

COVID-19 MORTALITY PREDICTION USING MACHINE LEARNING MODELS

: A COMPARITIVE STUDY



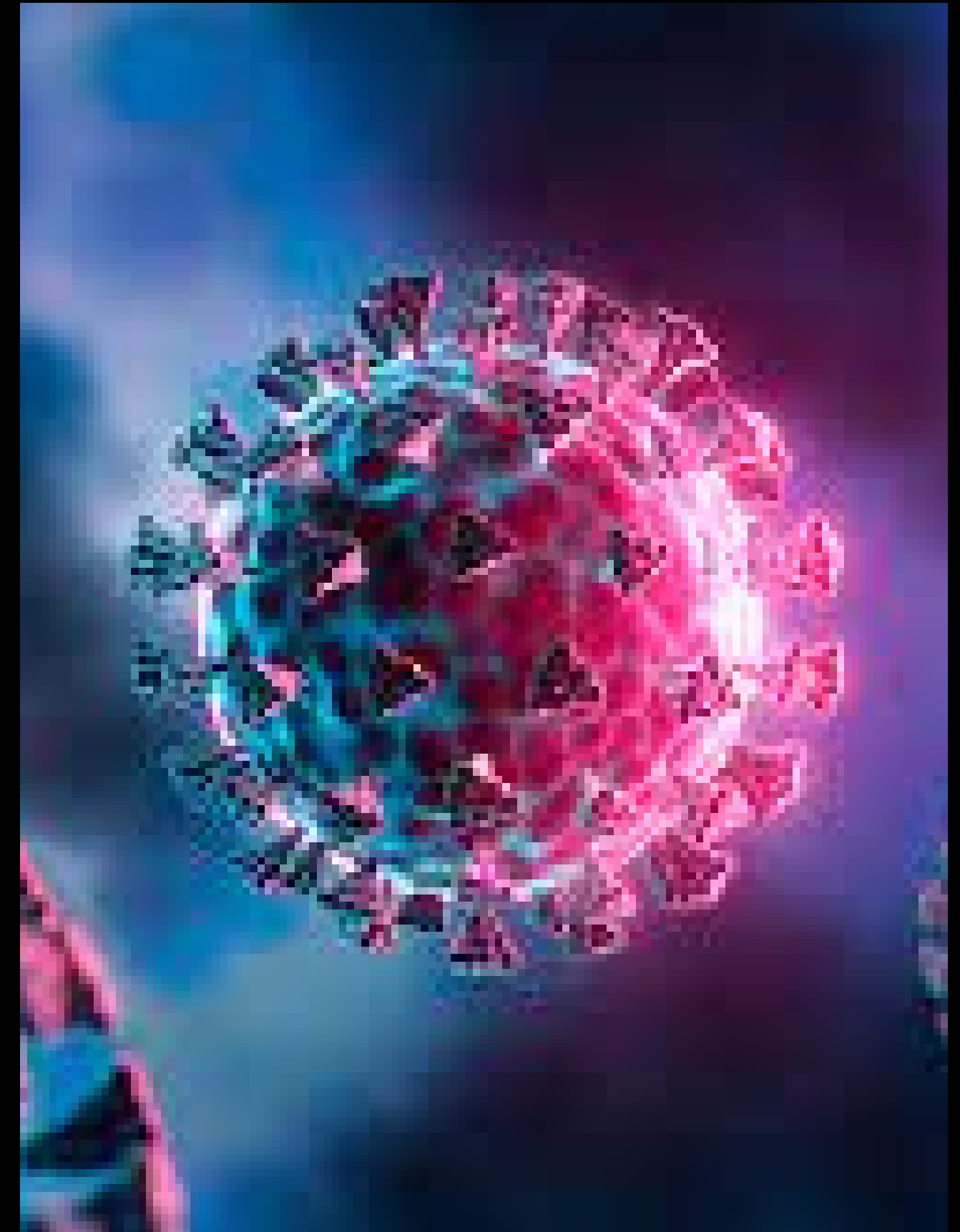
INTRODUCTION

COVID-19, caused by the highly infectious SARS-CoV-2 virus, has been declared a global public health emergency by the WHO. Epidemiological models have been deployed for outbreak prediction, peak estimation and mortality rate prediction.

The goal of this project is to provide assistance to medical units based on critical situations such as the following:

During the beginning of a pandemic wave, medical units generally do not have issues with medical infrastructures such as beds and medical supplies. In this scenario, we propose to use one of the mentioned models that have a better recall score (where a patient is considered critical even if there is a small chance that he might still recover later).

As the pandemic reaches a peak, medical supplies and infrastructure become sparse. In such scenarios, medical units can switch to a model with higher precision (to ensure the most needed patients are attended soon).



DATA PRE-PROCESSING

01

02

03

04

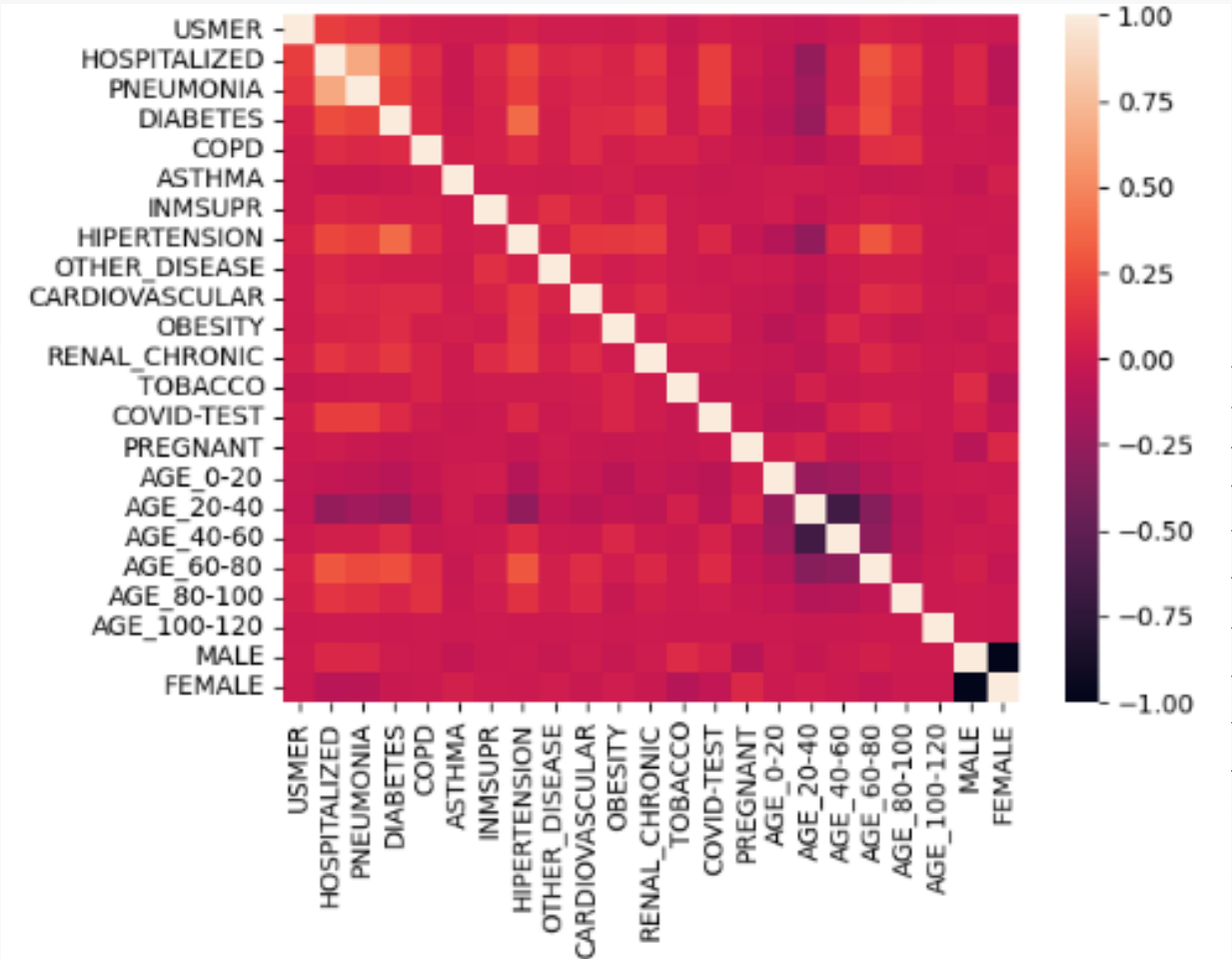
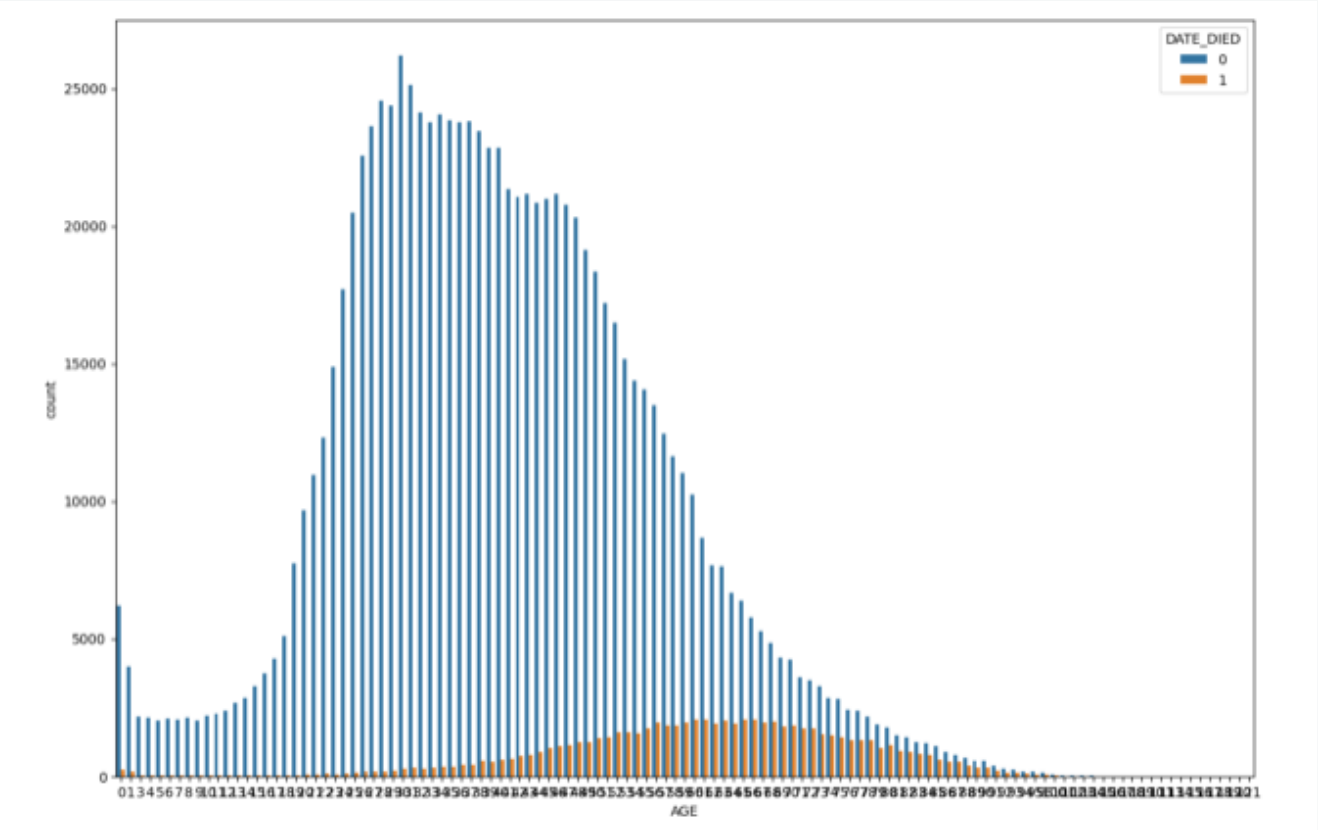
LOAD DATASET

