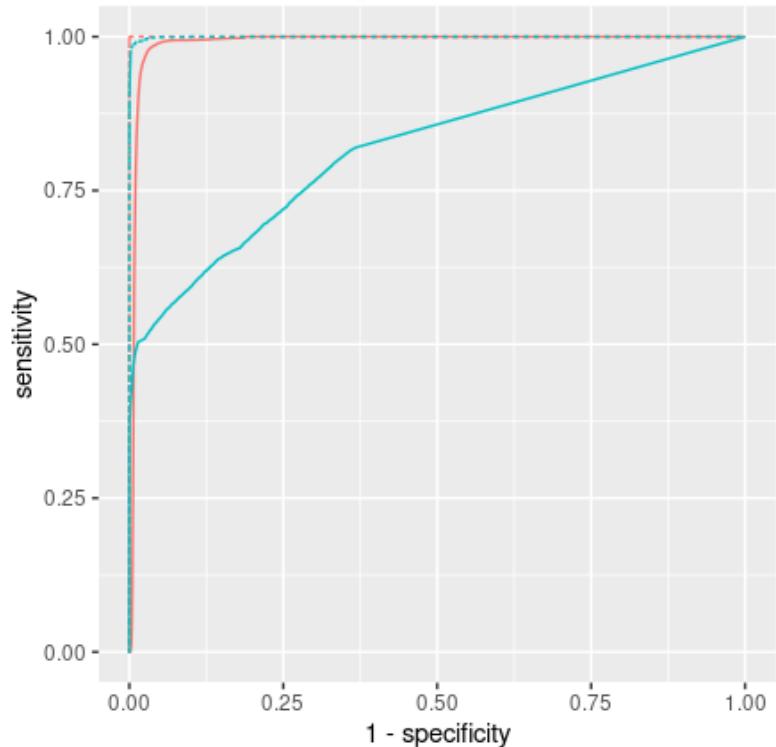
Comparison between SVM Models for Each Kernel in Different Feature Spaces

Linear kernel



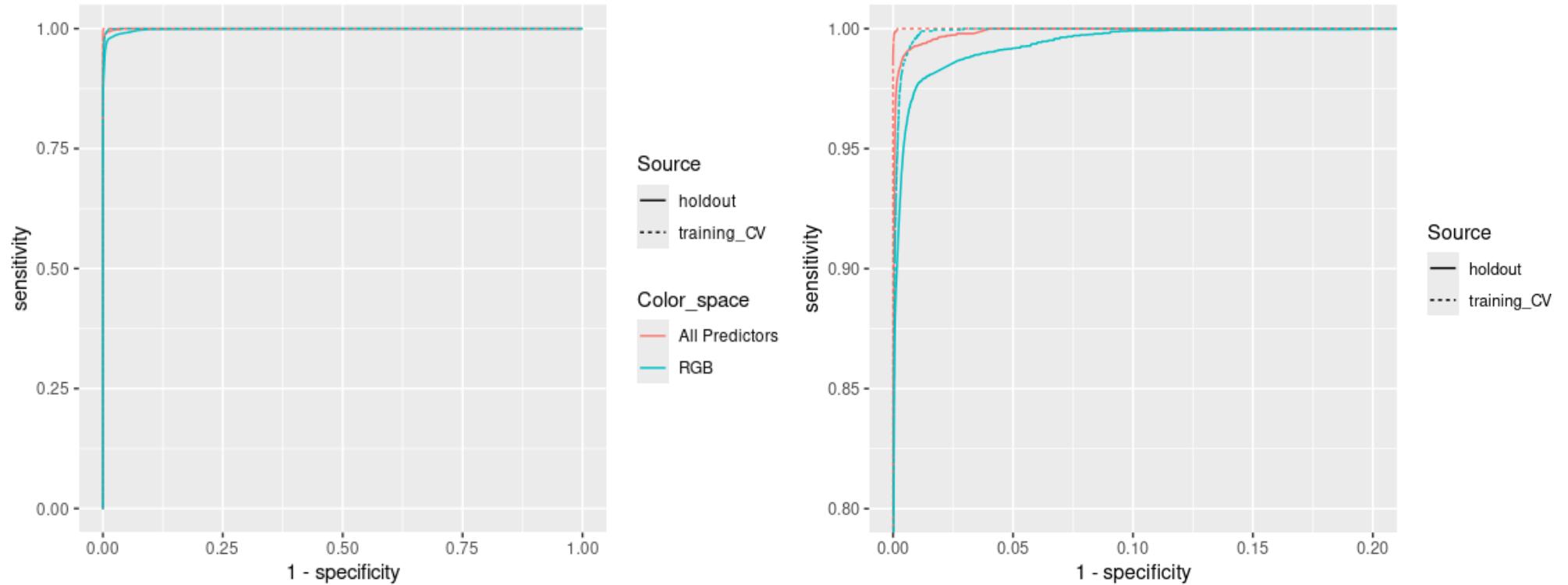
Comparison between SVM Models for Each Kernel in Different Feature Spaces

Polynomial kernel



Comparison between SVM Models for Each Kernel in Different Feature Spaces

Radial basis function kernel



Performance Metrics for All of the SVM Models Built in This Work

Performance Metrics for Tuned SVM Models at Optimal Threshold							
color_space	model	dataset	threshold	accuracy	kap	f_meas	roc_auc
All Predictors	SVM with linear kernel	train	0.41	1.000	0.996	0.996	1.000
All Predictors	SVM with linear kernel	holdout	0.99	0.980	0.411	0.418	0.994
All Predictors	SVM with polynomial kernel	train	0.31	1.000	0.996	0.997	1.000
All Predictors	SVM with polynomial kernel	holdout	0.99	0.953	0.222	0.232	0.990
All Predictors	SVM with radial basis function kernel	train	0.55	1.000	0.995	0.995	1.000
All Predictors	SVM with radial basis function kernel	holdout	0.99	0.992	0.639	0.643	1.000
RGB	SVM with linear kernel	train	0.23	0.996	0.932	0.934	0.998
RGB	SVM with linear kernel	holdout	0.99	0.998	0.883	0.884	0.999
RGB	SVM with polynomial kernel	train	0.25	0.997	0.956	0.957	1.000
RGB	SVM with polynomial kernel	holdout	0.99	0.994	0.486	0.489	0.819
RGB	SVM with radial basis function kernel	train	0.31	0.997	0.947	0.949	1.000
RGB	SVM with radial basis function kernel	holdout	0.99	0.998	0.887	0.888	0.999