

PROBLEM STATEMENT: PREDICTING BREAST CANCER SURVIVAL RATES

Leveraging the SEER database (2011-2015), our mission is to train a machine learning model with ambitious objectives:

- Exceptional Accuracy: Our aim is not only to surpass the 75% survival rate benchmark but also achieve accuracy levels exceeding 96%.
- Critical Parameter Exploration: We will delve into 16 influential factors (such as race and cancer type) that impact survival. These parameters will be instrumental in training our model effectively.

This project serves as a vital link between data science and patient care, empowering informed decisions.

Our approach involves statistical analyses to identify crucial parameters and evaluate their dependencies.

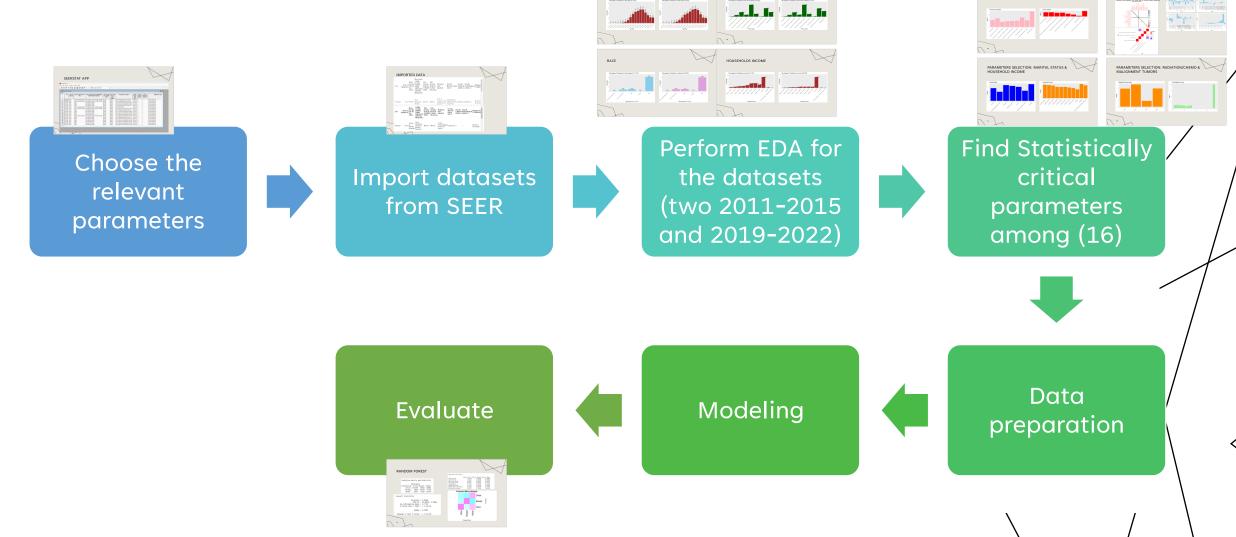
WHAT

- 670,000 have lost their life to breast cancers globally in 2022 (43,700 in USA)
- Breast cancer was the most common cancer in women in 157 countries out of 185 in 2022
- Breast cancer is the most diagnosed cancer among U.S. women.
- It is also personal to me.

WHY

- Accurate survival prediction is critical for patient management
- Precise survival estimates help allocate healthcare resources effectively
- Patients and their families can make informed decisions about treatment options.
- Quality of Life Considerations
- And Economic consideration.

HOW - FLOWCHART



HOW: DATA PREPARATION AND MODELING (ML)

- · Clean data
- Remove NA and empty value
- Add new categorical column like COD, Radiation, Age, for simplification
- Creating correct data structure

Data transformation (>300 K row)

Data Preparation

- Data Encoding
- Imputing the data as needed
- Dealing with different data-types
- Removing and simplifying categories
- Simplify problem to binomial for simplification, Alive/Dead

- Defining the models
 - RF, LR, GBM, SVM, ...
- Setting up parameters and fine tuning the model
- Run and have a cup of tea!

ML Models

Models Evaluation

- Running the test data
- Finding confusion matrix
- Plotting AOC
- Calculating Accuracy and more



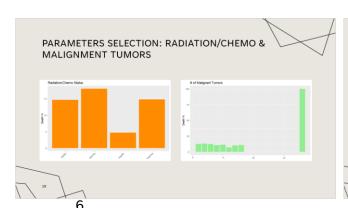
RESULTS: STATISTICAL SURVIVAL RATES AND EAD

Survival rate 2011-2015 of 300K: 75%

COD	count	Total Count Popi	ılation
Alive	228221	303557	75
Breast	38472	303557	13
Other	36864	303557	12

