

Assignment2

October 8, 2023

1 Assignment 2

1.0.1 Name: Yelisetty

1.0.2 Roll Number: 21CS30036

1.1 Importing Libraries

```
[2]: # Base libraries
import pandas as pd
import numpy as np
from mpl_toolkits.mplot3d import Axes3D
import seaborn as sns; sns.set()
import matplotlib.pyplot as plt
%matplotlib inline

# Preprocessing
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler, scale

# Models
from sklearn.svm import SVC, LinearSVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.feature_selection import SelectFromModel
from sklearn.model_selection import GridSearchCV

# Metrics
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, \
    recall_score, f1_score
```

1.2 Target Data

1.2.1 Loading dataset

```
[3]: cancer_targets = pd.read_csv("../data/Copy of actual.csv")
```

```
[4]: cancer_targets.head()
```

```
[4]: patient cancer
      0          1    ALL
      1          2    ALL
      2          3    ALL
      3          4    ALL
      4          5    ALL
```

```
[5]: cancer_targets.dtypes
```

```
[5]: patient      int64
      cancer      object
      dtype: object
```

1.2.2 Class distribution

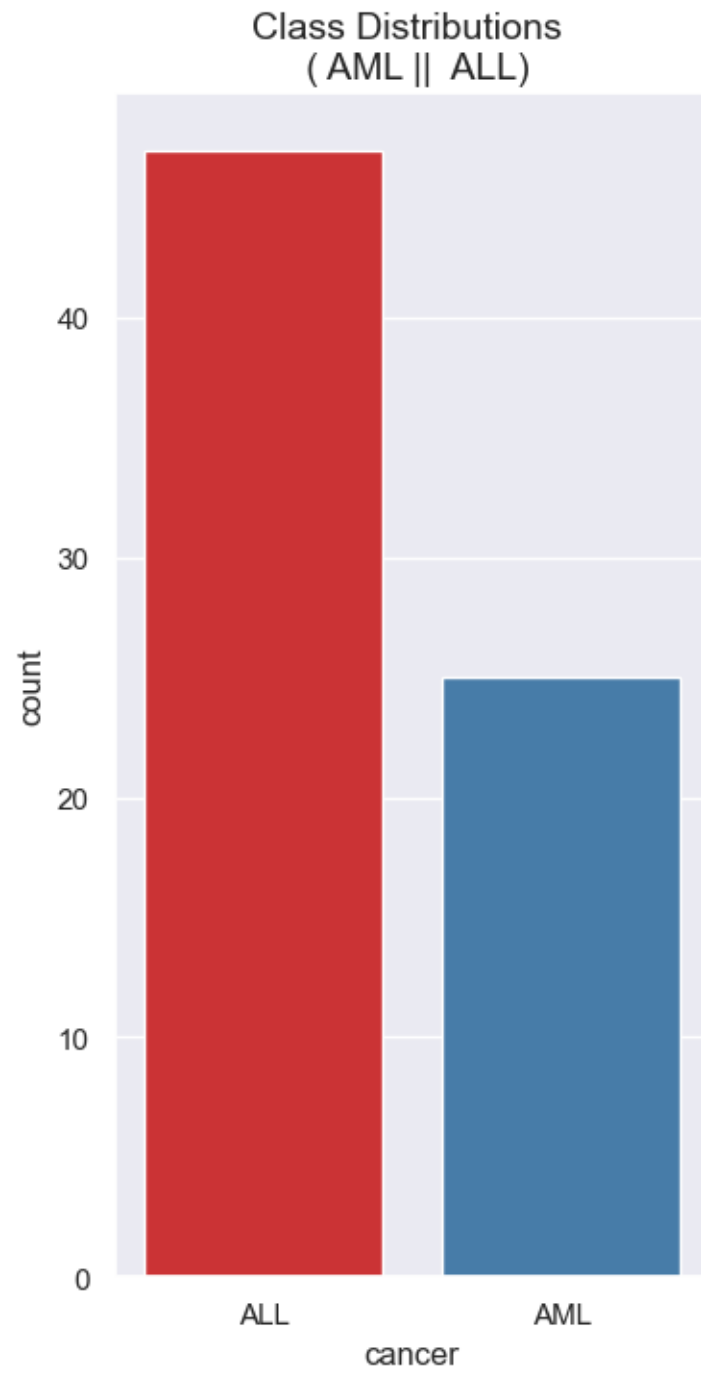
```
[6]: print(cancer_targets["cancer"].value_counts())
      print()
      print("Number of samples;", cancer_targets.shape)
```

```
cancer
ALL    47
AML    25
Name: count, dtype: int64
```

```
Number of samples; (72, 2)
```

```
[7]: plt.figure(figsize=(4, 8))
      colors = ["AML", "ALL"]
      sns.countplot(data=cancer_targets, x='cancer', palette="Set1")
      plt.title('Class Distributions \n ( AML || ALL)', fontsize=14)
```

```
[7]: Text(0.5, 1.0, 'Class Distributions \n ( AML || ALL)')
```