FINDING RELATIONS

PRE-PROCESSING

FINAL FORMATTING

	Total_missing_count	Percentage_missing
ICU	856032	81.64
INTUBED	855869	81.62
PREGNANT	527265	50.28
PNEUMONIA	16003	1.53
OTHER_DISEASE	5045	0.48
INMSUPR	3404	0.32
DIABETES	3338	0.32
TOBACCO	3220	0.31
HIPERTENSION	3104	0.30
RENAL_CHRONIC	3006	0.29
OBESITY	3032	0.29
CARDIOVASCULAR	3076	0.29
COPD	3003	0.29
ASTHMA	2979	0.28
AGE	345	0.03
MEDICAL_UNIT	0	0.00
DATE_DIED	0	0.00
PATIENT_TYPE	0	0.00
SEX	0	0.00
CLASIFFICATION_FINAL	0	0.00
USMER	0	0.00



FEATURE SELECTION AND DATA RE-SAMPLING

Not PCA

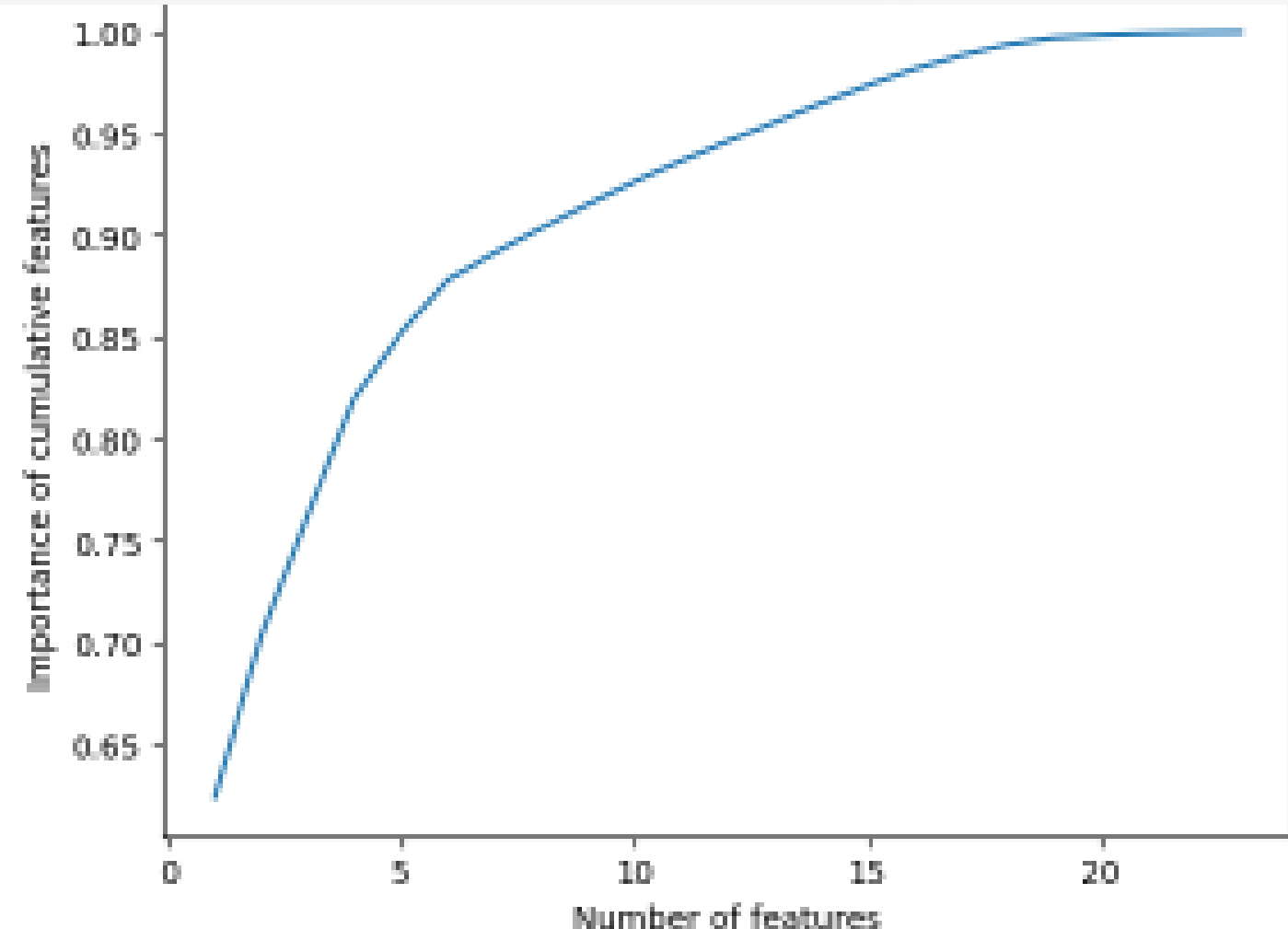
Principal component analysis works best when the feature set has continuous values. In our case, all features are binary values and therefore PCA is ruled out

Decision Trees

We use Decision trees with a higher max_depth value so as to get the feature_importance based on the gini index

Resampling

We use SMOTE and RandomUnderSampler modules provided by imblearn package to under sample the majority class and oversample the minority class



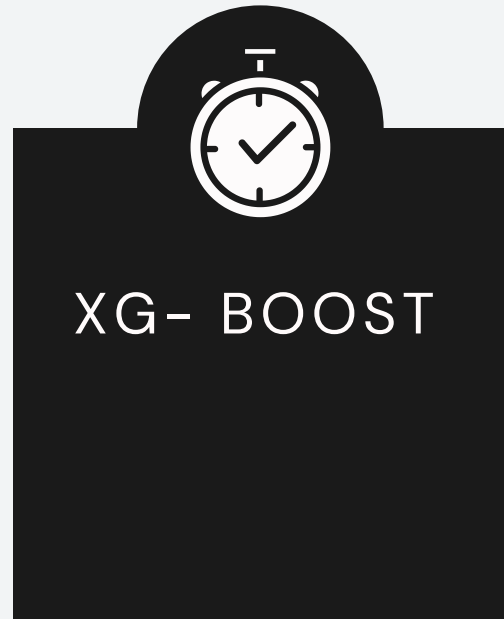
```
np.cumsum(list(important_features.values()))
```

```
array([0.62368734, 0.78295856, 0.76285882, 0.82817337, 0.85182216,  
       0.87815796, 0.89113641, 0.9833984 , 0.91524446, 0.92629333,  
       0.93638829, 0.94599816, 0.95553693, 0.96485467, 0.9736132 ,  
       0.9815581 , 0.98816825, 0.99388838, 0.99713923, 0.99858495,  
       0.99927187, 0.99981512, 1.          ])
```

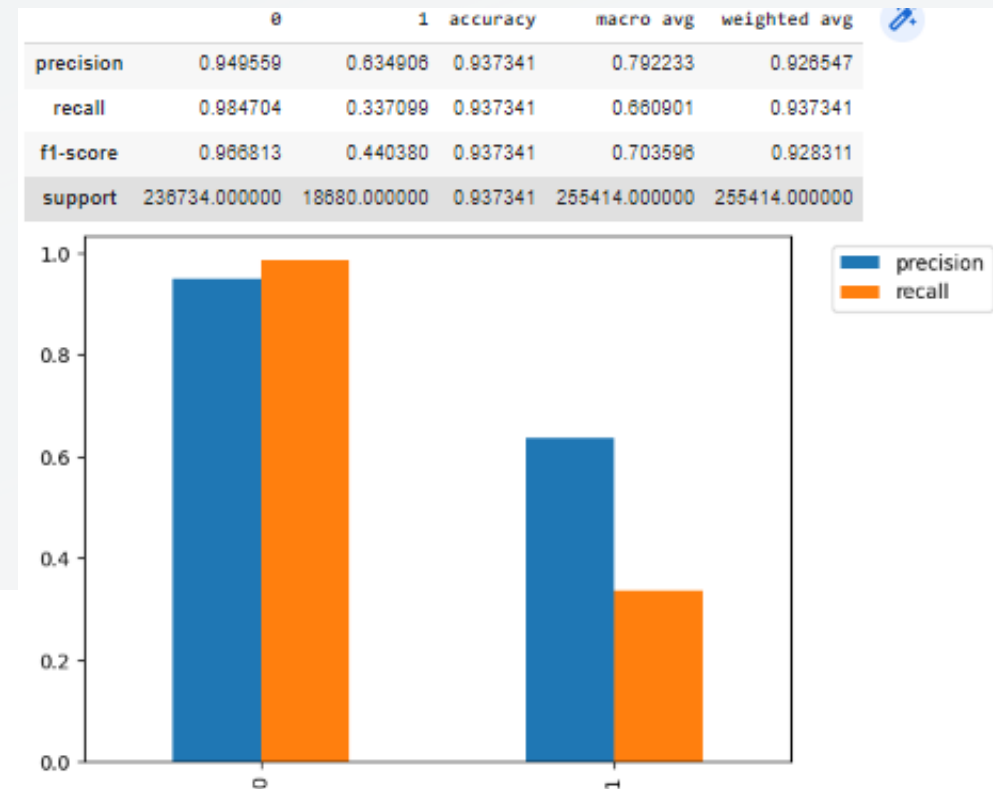
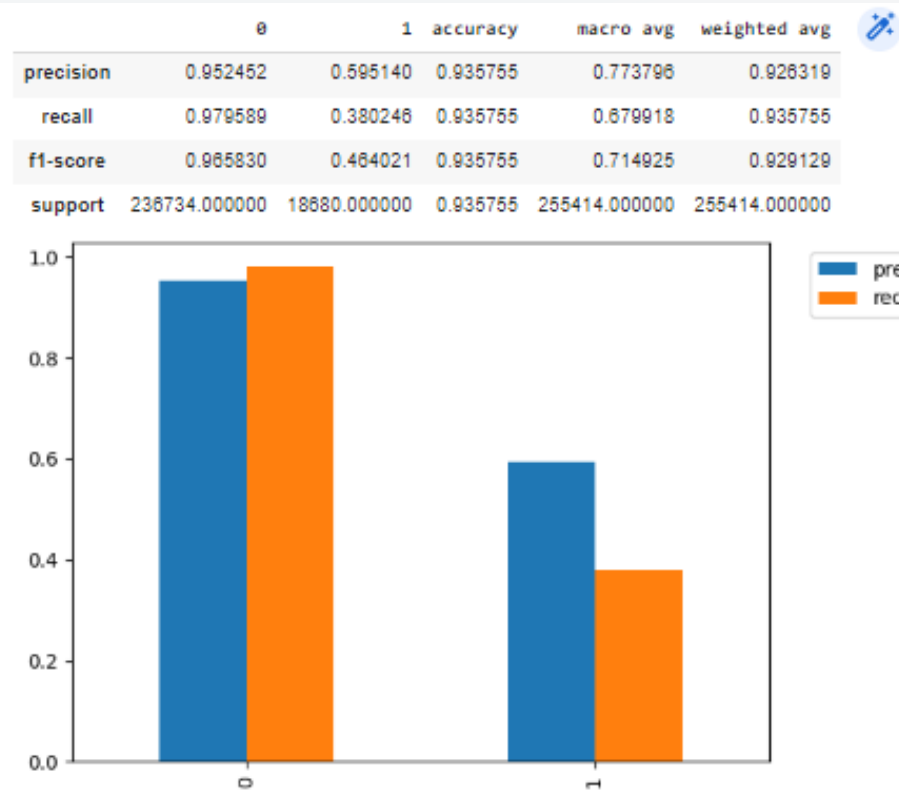
```
Best_features = list(important_features.keys())[np.argmax(np.cumsum(list(important_features.values())) >= 0.9)+1]  
Best_features
```

```
['HOSPITALIZED',  
 'AGE_60-80',  
 'PNEUMONIA',  
 'COVID-TEST',  
 'AGE_80-100',  
 'AGE_40-60',  
 'HYPERTENSION',  
 'DIABETES']
```