Marital status and survival

Marital status at diagnosis	Event Population	Population	Group % in total	Death %
Divorced	4399	32214	10.61	13.66
Married (including common law)	15694	160551	52.89	9.78
Separated	544	3225	1.06	16.87
Single (never married)	7161	44678	14.72	16.03
Unknown	2774	18481	6.09	15.01
Unmarried or Domestic Partner	110	1014	0.33	10.85
Widowed	7790	43394	14.30	17.95





Principal Parameter selection

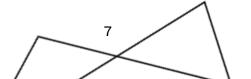
- Evaluation the data, empty, correlation analyses, normality analyses,
- Among 36 parameters 16 found critical: treatment (chemo/radiation, surgery), # tumors, months from diagnosis to treatment, race, grade, and type
- Data were analyzed using bootstrapping and random sampling to avoid the size using Chissquare and Fisher exact test
- Many collinearities were identified and removed like sex, Origin Recode, Diagnostic confirmation, ...

		\
variable	p_value	\
Race recode (W, B, AI, API)	0.0004998	Fisher
Primary Site - labeled	0.0004998	
Grade Recode (thru 2017)	0.0004998	/ Exact with
Laterality	0.0004998	simulation
Chemotherapy recode (yes, no/unk)	0.0004998	Simulation
Reason no cancer-directed surgery	0.0004998	.p.value=
Survival months flag	0.0004998	. / /
First malignant primary indicator	0.0004998	RUE due \
Marital status at diagnosis	0.0004998	to size of
Median household income inflation adj to 2021	0.0004998	10/3120 01
Age recode (<60,60-69,70+)	0.0004998	the
COD	0.0004998	
Radiation	0.0004998	s¢mple!
Rural-Urban Continuum Code	0.0011294	

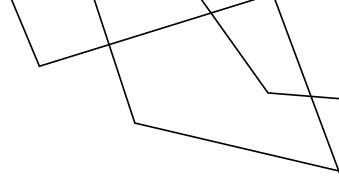
MODEL EVALUATION:

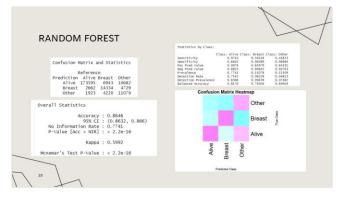
- Different models were used such like logistic regression, random forest, and SVM
- Summary
 - Random Forest was the easiest to apply and reasonably fast
 - Logistic Regression was the fast, but still accurate
 - Survival specific packages were fast, but required domain knowledge for successful use

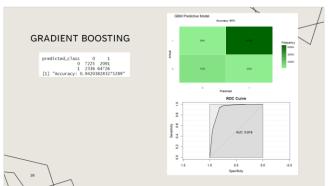
Method	Accuracy (Survival)
Logistic Regression	93%
Random Forest	94%
GBM	94%
CoxPH	92%
DNN	94%