1.3 Train and test dataset

```
[8]: cancer_train = pd.read_csv("../data/data_train.csv")
cancer_test = pd.read_csv("../data/data_test.csv")

print("Train shape:", cancer_train.shape)
print("Test shape:", cancer_test.shape)

cancer_train.head(4)
```

Train shape: (7129, 78)

Test shape: (7129, 70)

```
[8]:
```

	Gene Description	Gene Accession Number	1	call	2	\
0	AFFX-BioB-5_at (endogenous control)	AFFX-BioB-5_at	-214	A	-139	
1	AFFX-BioB-M_at (endogenous control)	AFFX-BioB-M_at	-153	A	-73	
2	AFFX-BioB-3_at (endogenous control)	AFFX-BioB-3_at	-58	A	-1	
3	AFFX-BioC-5_at (endogenous control)	AFFX-BioC-5_at	88	A	283	

	call.1	3	call.2	4	call.3	...	29	call.33	30	call.34	31	call.35	\
0	A	-76	A	-135	A	...	15	A	-318	A	-32	A	
1	A	-49	A	-114	A	...	-114	A	-192	A	-49	A	
2	A	-307	A	265	A	...	2	A	-95	A	49	A	
3	A	309	A	12	A	...	193	A	312	A	230	P	

	32	call.36	33	call.37
0	-124	A	-135	A
1	-79	A	-186	A
2	-37	A	-70	A
3	330	A	337	A

[4 rows x 78 columns]

1.3.1 Preprocessing

We will be combining the train and test dataset for preprocessing and then we will split them again.

```
[9]: def rename_columns(df):
    for col in df.columns:
        if "call" in col:
            loc = df.columns.get_loc(col)
            patient = df.columns[loc-1]
            df.rename(columns={col: f'Call_{patient}'}, inplace=True)
```

```
[10]: rename_columns(df=cancer_train)
rename_columns(df=cancer_test)

cancer_train["Gene"] = cancer_train["Gene Description"] + \
```

```

    '_' + cancer_train["Gene Accession Number"]
cancer_test["Gene"] = cancer_test["Gene Description"] + \
    '_' + cancer_test["Gene Accession Number"]

cancer_train = cancer_train.T
cancer_train.columns = cancer_train.iloc[-1]
cancer_train = cancer_train[2:-1]
cancer_train['dataset'] = 'train'

cancer_test = cancer_test.T
cancer_test.columns = cancer_test.iloc[-1]
cancer_test = cancer_test[2:-1]
cancer_test['dataset'] = 'test'

df = pd.concat([cancer_train, cancer_test], axis=0, join='inner', sort=False)
df.shape

```

[10]: (144, 7130)

The columns labeled “Present,” “Absent,” and “Marginal” represent the detection calls made by the DNA Microarray manufacturer in the paper. These designations are based on comparing p-values of intensity calls to a predefined noise frequency cutoff. Consequently, it is advisable to remove rows where all values are designated as “Absent” (A) calls, as these are deemed unreliable.

Reference: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1409797/>

1.3.2 Dropping the columns with all A in calls

```

[11]: call_rows = [row for row in df.index if "Call" in row]
conditional = df.filter(call_rows, axis=0).apply(
    lambda x: x == 'A', axis=1).all()
print(conditional.value_counts())
df = df.loc[:, ~conditional]

```

```

False    5328
True      1802
Name: count, dtype: int64

```

1.3.3 Removing the call columns

```

[12]: df.drop(call_rows, axis=0, inplace=True)
df['patient'] = df.index
df['patient'] = df['patient'].astype('int')
df.reset_index(drop=True)

```

```

[12]: Gene AFFX-BioC-5_at (endogenous control)_AFFX-BioC-5_at \
0 88
1 283
2 309
3 12
4 168
.. ...
67 141
68 95
69 146
70 431
71 9

Gene hum_alu_at (miscellaneous control)_hum_alu_at \
0 15091
1 11038
2 16692
3 15763
4 18128
.. ...
67 22818
68 39323
69 15689
70 41570
71 39538

Gene AFFX-DapX-5_at (endogenous control)_AFFX-DapX-5_at \
0 7
1 37
2 183
3 45
4 -28
.. ...
67 2
68 -26
69 6
70 94
71 -104

Gene AFFX-DapX-M_at (endogenous control)_AFFX-DapX-M_at \
0 311
1 134
2 378
3 268
4 118
.. ...
67 46