MODELS

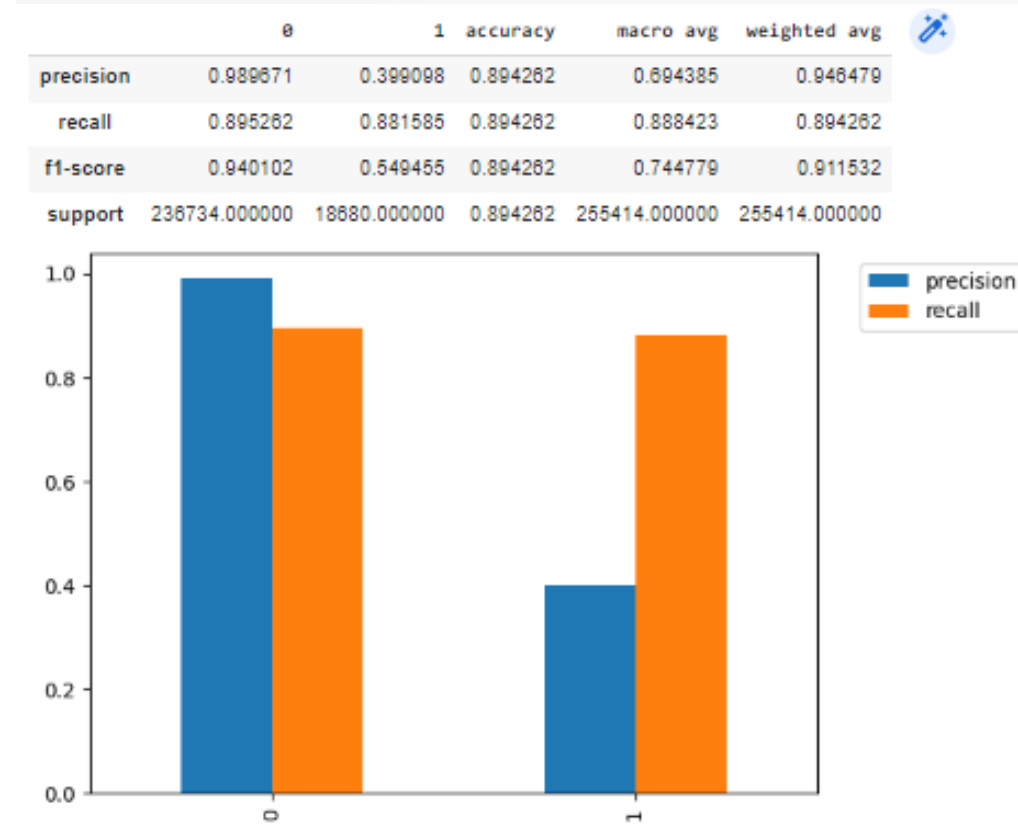


Unsampled training set

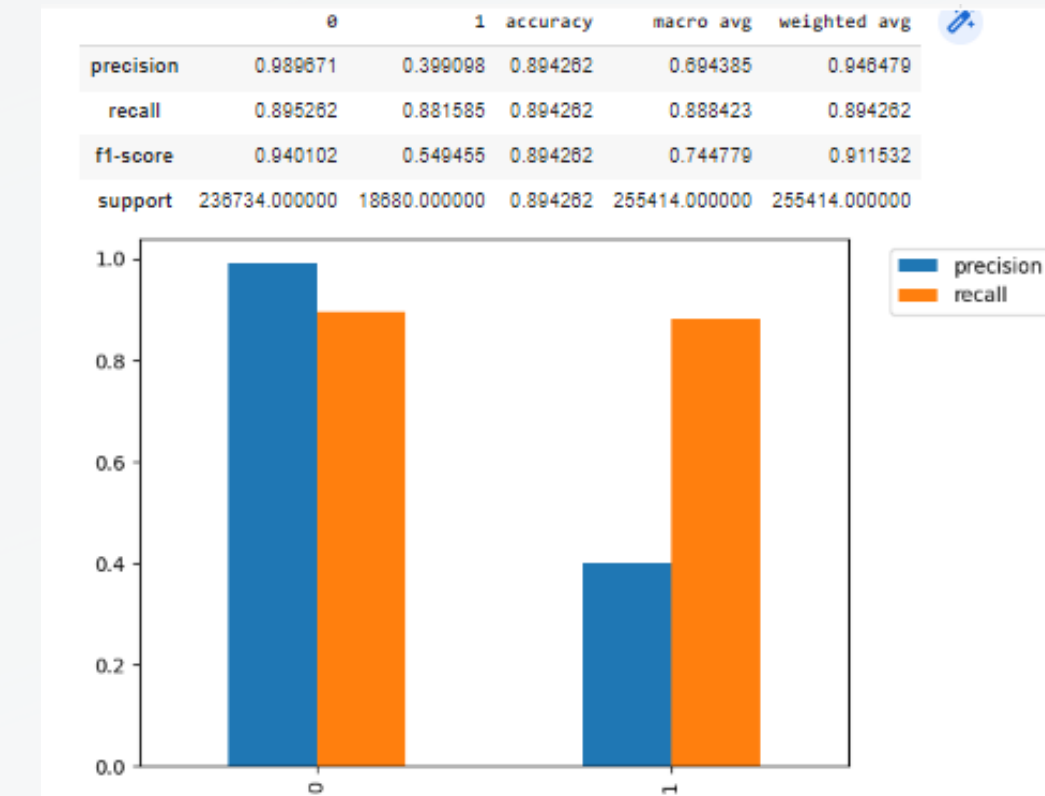


Unsampled training set with reduced feature set

Re-sampled training set



Resampled Training set with reduced features

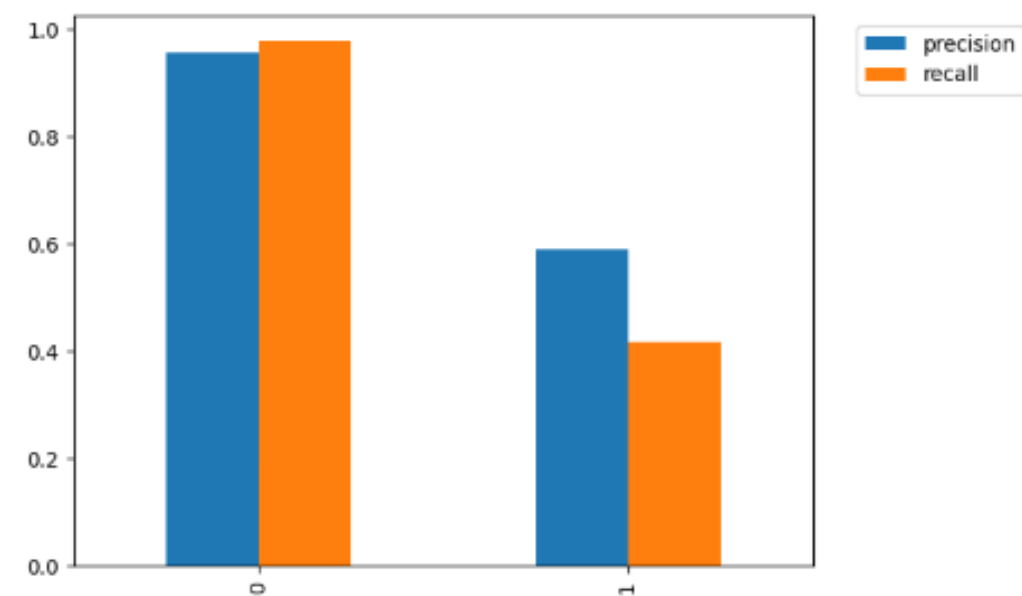


MODELS



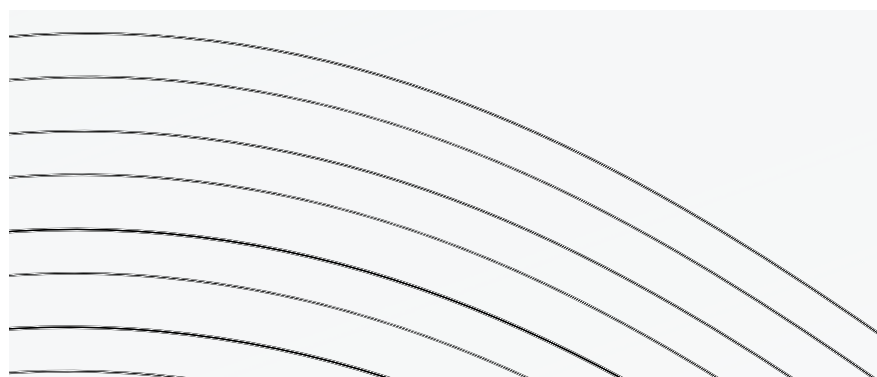
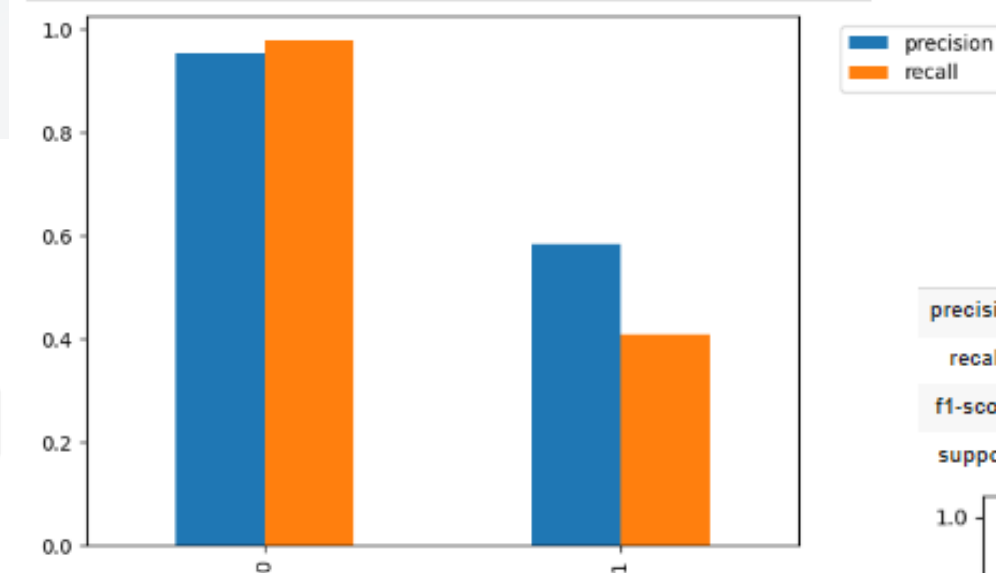
Unsampled training set

	0	1	accuracy	macro avg	weighted avg
precision	0.955089	0.590108	0.936194	0.772599	0.928396
recall	0.977105	0.417719	0.936194	0.697412	0.936194
f1-score	0.965972	0.489170	0.936194	0.727571	0.931100
support	236734.000000	18680.000000	0.936194	255414.000000	255414.000000



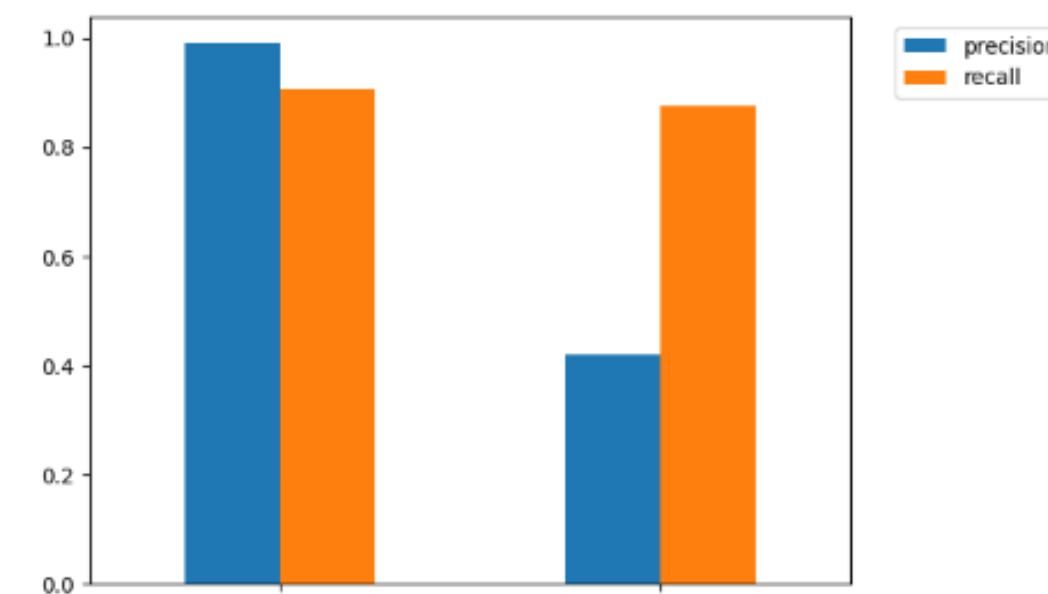