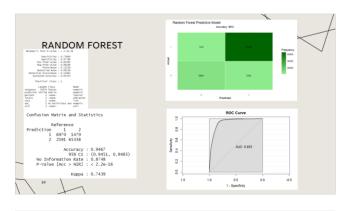


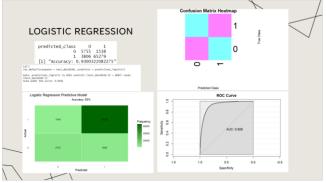
RESULTS SUMMARY

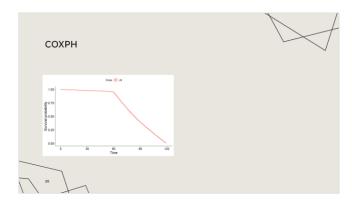


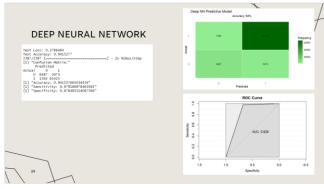










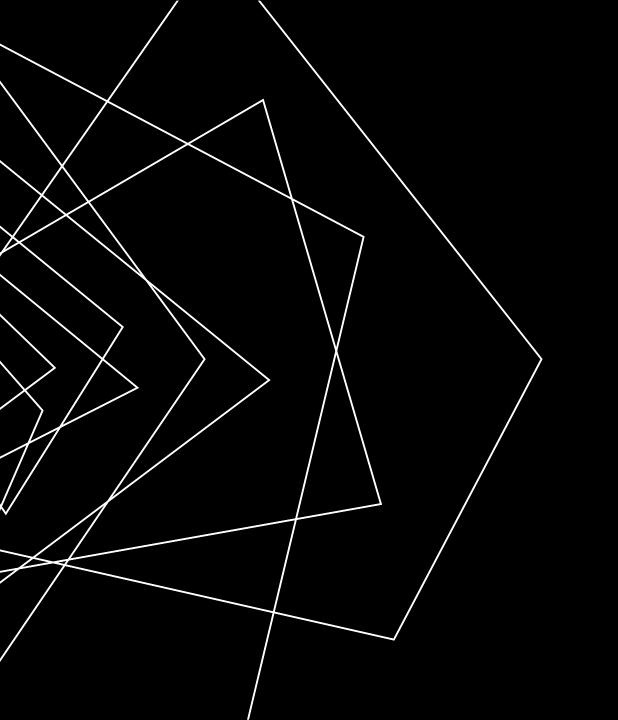


CHALLENGES AND LESSONS LEARNED

- Choose ML Models Wisely: Understand model foundations before using them.
- Domain Knowledge First: Don't tackle complex projects without domain expertise.
- Random Forest Simplicity: Opt for user-friendly models like Random Forest.
- Categorical Data Challenges: Handling medical categorical data is tough.
- Data Encoding Matters: Address missing values and encode features carefully.
- R Packages Rock: Explore the powerful R package ecosystem.!

REFERENCES:

- [1] SEER (https://seer.cancer.gov/data/access.html)
- [2] zgalochkina/SEER_solid_tumor: R code for SEER data analysis of solid tumor in different populations (github.com)
- [3] XAI_Healthcare_eXplainable_AI_in_Healthcare.pdf (upc.edu)
- [4] Pargen, F., Pfisterer, F., Thomas, J., Bischl, B.: Regularized target encoding out performs traditional methods in supervised machine learning with high cardinality features. Computational Statistics 37(5), 2671–2692 (Nov 2022)
- [5] American Cancer Society Breast Cancer Survival Rates
- GitHub: <u>koohpi/Breast_Cancer_Survival_Project</u>: A <u>non-scientific project for breast cancer survival rate estimate in women based on SEER DB (github.com)</u>
- Rpub: RPubs Breast Cancer Survival Rate With SEER



THANK YOU

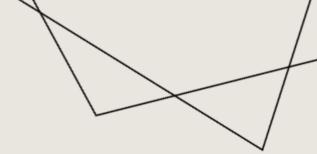
Koohyar Pooladvand koohyar.pooladvand69@cuny.spsmail.edu

IMPORTED DATA

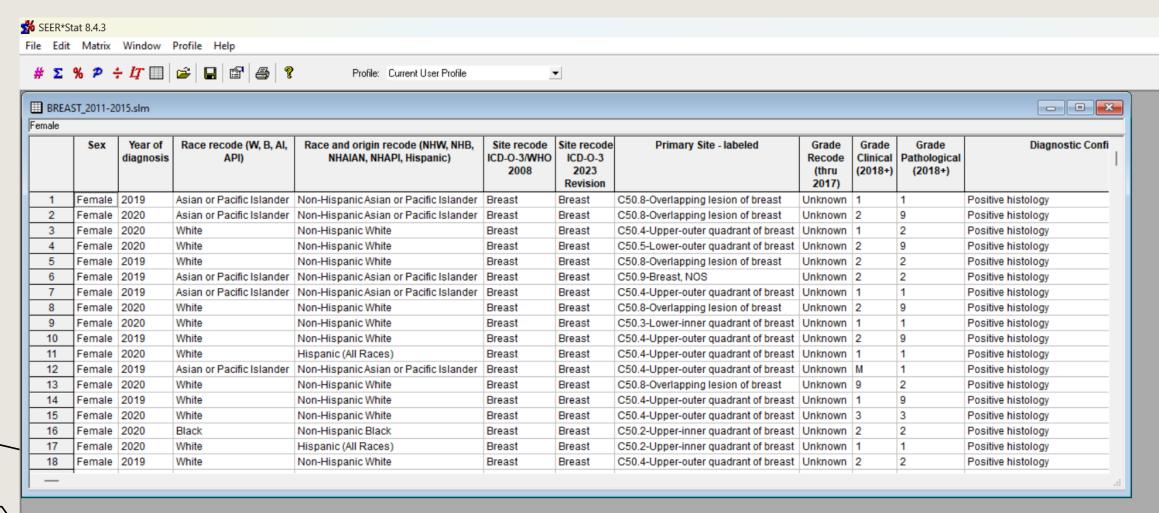
Sex	Race Year of recode diagnosis (W, B, AI, API)	Race and origin recode (NHW, NHB, NHAIAN, NHAPI, Hispanic)	ICD-O-	ICD-O-	labeled	Recode (thru	Grade Clinical (2018+)	Pathological	Diagno Confir
Female	2015 White	Non- Hispanic White	Breast	Breast	C50.4- Upper-outer quadrant of	Moderately differentiated; Grade II	Blank(s)	Blank(s)	Positive histolog
		aniain							