```

68	73
69	302
70	235
71	101

Gene AFFX-LysX-5_at (endogenous control)_AFFX-LysX-5_at \

0	21
1	-21
2	67
3	43
4	-8
..	...
67	26
68	39
69	25
70	27
71	106

Gene AFFX-HUMISGF3A/M97935_MA_at (endogenous control)_AFFX-HUMISGF3A/M97935_MA_at \

0	-13
1	-219
2	104
3	-148
4	-55
..	...
67	-203
68	-60
69	-209
70	-626
71	-240

Gene AFFX-HUMISGF3A/M97935_MB_at (endogenous control)_AFFX-HUMISGF3A/M97935_MB_at \

0	215
1	116
2	476
3	155
4	122
..	...
67	25
68	60
69	183
70	-249
71	113

Gene AFFX-HUMISGF3A/M97935_3_at (endogenous control)_AFFX-HUMISGF3A/M97935_3_at

\	
0	797
1	433
2	1474
3	415
4	483
..	...
67	264
68	306
69	657
70	477
71	1313

Gene	AFFX-HUMRGE/M10098_5_at (endogenous control)	AFFX-HUMRGE/M10098_5_at \
0		14538
1		615
2		5669
3		4850
4		1284
..		...
67		104
68		569
69		3762
70		-159
71		34

Gene	AFFX-HUMRGE/M10098_M_at (endogenous control)	AFFX-HUMRGE/M10098_M_at \
0		9738
1		115
2		3272
3		2293
4		2731
..		...
67		-159
68		478
69		2164
70		-745
71		-62

Gene	...	Transcription factor Stat5b (stat5b) mRNA_U48730_at \
0	...	185
1	...	169
2	...	315
3	...	240
4	...	156
..
67	...	92

68	...	63
69	...	130
70	...	84
71	...	81

Gene Breast epithelial antigen BA46 mRNA_U58516_at \

0	511
1	837
2	1199
3	835
4	649
..	...
67	532
68	297
69	639
70	1141
71	574

Gene TUBULIN ALPHA-4 CHAIN_X06956_at \

0	389
1	442
2	168
3	174
4	504
..	...
67	239
68	358
69	548
70	197
71	618

Gene PTGER3 Prostaglandin E receptor 3 (subtype EP3) {alternative products}_X83863_at \

0	793
1	782
2	1138
3	627
4	250
..	...
67	707
68	423
69	809
70	466
71	551

Gene HMG2 High-mobility group (nonhistone chromosomal) protein 2_Z17240_at \

0	329
---	-----

1	295
2	777
3	170
4	314
..	...
67	354
68	41
69	445
70	349
71	194

Gene RB1 Retinoblastoma 1 (including osteosarcoma)_L49218_f_at \

0	36
1	11
2	41
3	-50
4	14
..	...
67	-22
68	0
69	-2
70	0
71	20

Gene GB DEF = Glycophorin Sta (type A) exons 3 and 4; partial_M71243_f_at \

0	191
1	76
2	228
3	126
4	56
..	...
67	260
68	1777
69	210
70	284
71	379

Gene GB DEF = mRNA (clone 1A7)_Z78285_f_at dataset patient

0	-37	train	1
1	-14	train	2
2	-41	train	3
3	-91	train	4
4	-25	train	5
..
67	5	test	65
68	-49	test	66
69	16	test	63

70	-73	test	64
71	-60	test	62

[72 rows x 5329 columns]

1.3.4 Combining features and labels

```
[13]: df = pd.merge(left=df, right=cancer_targets,
                    left_on='patient', right_on='patient')
print(df.shape)
df.head(5)
```

(72, 5330)

```
[13]: AFX-BioC-5_at (endogenous control)_AFX-BioC-5_at \
0 88
1 283
2 309
3 12
4 168

hum_alu_at (miscellaneous control)_hum_alu_at \
0 15091
1 11038
2 16692
3 15763
4 18128

AFX-DapX-5_at (endogenous control)_AFX-DapX-5_at \
0 7
1 37
2 183
3 45
4 -28

AFX-DapX-M_at (endogenous control)_AFX-DapX-M_at \
0 311
1 134
2 378
3 268
4 118

AFX-LysX-5_at (endogenous control)_AFX-LysX-5_at \
0 21
1 -21
2 67
3 43
```