Unsampled training set with reduced features

	0	1	accuracy	macro avg	weighted avg
precision	0.954538	0.584860	0.935571	0.769699	0.927501
recall	0.977021	0.410278	0.935571	0.693649	0.935571
f1-score	0.965648	0.482265	0.935571	0.723952	0.930295
support	236734.000000	18680.000000	0.935571	255414.000000	255414.000000

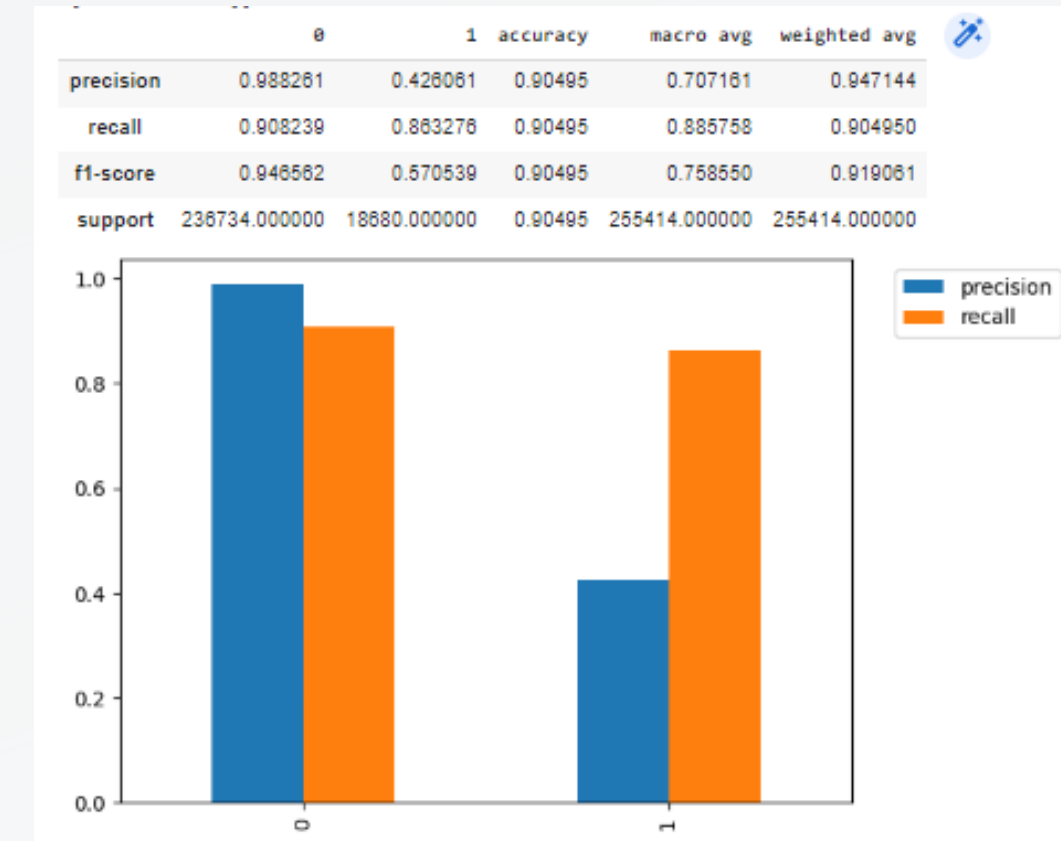


Resampled Training set with reduced features

	0	1	accuracy	macro avg	weighted avg
precision	0.989136	0.420452	0.902676	0.704794	0.947544
recall	0.904935	0.874036	0.902676	0.889486	0.902676
f1-score	0.945164	0.567777	0.902676	0.756471	0.917563
support	236734.000000	18680.000000	0.902676	255414.000000	255414.000000