Sex	Race Year of (W, B, diagnosis AI, API)	NHR	ICD-O-	ICD-O-	labeled	(thru	Grade Clinical (2018+)	Pathological	Diagnostic Confirmat
Female	Asian 2019 or Pacific Islander	Pacific	Breast	Breast	C50.8- Overlapping lesion of breast	Unknown	1	1	Positive histology

1

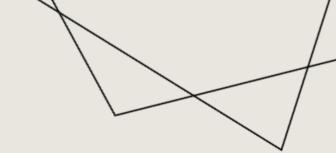


SEERSTAT APP

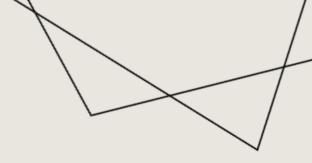


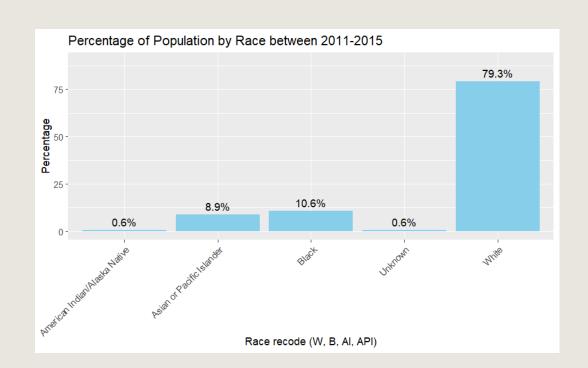


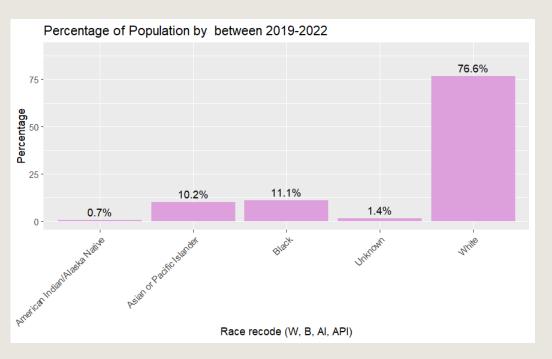
— Data Summary ————	
Name Number of rows Number of columns	Values BREAST_DF_surv_clean 303557 18
Column type frequency: factor numeric	14 4
Group variables — Data Summary —	None
Name Number of rows Number of columns	Values BREAST_DF_eval_clean 131395 17
Column type frequency: factor numeric	13 4
Group variables	None