4	-8	
AFFX-HUMISGF3A/M97935_MA_at (endogenous control)_AFFX-HUMISGF3A/M97935_MA_at		
\		
0	-13	
1	-219	
2	104	
3	-148	
4	-55	
AFFX-HUMISGF3A/M97935_MB_at (endogenous control)_AFFX-HUMISGF3A/M97935_MB_at		
\		
0	215	
1	116	
2	476	
3	155	
4	122	
AFFX-HUMISGF3A/M97935_3_at (endogenous control)_AFFX-HUMISGF3A/M97935_3_at \		
0	797	
1	433	
2	1474	
3	415	
4	483	
AFFX-HUMRGE/M10098_5_at (endogenous control)_AFFX-HUMRGE/M10098_5_at \		
0	14538	
1	615	
2	5669	
3	4850	
4	1284	
AFFX-HUMRGE/M10098_M_at (endogenous control)_AFFX-HUMRGE/M10098_M_at ... \		
0	9738	...
1	115	...
2	3272	...
3	2293	...
4	2731	...
Breast epithelial antigen BA46 mRNA_U58516_at \		
0	511	
1	837	
2	1199	
3	835	
4	649	
TUBULIN ALPHA-4 CHAIN_X06956_at \		

0	389
1	442
2	168
3	174
4	504

PTGER3 Prostaglandin E receptor 3 (subtype EP3) {alternative products}_X83863_at \

0	793
1	782
2	1138
3	627
4	250

HMG2 High-mobility group (nonhistone chromosomal) protein 2_Z17240_at \

0	329
1	295
2	777
3	170
4	314

RB1 Retinoblastoma 1 (including osteosarcoma)_L49218_f_at \

0	36
1	11
2	41
3	-50
4	14

GB DEF = Glycophorin Sta (type A) exons 3 and 4; partial_M71243_f_at \

0	191
1	76
2	228
3	126
4	56

GB DEF = mRNA (clone 1A7)_Z78285_f_at dataset patient cancer

0	-37	train	1	ALL
1	-14	train	2	ALL
2	-41	train	3	ALL
3	-91	train	4	ALL
4	-25	train	5	ALL

[5 rows x 5330 columns]

1.3.5 Separate train and test data

```
[14]: train = df[df['dataset'] == 'train'].iloc[:, 0:-3]
train_target = df[df['dataset'] == 'train'].iloc[:, -1]
test = df[df['dataset'] == 'test'].iloc[:, 0:-3]
test_target = df[df['dataset'] == 'test'].iloc[:, -1]

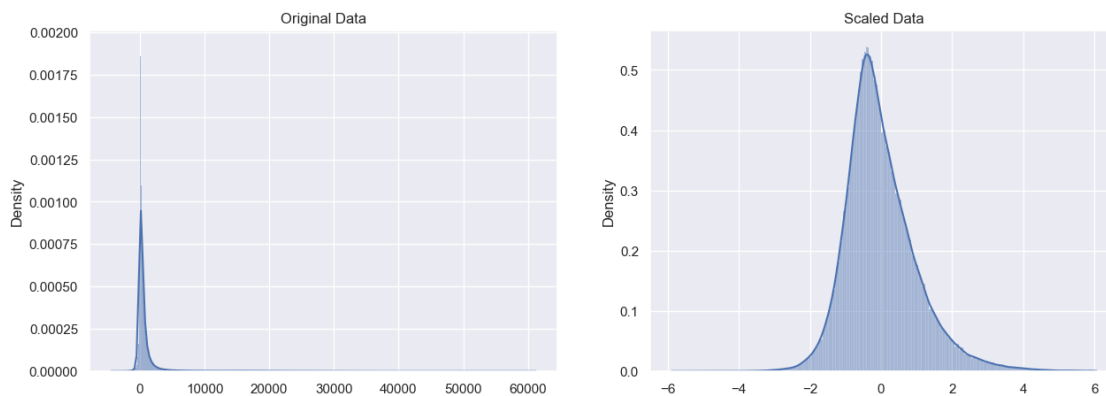
print(train.shape, train_target.shape)
print(test.shape, test_target.shape)
```

(38, 5327) (38,)

(34, 5327) (34,)

```
[15]: scaler = StandardScaler().fit(train)
train_scaled = pd.DataFrame(scaler.transform(train), columns=train.columns)
test_scaled = pd.DataFrame(scaler.transform(test), columns=test.columns)

fig, ax = plt.subplots(ncols=2, figsize=(15, 5))
sns.histplot(np.concatenate(train.values), ax=ax[0], kde=True, stat="density")
sns.histplot(np.concatenate(train_scaled.values),
             ax=ax[1], kde=True, stat="density")
ax[0].set_title('Original Data')
ax[1].set_title('Scaled Data')
plt.tight_layout
plt.show()
```