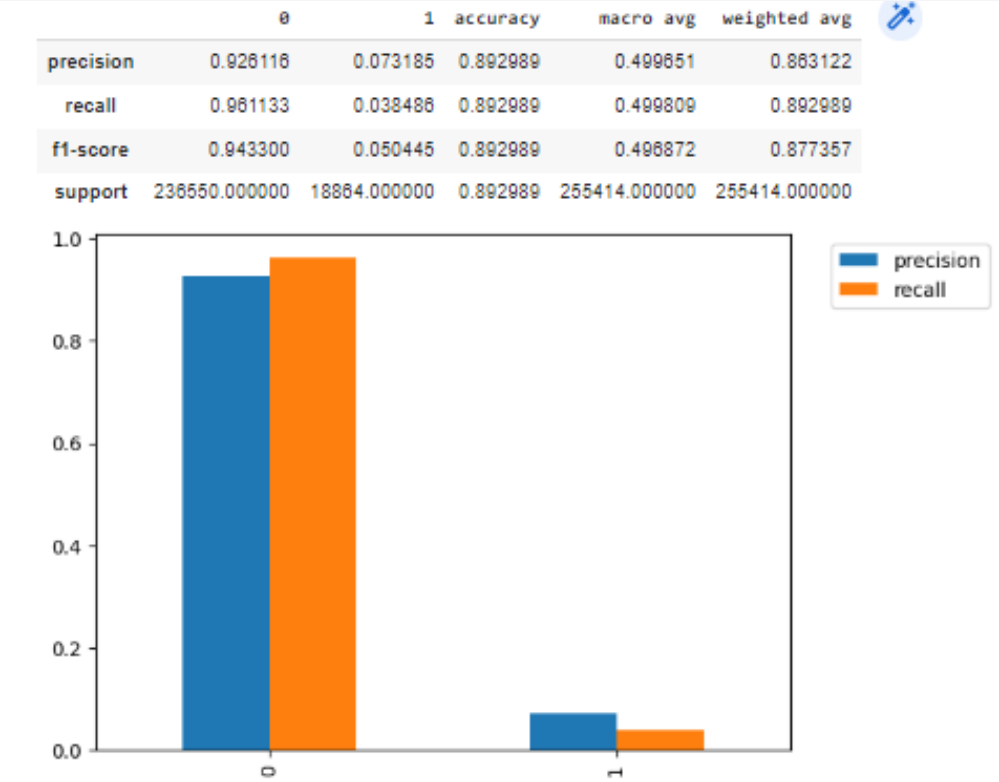
Re-sampled training set



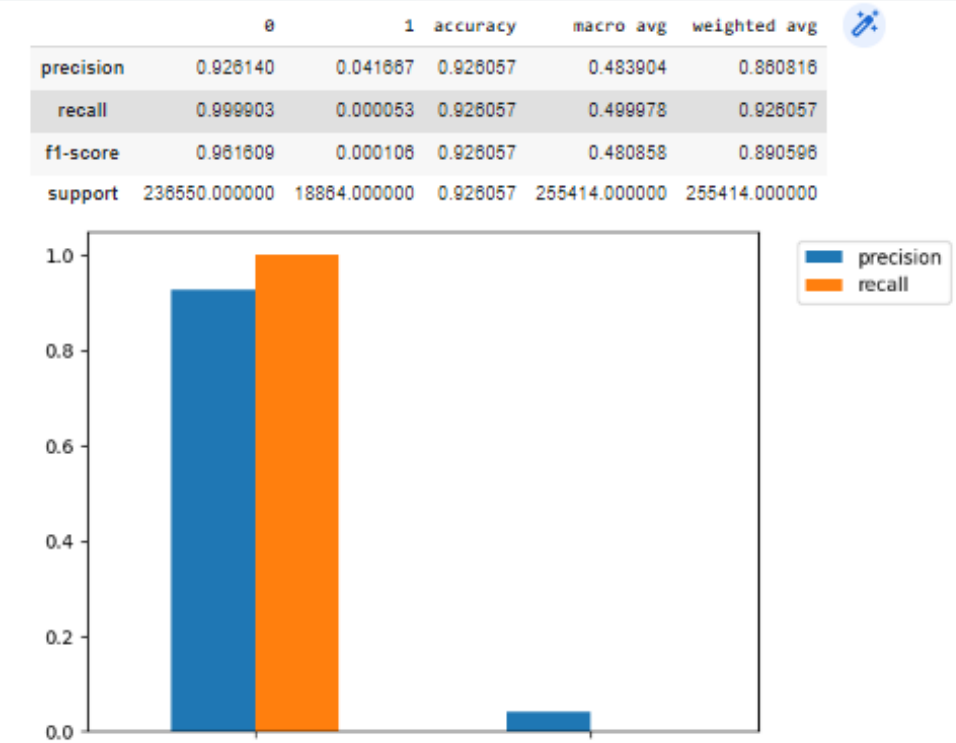
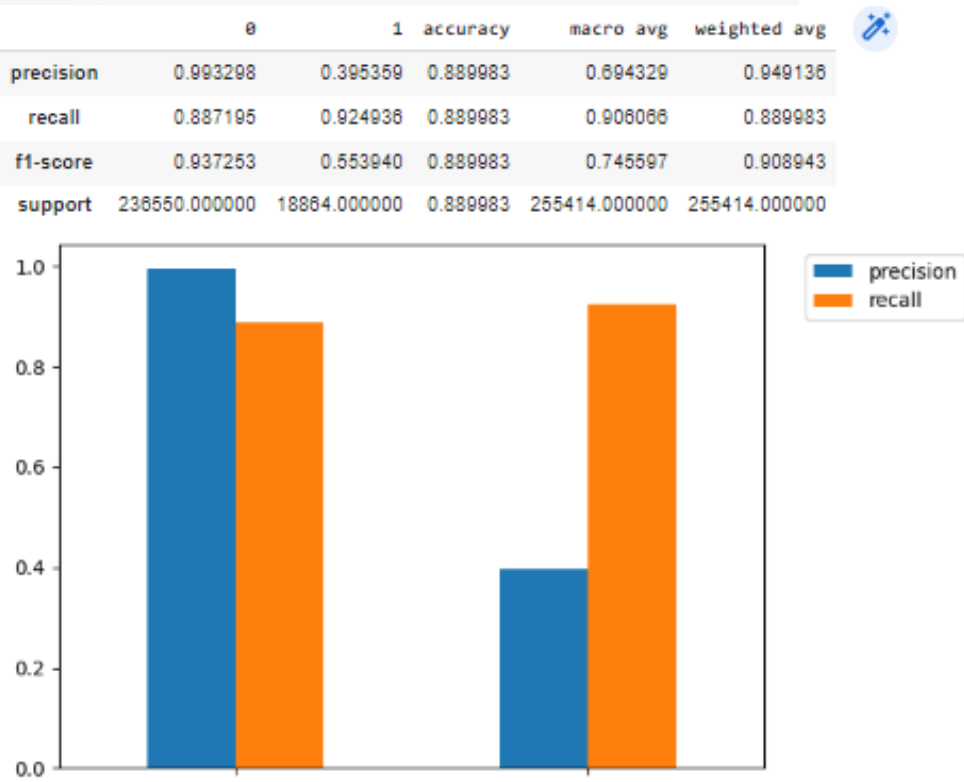