RACE



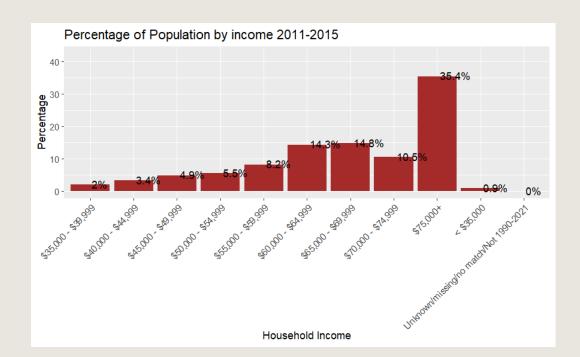


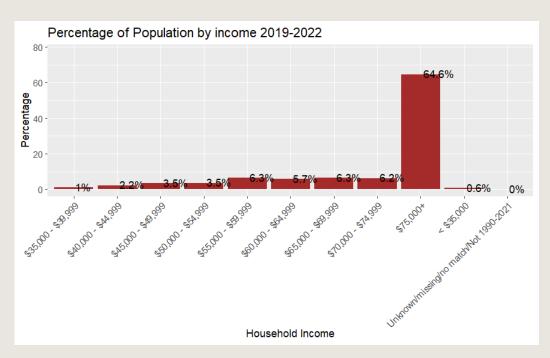


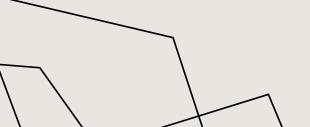




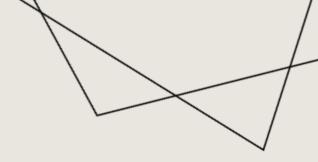
HOUSEHOLDS INCOME

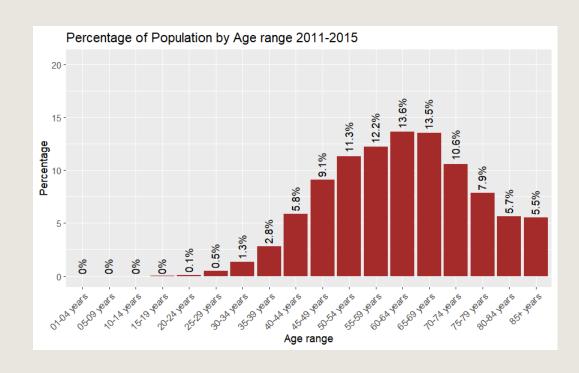


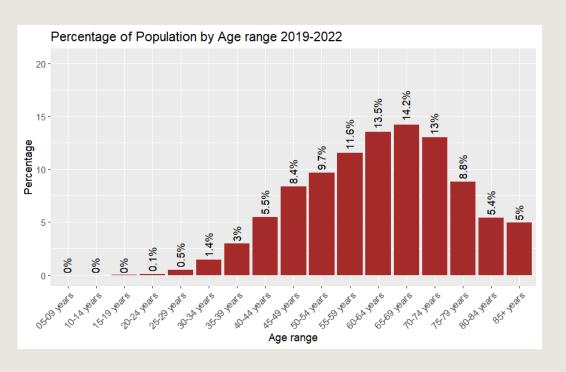




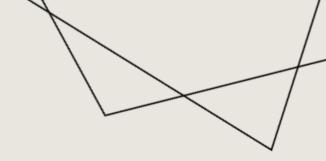




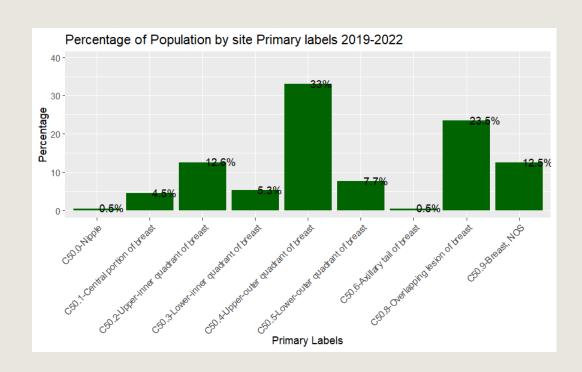


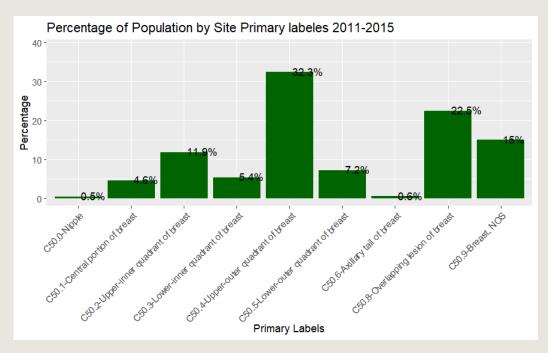




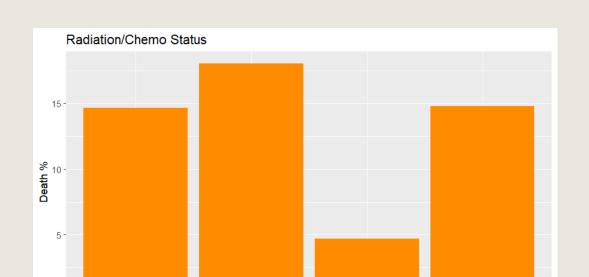


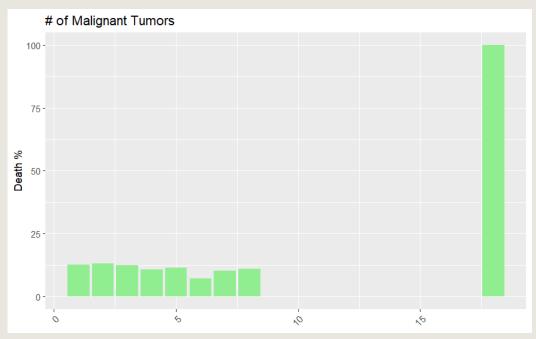
CANCER PRIMARY SITE LABELS





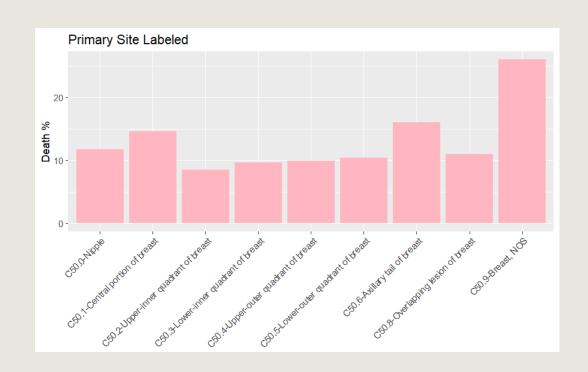
PARAMETERS SELECTION: RADIATION/CHEMO & MALIGNMENT TUMORS