1.3.6 Feature Selection

```
[16]: from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import SelectFromModel

print("Original Shape:", train_scaled.shape)
```

```

logistic_regression = LogisticRegression(penalty="l1", solver='saga',
    ↪max_iter=2000).fit(
    train_scaled, train_target) # l1 for sparsity
log_coefficients = logistic_regression.coef_
selector_log = SelectFromModel(logistic_regression, prefit=True)
train_scaled_logreg = selector_log.transform(train_scaled)
test_scaled_logreg = selector_log.transform(test_scaled)
print("Features after selection using Logistic Regression:",
    train_scaled_logreg.shape)

log_coefficients_abs = abs(log_coefficients)
log_coefficients_abs_sort = np.sort(log_coefficients_abs).flatten()
sortedidx = log_coefficients_abs.argsort()
log_labels = train_scaled.columns.values[sortedidx].flatten()
sns.barplot(x=log_coefficients_abs_sort[-20:], y=log_labels[-20:])

```

Original Shape: (38, 5327)

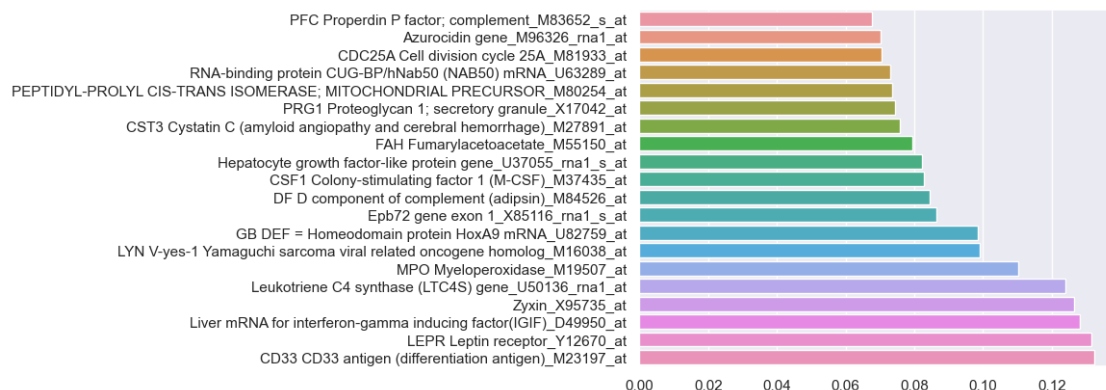
Features after selection using Logistic Regression: (38, 146)

```

/home/karthi/anaconda3/envs/ml/lib/python3.11/site-
packages/sklearn/linear_model/_sag.py:350: ConvergenceWarning: The max_iter was
reached which means the coef_ did not converge
    warnings.warn(
/home/karthi/anaconda3/envs/ml/lib/python3.11/site-packages/sklearn/base.py:457:
UserWarning: X has feature names, but SelectFromModel was fitted without feature
names
    warnings.warn(
/home/karthi/anaconda3/envs/ml/lib/python3.11/site-packages/sklearn/base.py:457:
UserWarning: X has feature names, but SelectFromModel was fitted without feature
names
    warnings.warn(