MODELS

Unsampled training set



Re-sampled training set

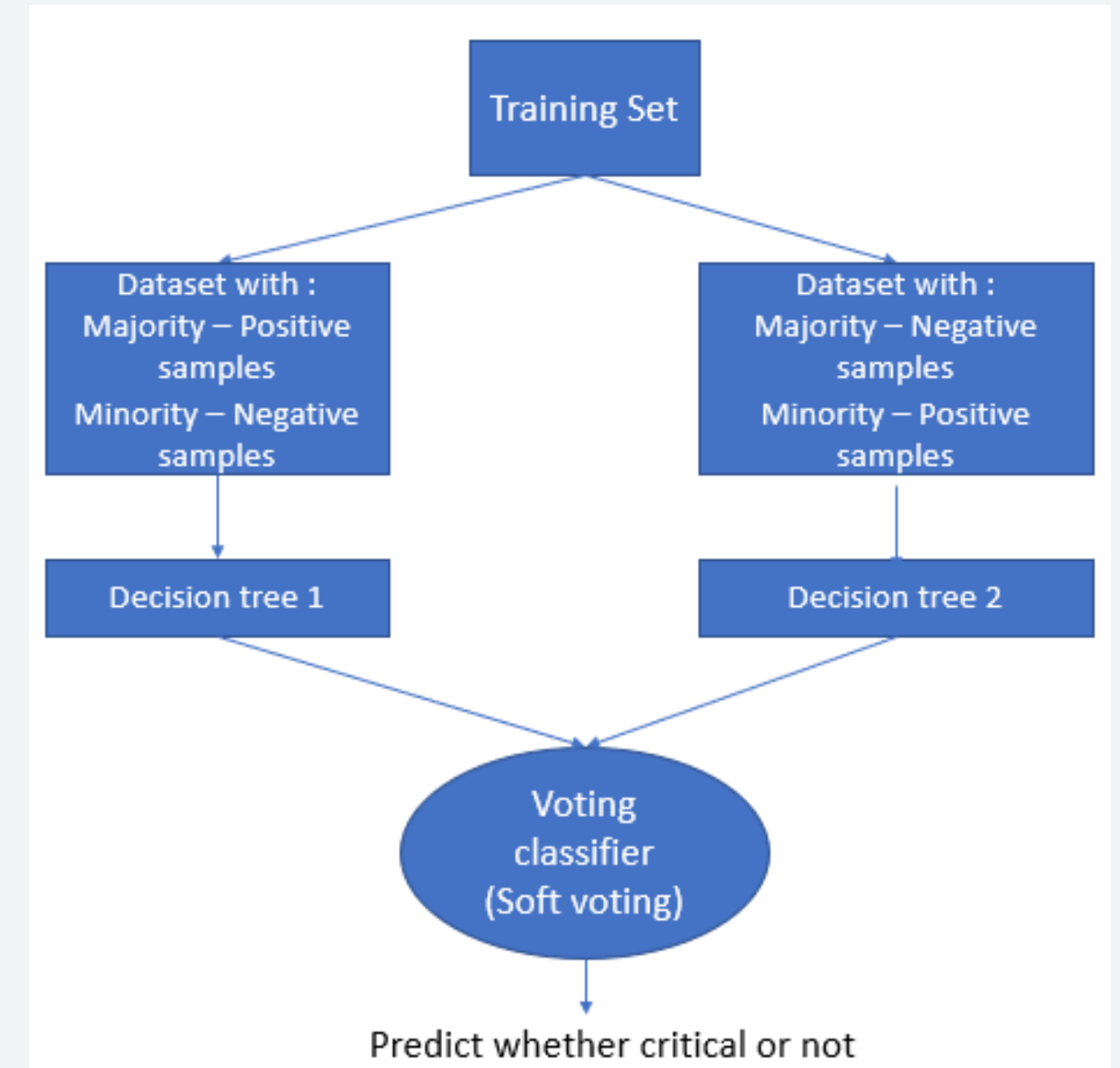
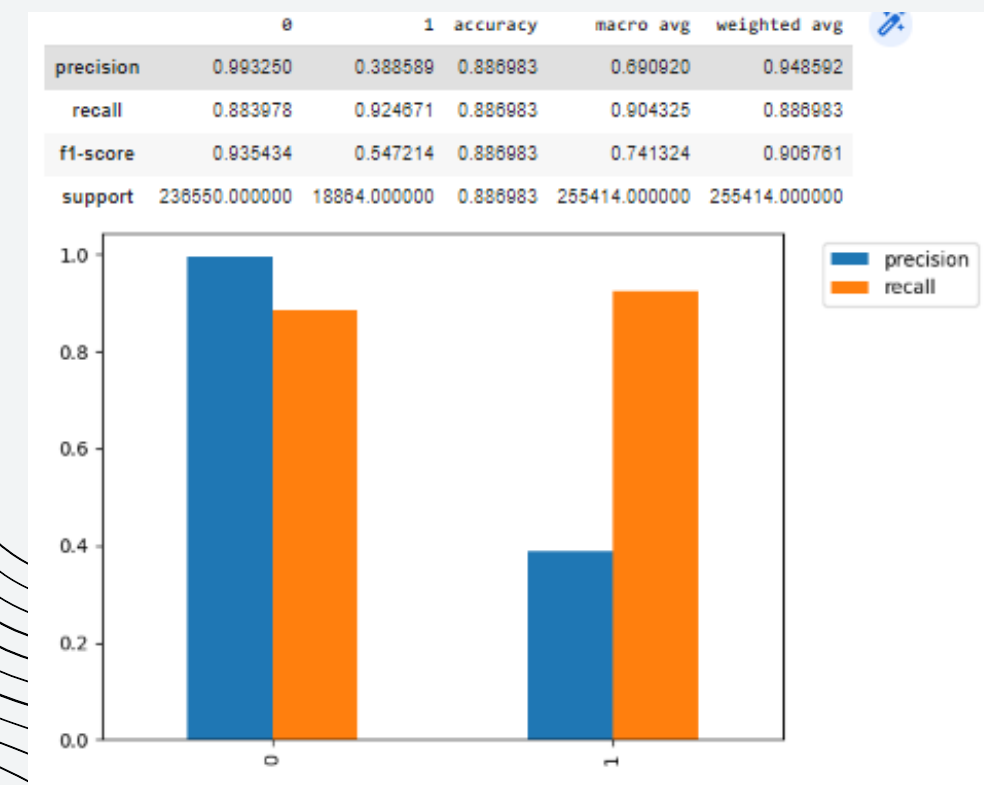
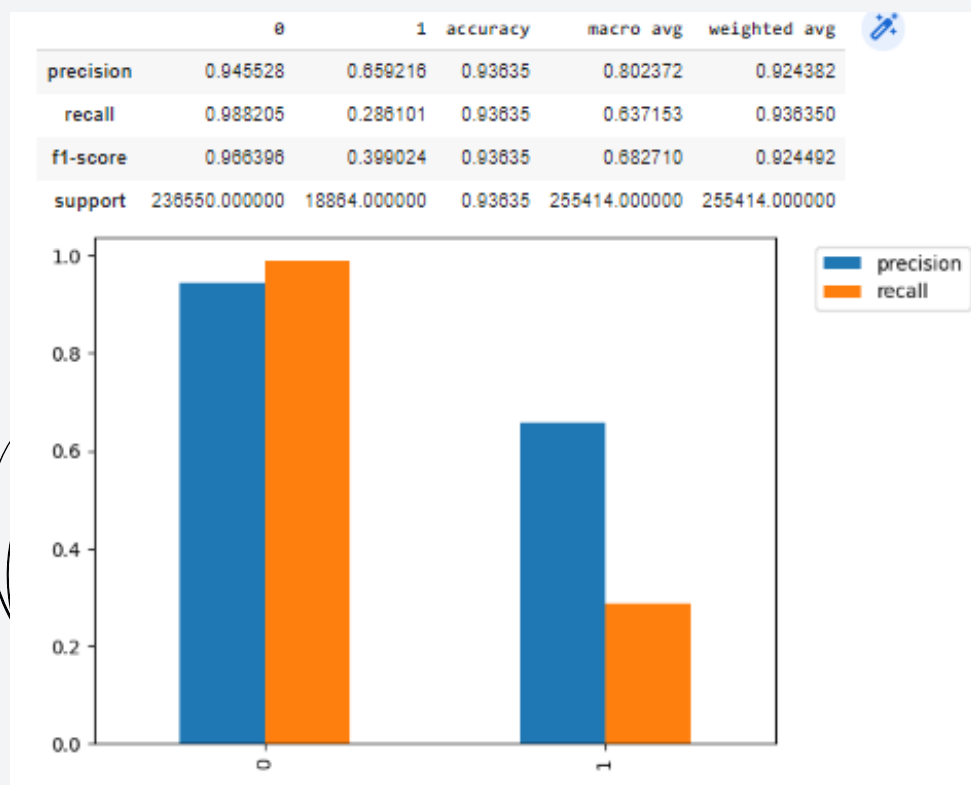
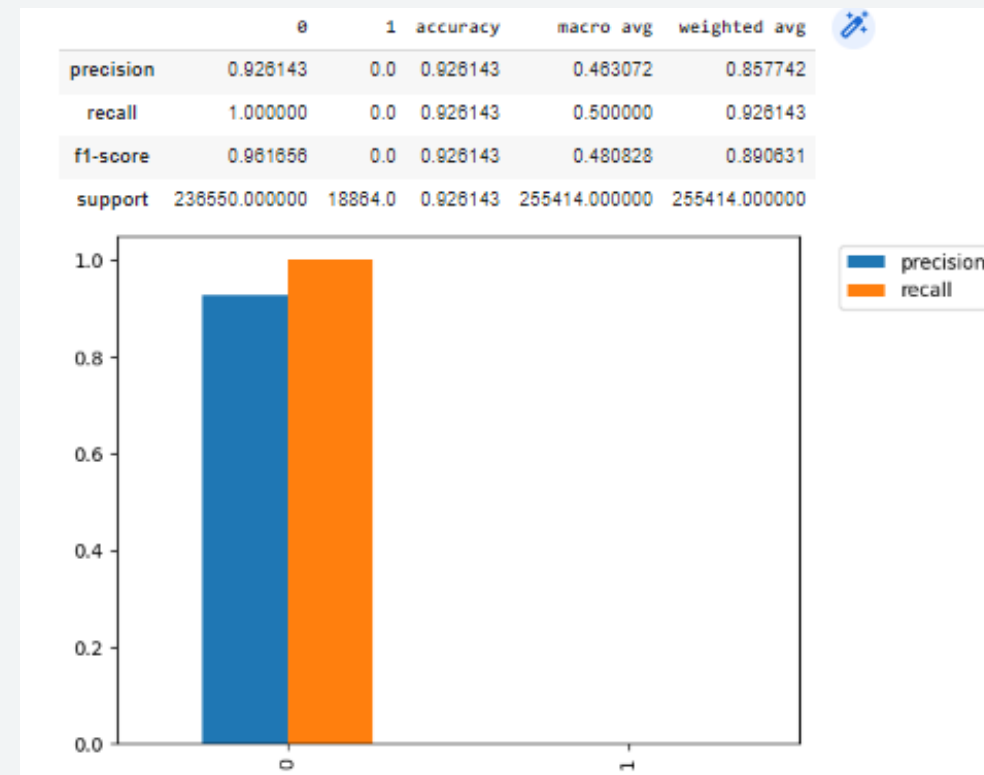
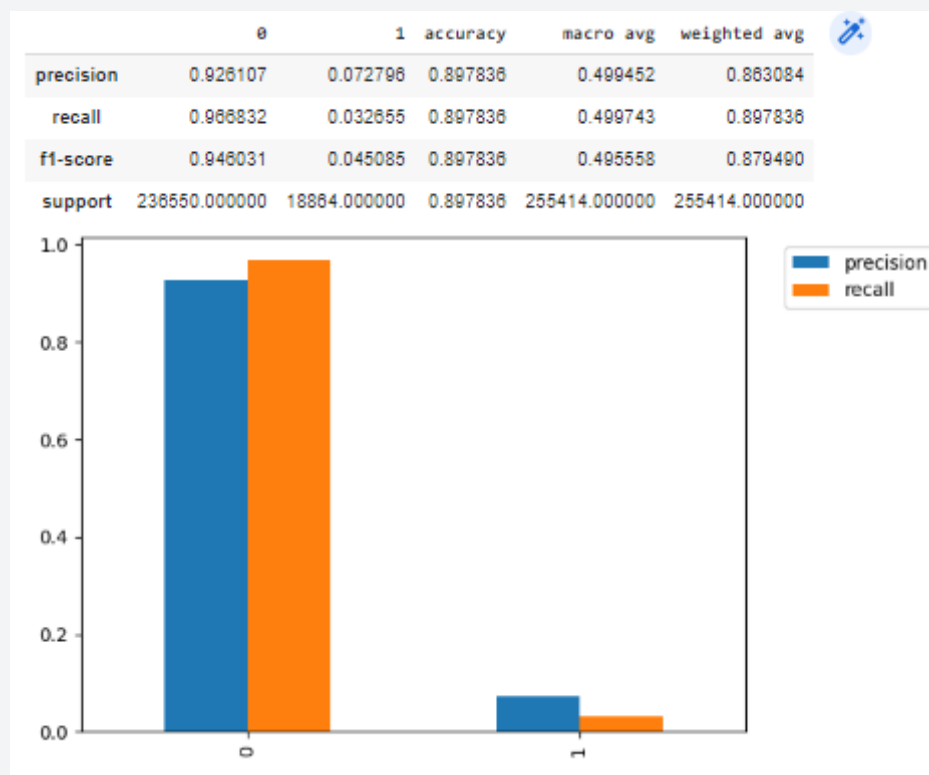