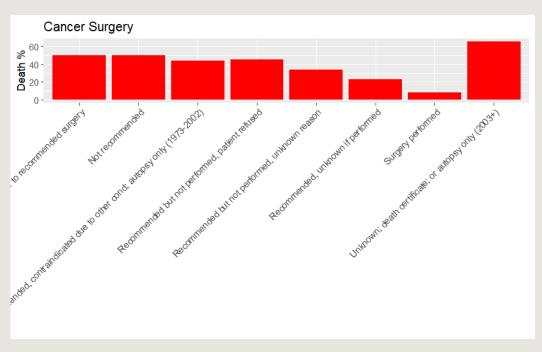




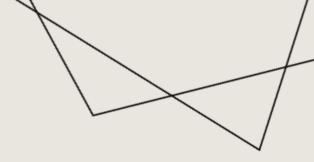


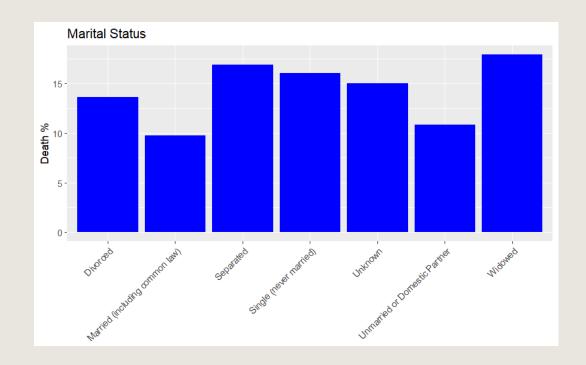
PARAMETERS SELECTION: PRIMARY SITE & SURGERY

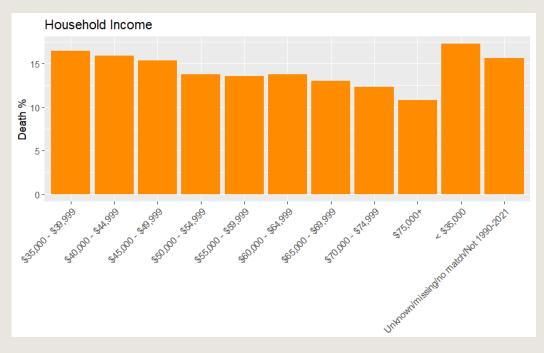


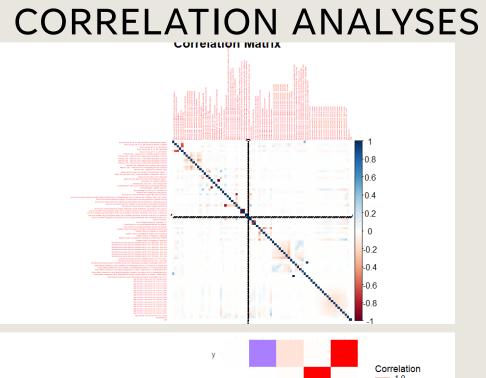


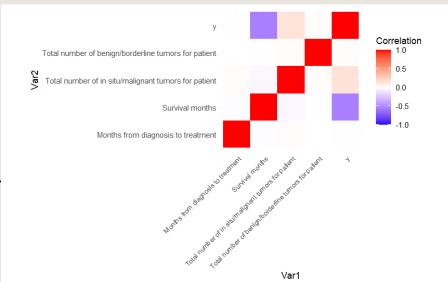


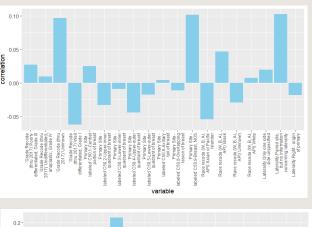


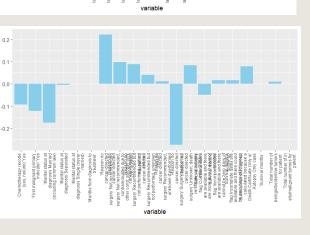


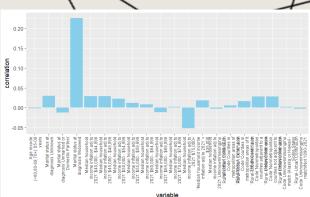


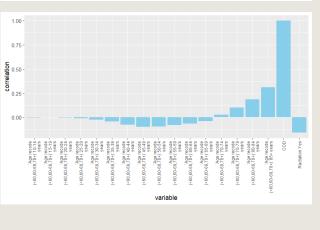












RANDOM FOREST

Confusion Matrix and Statistics

Reference

Prediction Alive Breast Other Alive 173595 6943 10682 Breast 2662 14334 4729 Other 1923 4220 11079