```

[16]: <Axes: >



1.3.7 Feature Scaling using PCA

```
[17]: pca = PCA(n_components=3)
pca.fit_transform(train_scaled_logreg)
print(pca.explained_variance_ratio_)

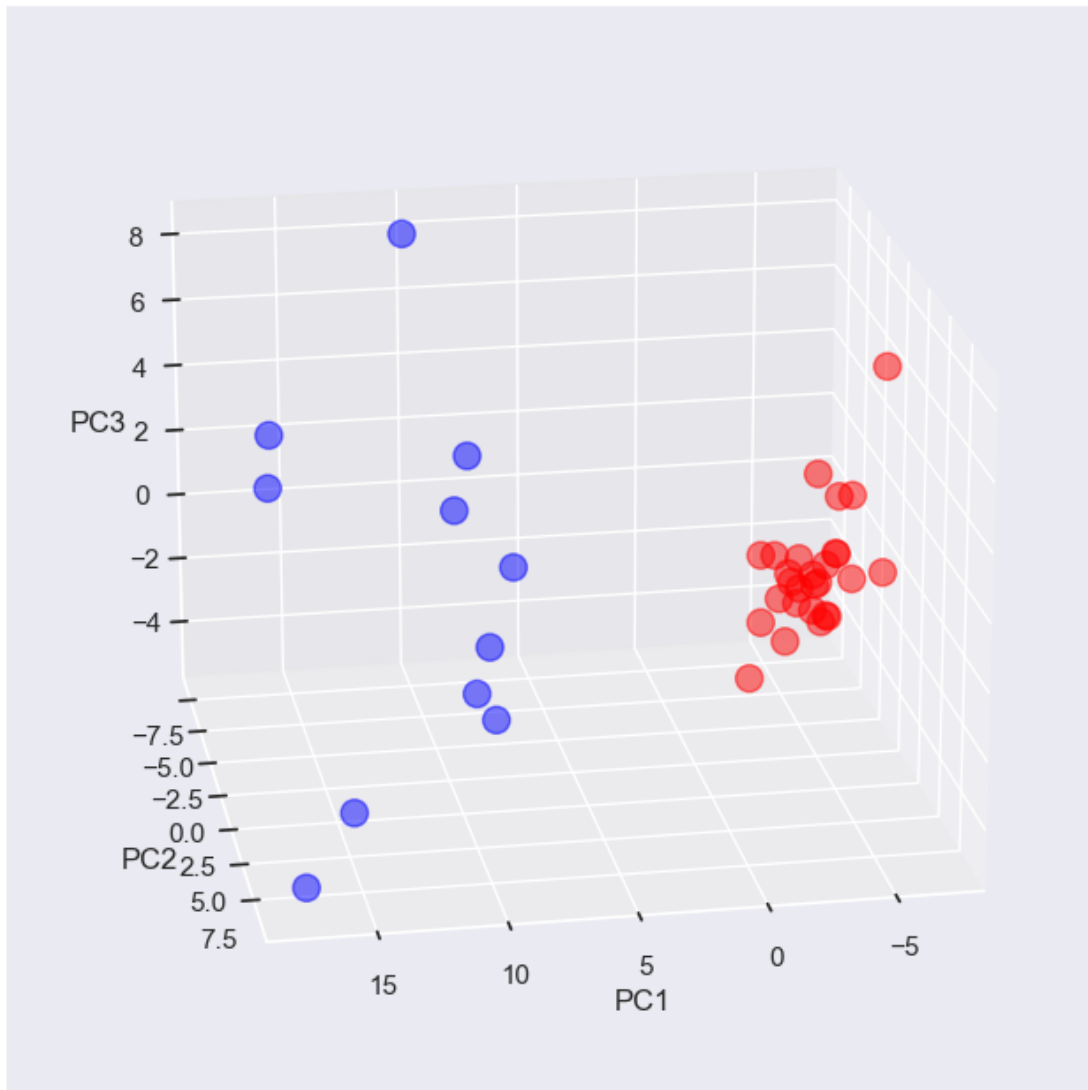
PCA_df = pd.DataFrame(data=pca.fit_transform(train_scaled_logreg),
                      columns=['pc1', 'pc2', 'pc3'])
```

```
[0.39758334 0.08187505 0.0603069 ]
```

```
[18]: PCA_df = pd.concat([PCA_df, train_target], axis=1)

fig = plt.figure(figsize=(10, 8))
ax = fig.add_subplot(111, projection='3d')
colors = {'ALL': 'red', 'AML': 'blue'}
ax.scatter(PCA_df.pc1, PCA_df.pc2, PCA_df.pc3,
           c=train_target.apply(lambda x: colors[x]),
           s=120, alpha=0.5
           )
plt.title('First 3 Principal Components after PCA')
ax.set_xlabel('PC1')
ax.set_ylabel('PC2')
ax.set_zlabel('PC3')
ax.view_init(20, 80)
plt.tight_layout
plt.show()
```


First 3 Principal Components after PCA



2 Models being tested

1. C-Support Vector Classification (SVM)
 - Using Grid search for tuning hyperparameters
2. Random forest Classifier
 - Using Grid search for tuning hyperparameters
3. Neural Networks
 - Using only Grid search

2.1 SVM

2.1.1 Grid search for SVM

```
[19]: svc = SVC()
```

2.1.2 Grid search parameters

```
[20]: param_grid = {'C': [0.1, 1, 10, 100],  
                  'gamma': [1, 0.1, 0.01, 0.001, 0.0001],  
                  'kernel': ['rbf', 'poly', 'linear', 'sigmoid'], }  
  
grid = GridSearchCV(svc, param_grid, cv=5)
```