Resampled Training set with reduced features



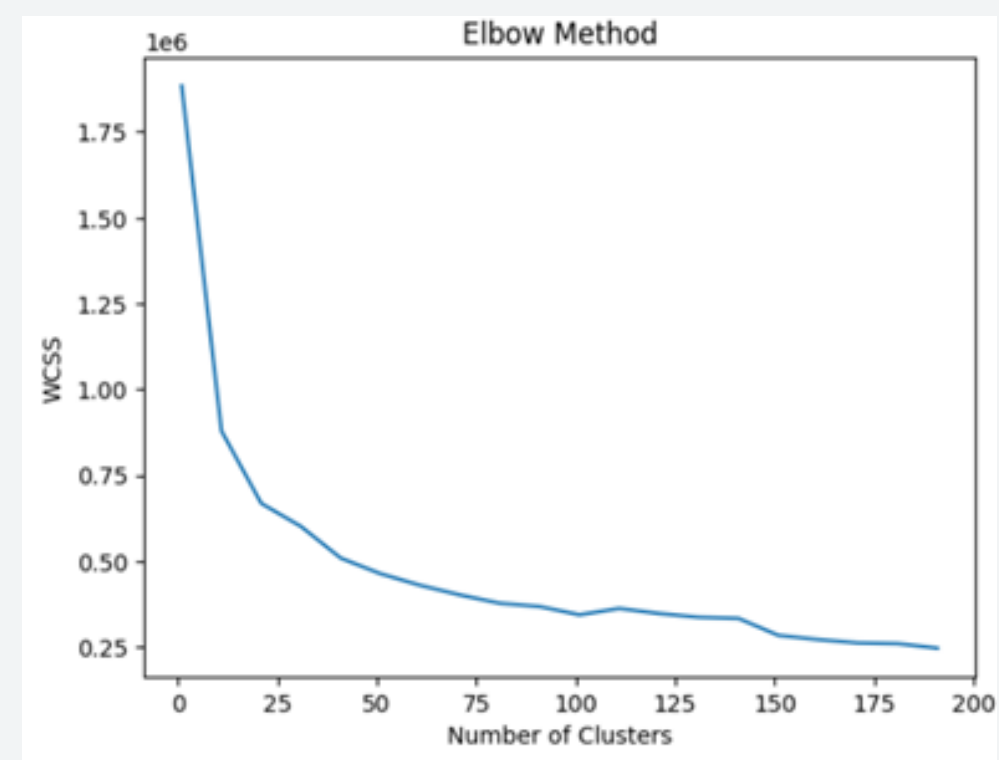
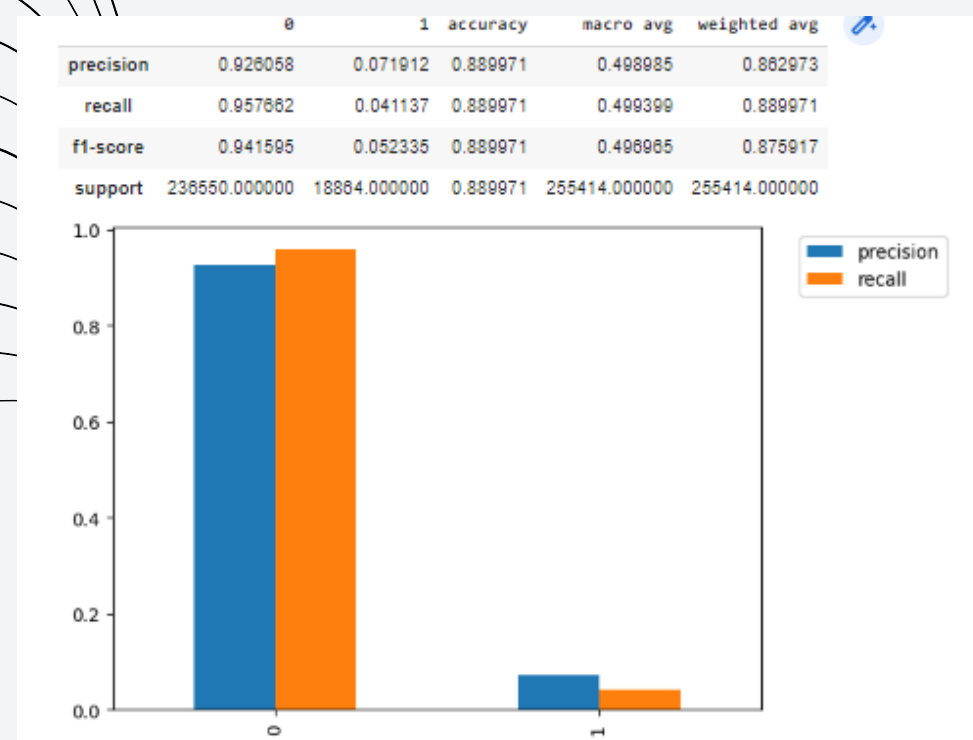
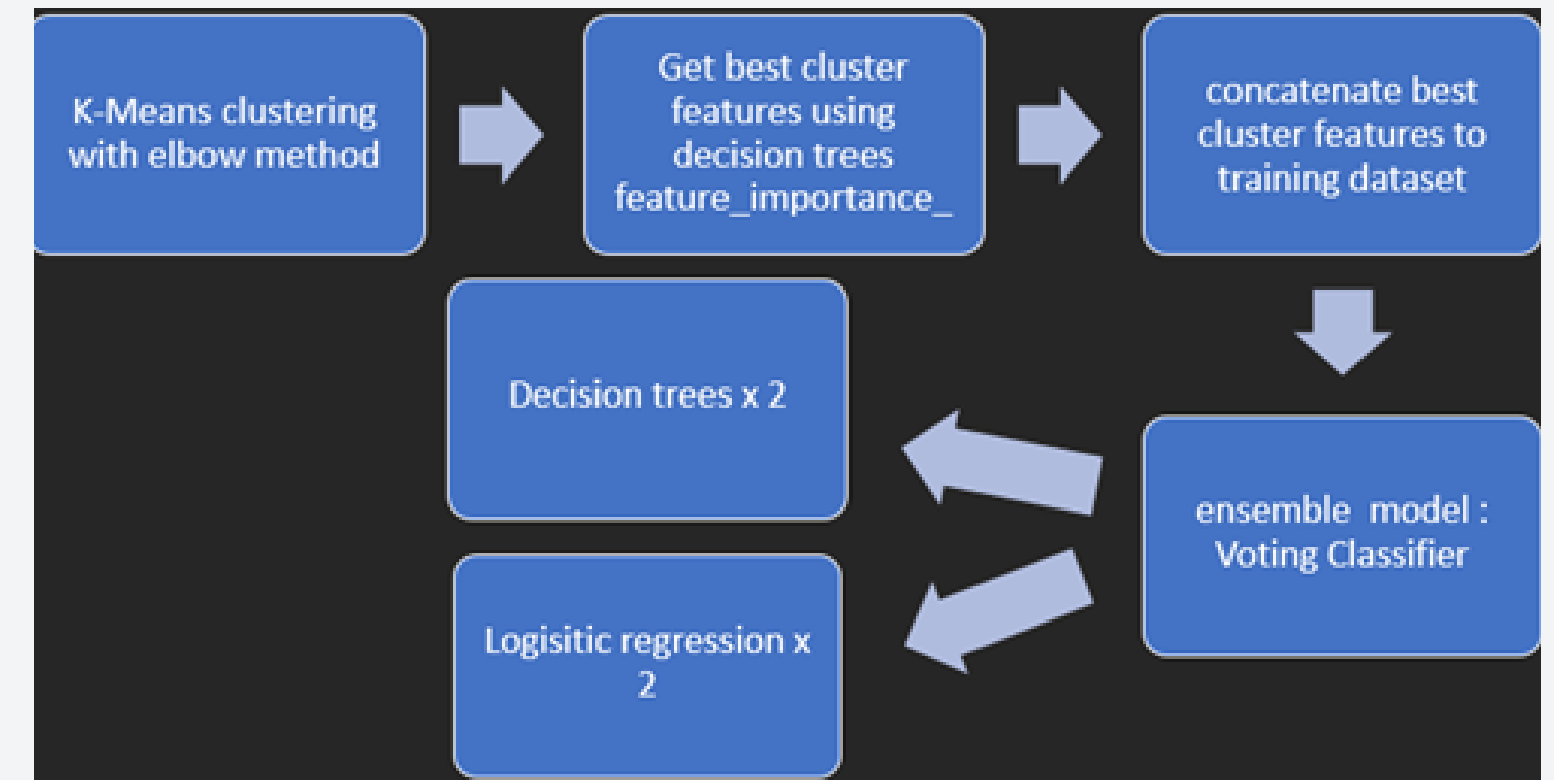
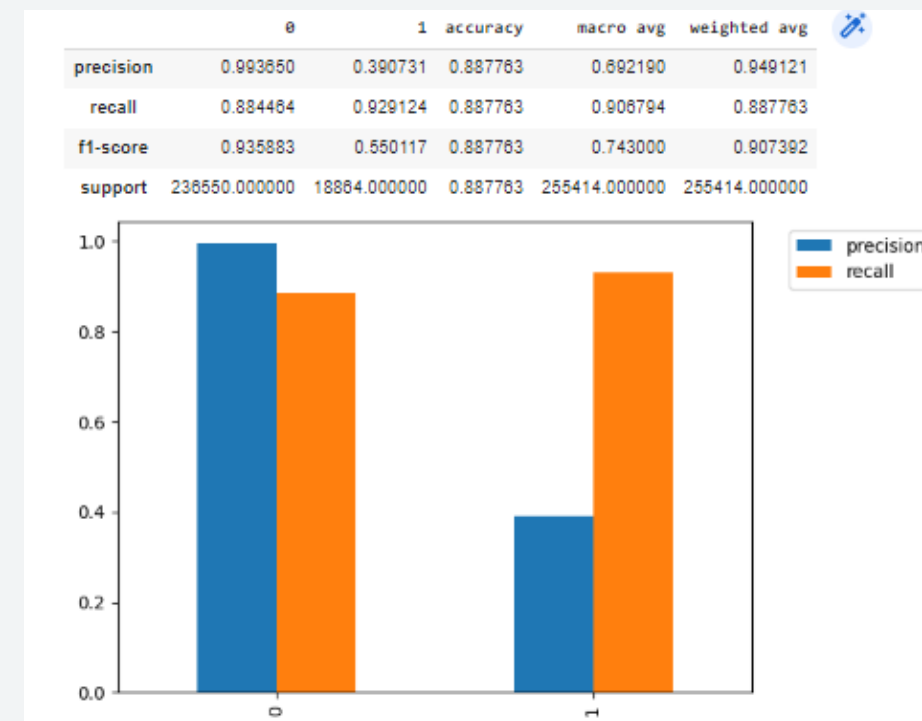
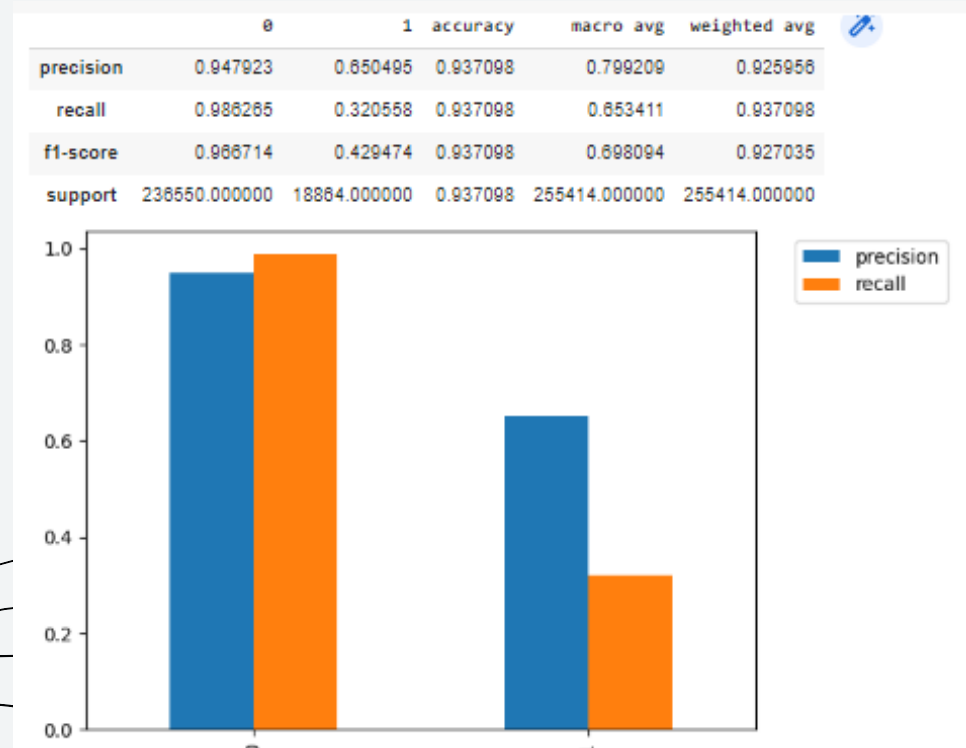
Class-Specific Ensemble Model