Overall Statistics

Accuracy: 0.8646

95% CI: (0.8632, 0.866)

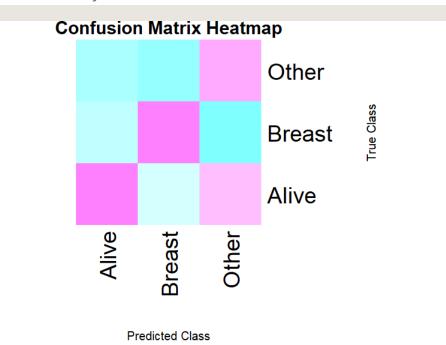
No Information Rate : 0.7741 P-Value [Acc > NIR] : < 2.2e-16

Kappa: 0.5992

Mcnemar's Test P-Value : < 2.2e-16

Statistics by Class:

	Class: Alive	Class: Breast	Class: Other
Sensitivity	0.9743	0.56218	0.41823
Specificity	0.6610	0.96389	0.96984
Pos Pred Value	0.9078	0.65979	0.64331
Neg Pred Value	0.8823	0.94645	0.92763
Prevalence	0.7741	0.11078	0.11509
Detection Rate	0.7542	0.06228	0.04813
Detection Prevalence	0.8308	0.09439	0.07482
Balanced Accuracy	0.8176	0.76304	0.69404



RANDOM FOREST

```
Sensitivity: 0.72900
           Specificity: 0.97786
        Pos Pred Value: 0.82495
        Neg Pred Value: 0.96186
            Prevalence: 0.12518
        Detection Rate: 0.09126
  Detection Prevalence: 0.11062
     Balanced Accuracy: 0.85343
       'Positive' Class : 1
         Length Class
                                  Mode
response 76378 factor
                                  numeric
predictor 152756 matrix
                                  numeric
percent
              1 -none-
                                  logical
levels
              2 -none-
                                  character
rocs
              1 -none-
                                  list
              1 mv.multiclass.auc numeric
auc
call
              3 -none-
                                  call
```

Mcnemar's Test P-Value : < 2.2e-16

Confusion Matrix and Statistics

Reference

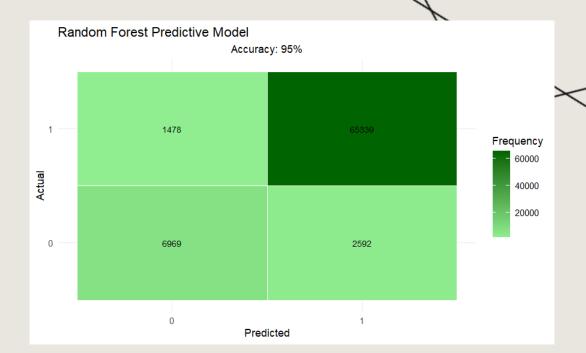
Prediction 1 2 1 6970 1479 2 2591 65338

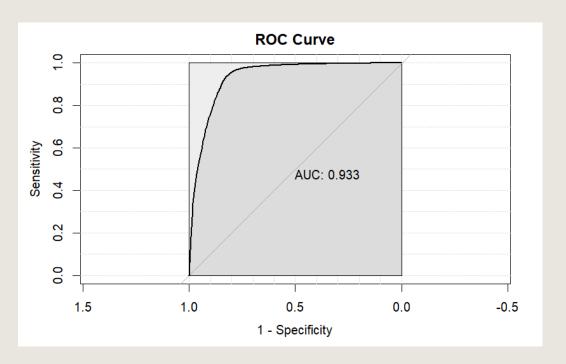
Accuracy: 0.9467

95% CI: (0.9451, 0.9483)