2.1.3 Best parameters

```
[21]: grid.fit(train_scaled_logreg, train_target)  
print(f"Best parameters for SVM are: {grid.best_params_}")
```

Best parameters for SVM are: {'C': 0.1, 'gamma': 1, 'kernel': 'linear'}

2.1.4 Selecting the best svm model

```
[22]: svc = grid.best_estimator_
```

2.1.5 Fitting the model

```
[23]: svc.fit(train_scaled_logreg, train_target)
```

```
[23]: SVC(C=0.1, gamma=1, kernel='linear')
```

2.1.6 Evaluation of the model

```
[24]: # predicting the values  
test_pred = svc.predict(test_scaled_logreg)  
  
# calculating the accuracy, precision, recall, f1-score, roc_auc_score  
print(  
    f"Accuracy of the best SVM model is: {accuracy_score(test_target,   
    ↪ test_pred)}")  
print(  
    f"Precision of the best SVM model is: {precision_score(test_target,   
    ↪ test_pred, pos_label='AML')}")  
print(  
    f"Recall of the best SVM model is: {recall_score(test_target, test_pred,   
    ↪ pos_label='AML')}")  
print(  
    f"AUC of the best SVM model is: {roc_auc_score(test_target, test_pred,   
    ↪ pos_label='AML')}")
```

```
f"F1-score of the best SVM model is: {f1_score(test_target, test_pred,
pos_label='AML')}}")
```

Accuracy of the best SVM model is: 0.9705882352941176

Precision of the best SVM model is: 0.9333333333333333

Recall of the best SVM model is: 1.0

F1-score of the best SVM model is: 0.9655172413793104

```
-----
TypeError                                Traceback (most recent call last)
/mnt/garuda/karthikeya/college/mlbio/Assignment2/Assignment2.ipynb Cell 46 line 1

    <a href='vscode-notebook-cell:/mnt/garuda/karthikeya/college/mlbio/
    ↪Assignment2/Assignment2.ipynb#Y600sZmlsZQ%3D%3D?line=8'>9</a> print(
    <a href='vscode-notebook-cell:/mnt/garuda/karthikeya/college/mlbio/
    ↪Assignment2/Assignment2.ipynb#Y600sZmlsZQ%3D%3D?line=9'>10</a>      f"Recall c
    ↪the best SVM model is: {recall_score(test_target, test_pred,
    ↪pos_label='AML')}}")
    <a href='vscode-notebook-cell:/mnt/garuda/karthikeya/college/mlbio/
    ↪Assignment2/Assignment2.ipynb#Y600sZmlsZQ%3D%3D?line=10'>11</a> print(
    <a href='vscode-notebook-cell:/mnt/garuda/karthikeya/college/mlbio/
    ↪Assignment2/Assignment2.ipynb#Y600sZmlsZQ%3D%3D?line=11'>12</a>      f"F1-scor
    ↪of the best SVM model is: {f1_score(test_target, test_pred, pos_label='AML')}} )
    <a href='vscode-notebook-cell:/mnt/garuda/karthikeya/college/mlbio/
    ↪Assignment2/Assignment2.ipynb#Y600sZmlsZQ%3D%3D?line=12'>13</a> print(
---> <a href='vscode-notebook-cell:/mnt/garuda/karthikeya/college/mlbio/
    ↪Assignment2/Assignment2.ipynb#Y600sZmlsZQ%3D%3D?line=13'>14</a>      f"ROC-AUC
    ↪score of the best SVM model is: {roc_auc_score(test_target, test_pred,
    ↪pos_label='AML')}}")

File ~/anaconda3/envs/ml/lib/python3.11/site-packages/sklearn/utils/
    ↪_param_validation.py:189, in validate_params.<locals>.decorator.<locals>.
    ↪wrapper(*args, **kwargs)
    186 func_sig = signature(func)
    188 # Map *args/**kwargs to the function signature
--> 189 params = func_sig.bind(*args, **kwargs)
    190 params.apply_defaults()
    192 # ignore self/cls and positional/keyword markers

File ~/anaconda3/envs/ml/lib/python3.11/inspect.py:3212, in Signature.bind(self
    ↪*args, **kwargs)
    3207 def bind(self, /, *args, **kwargs):
    3208     """Get a BoundArguments object, that maps the passed `args`
    3209     and `kwargs` to the function's signature. Raises `TypeError`
    3210     if the passed arguments can not be bound.
    3211     """
-> 3212     return self._bind(args, kwargs)

File ~/anaconda3/envs/ml/lib/python3.11/inspect.py:3201, in Signature.
    ↪_bind(self, args, kwargs, partial)
```

```

3199         arguments[kwargs_param.name] = kwargs
3200     else:
-> 3201         raise TypeError(
3202             'got an unexpected keyword argument {arg!r}'.format(
3203                 arg=next(iter(kwargs)))
3205     return self._bound_arguments_cls(self, arguments)