MODELS



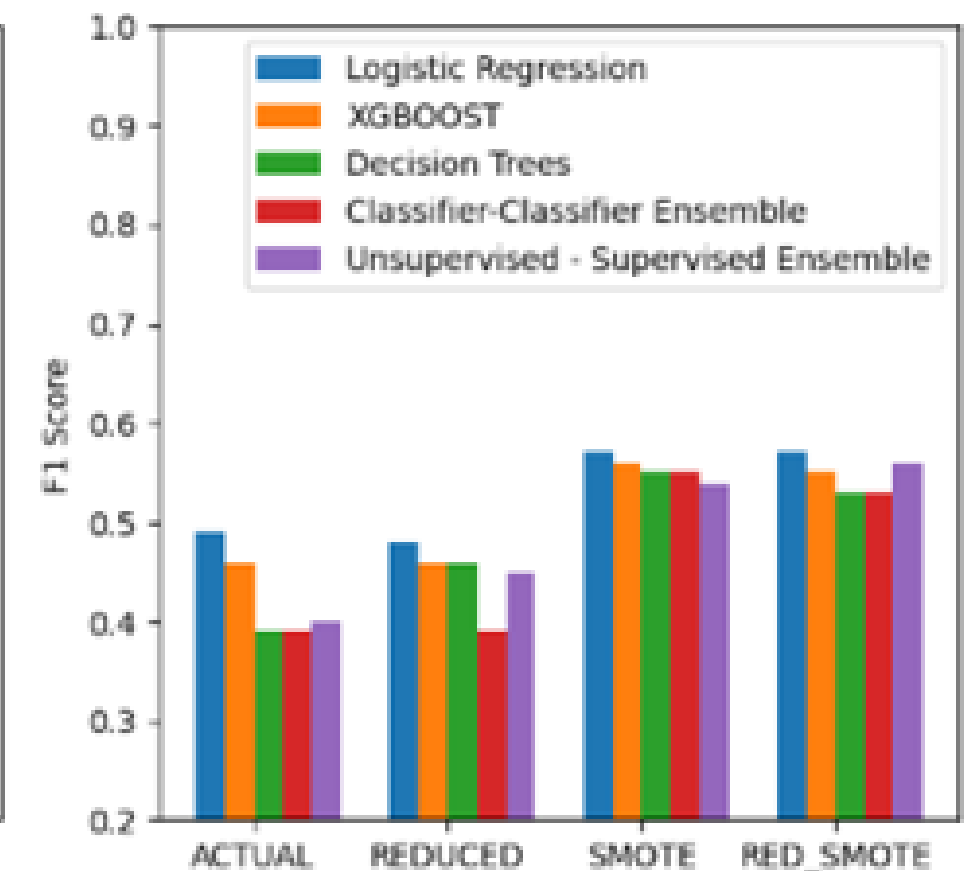
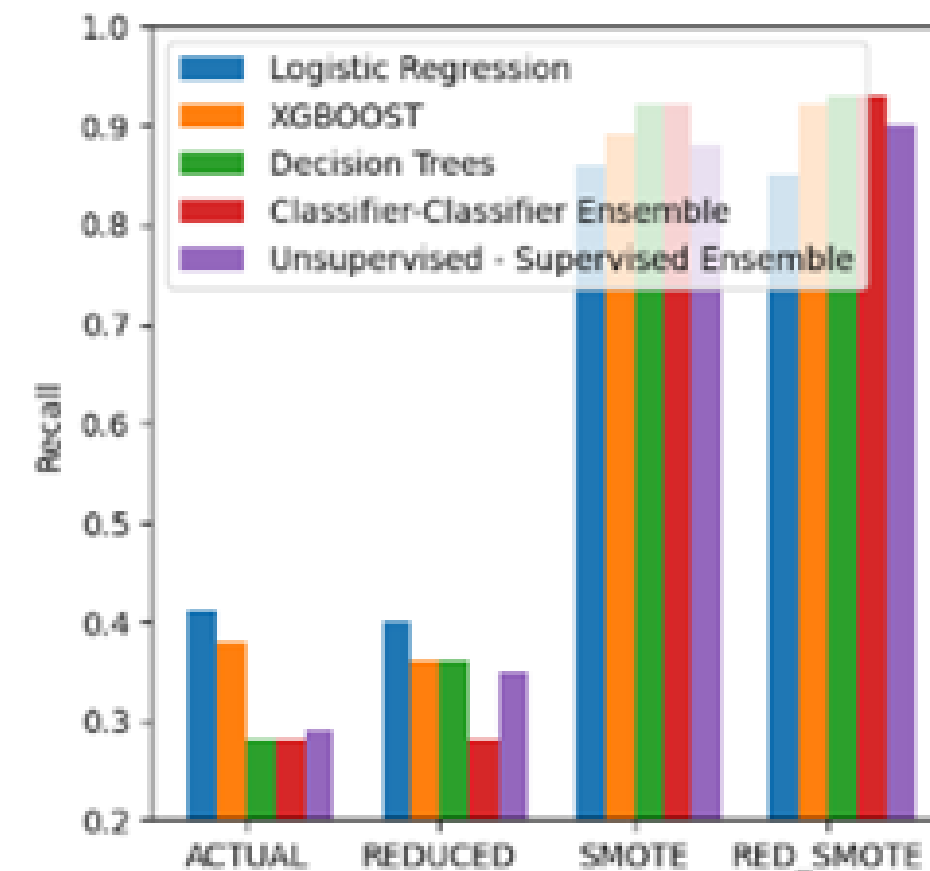
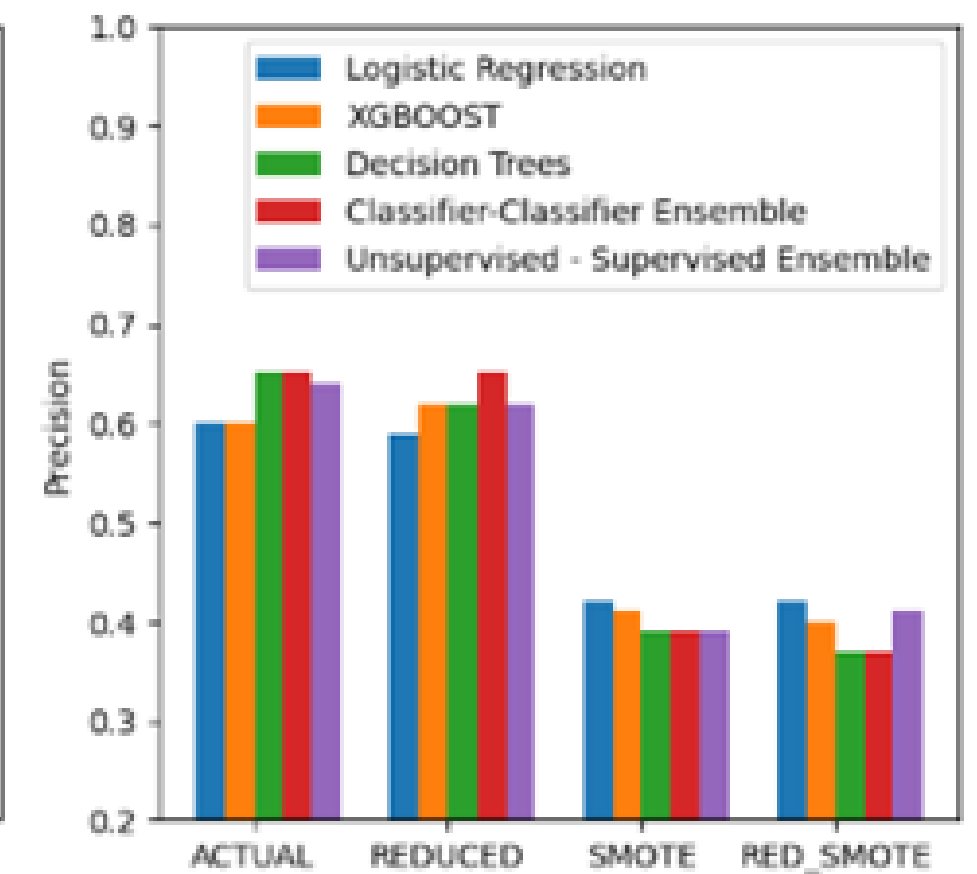
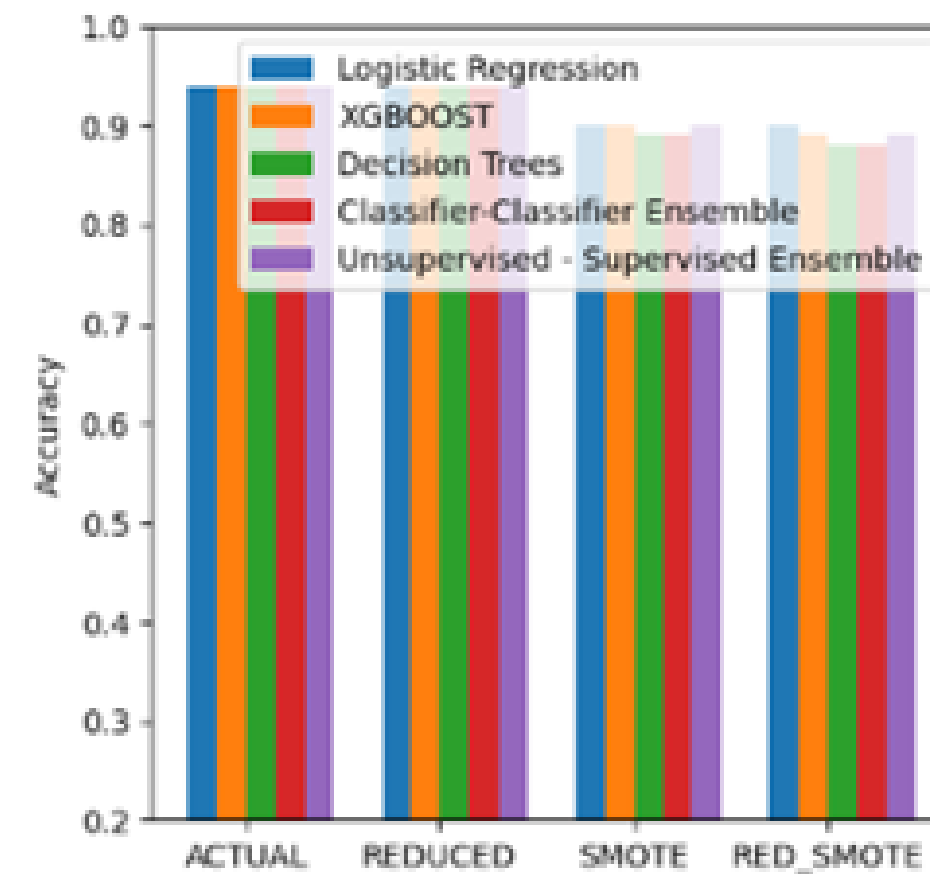
MODELS

Hybrid
Ensemble
Model



STATISTICS

*****METRICS FOR POSITIVE SAMPLES*****



OUR TEAM



Anirudh S
Bhargav

- *Data exploration and Preprocessing*
- *Modelling*
- *Hyperparameter tuning for Hybrid and class-specific ensemble*
- *Literature survey*
- *GitHub*
- *IEEE report*



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- *Hyperparameter tuning for Logistic regression*
- *Literature survey*
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- *IEEE report*



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- *Literature survey*
- *Presentation*
- *IEEE report*



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- *Hyperparameter tuning for XG Boost*
- *Literature survey*
- *Github*
- *IEEE report*

**THANK
YOU**