No Information Rate : 0.8748 P-Value [Acc > NIR] : < 2.2e-16

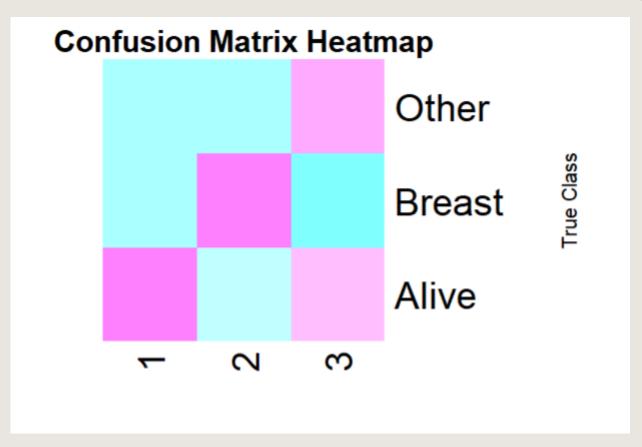
Kappa: 0.7439







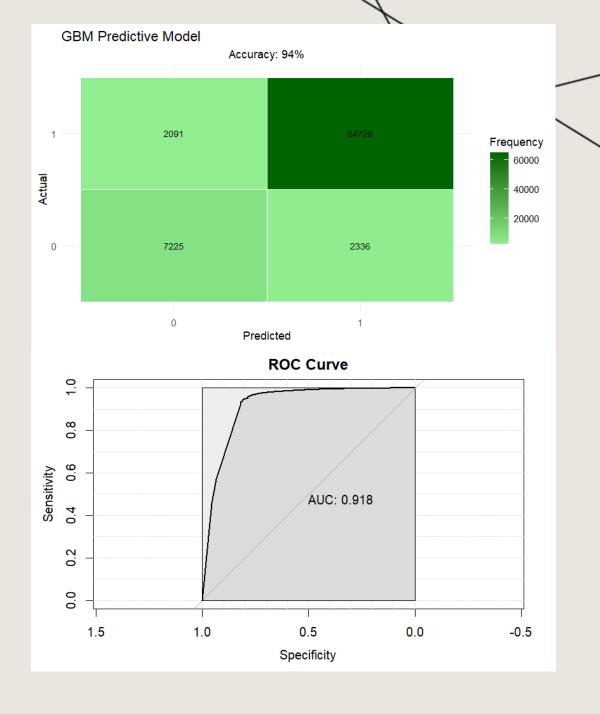
predicted_class 1 2 3 Alive 170984 5537 9856 Breast 4044 15950 5887 Other 3152 4010 10747 [1] "Accuracy: 0.858859002376535"





GRADIENT BOOSTING

predicted_class 0 1 0 7225 2091 1 2336 64726 [1] "Accuracy: 0.942038283275289"



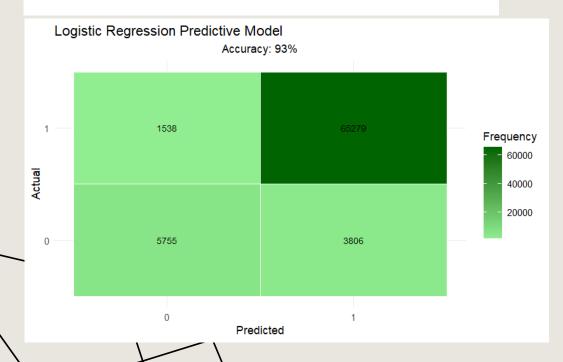
LOGISTIC REGRESSION

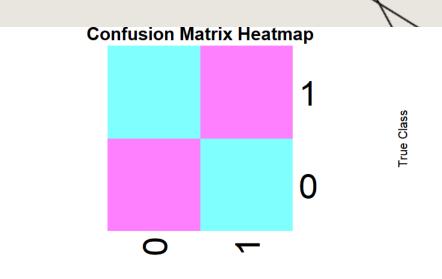
predicted_class 0 1 0 5755 1538 1 3806 65279 [1] "Accuracy: 0.9300322082275"

Call:
roc.default(response = test_data\$COD, predictor = predictions_logistic)

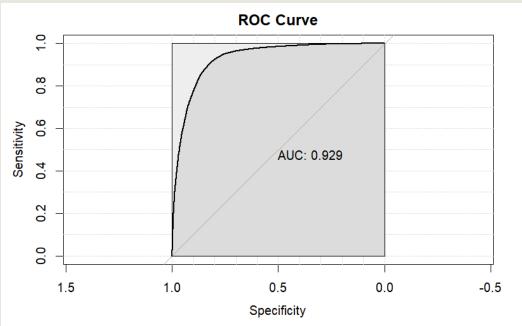
Data: predictions_logistic in 9561 controls (test_data\$COD 0) < 66817 cases (test_data\$COD 1).

Area under the curve: 0.9291

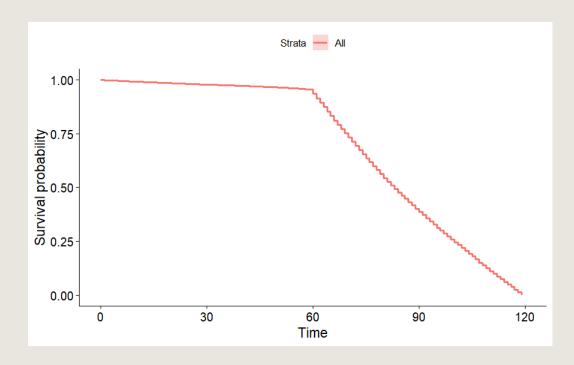


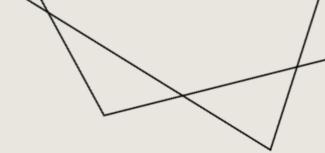






COXPH





DEEP NEURAL NETWORK