```

TypeError: got an unexpected keyword argument 'pos_label'

2.1.7 Plotting the confusion matrix

```

[ ]: # confusion matrix
cm = confusion_matrix(test_target, test_pred)

plt.figure(figsize=(5, 3))
sns.heatmap(cm, annot=True)
plt.xlabel('Predicted')
plt.ylabel('Truth')
plt.title('Confusion Matrix')
plt.show()

```

2.2 Random Forest

```

[ ]: # using Random Forest and performing grid search to find the best parameters
rfc = RandomForestClassifier(random_state=0)

# defining parameter range
param_grid = {'n_estimators': [60, 70, 80, 90, 100],
              'max_features': [0.6, 0.7, 0.8, 0.9],
              'min_samples_leaf': [8, 10, 12, 14],
              'min_samples_split': [3, 5, 7]}

grid = GridSearchCV(rfc, param_grid, cv=3, scoring='accuracy')

```

2.2.1 Best parameters

```

[ ]: grid.fit(train_scaled_logreg, train_target)
print(f"Best parameters for Random Forest are: {grid.best_params_}")

```

2.2.2 Selecting the best random forest model

```

[ ]: rfc = grid.best_estimator_

```

2.2.3 Fitting the model

```
[ ]: rfc.fit(train_scaled_logreg, train_target)
```

2.2.4 Evaluation of the model

```
[ ]: # predicting the values
test_pred = rfc.predict(test_scaled_logreg)

# calculating the accuracy, precision, recall, f1-score, roc_auc_score
print(
    f"Accuracy of the best Random Forest model is: {accuracy_score(test_target,
↪test_pred)}")
print(
    f"Precision of the best Random Forest model is:
↪{precision_score(test_target, test_pred, average='macro')}")
print(
    f"Recall of the best Random Forest model is: {recall_score(test_target,
↪test_pred, average='macro')}")
print(
    f"F1 Score of the best Random Forest model is: {f1_score(test_target,
↪test_pred, average='macro')}")
```

2.2.5 Plotting the confusion matrix

```
[ ]: # confusion matrix
cm = confusion_matrix(test_target, test_pred)

plt.figure(figsize=(5, 3))
sns.heatmap(cm, annot=True)
plt.xlabel('Predicted')
plt.ylabel('Truth')
plt.title('Confusion Matrix')
plt.show()
```

2.3 Neural Network

2.3.1 Grid search for MLP

```
[ ]: mlp = MLPClassifier(max_iter=1000)
```

2.3.2 Grid Parameters

```
[ ]: param_grid = {'hidden_layer_sizes': [(50, 50, 50), (50, 100, 50), (100,)],
                  'activation': ['tanh', 'relu', 'logistic'],
                  'solver': ['sgd', 'adam'],
                  'alpha': [0.0001, 0.05],
```

```
'learning_rate': ['constant', 'adaptive']}]}
```

```
grid = GridSearchCV(mlp, param_grid, cv=3, scoring='accuracy')
```

2.3.3 Best parameters

```
[ ]: grid.fit(train_scaled_logreg, train_target)
print(f"Best parameters for Neural Network are: {grid.best_params_}")
```

2.3.4 Selecting the best neural network model

```
[ ]: mlp = grid.best_estimator_
```

2.3.5 Fitting the model

```
[ ]: mlp.fit(train_scaled_logreg, train_target)
```

2.3.6 Evaluating the model

```
[ ]: # predicting the values
test_pred = mlp.predict(test_scaled_logreg)

# calculating the accuracy, precision, recall, f1-score, roc_auc_score
print(
    f"Accuracy of the best Neural Network model is:␣
    ↪{accuracy_score(test_target, test_pred)}")
print(
    f"Precision of the best Neural Network model is:␣
    ↪{precision_score(test_target, test_pred, average='macro')}")
print(
    f"Recall of the best Neural Network model is: {recall_score(test_target,␣
    ↪test_pred, average='macro')}")
print(
    f"F1 Score of the best Neural Network model is: {f1_score(test_target,␣
    ↪test_pred, average='macro')}")
```

2.3.7 Plotting the confusion matrix

```
[ ]: # confusion matrix
cm = confusion_matrix(test_target, test_pred)

plt.figure(figsize=(5, 3))
sns.heatmap(cm, annot=True)
plt.xlabel('Predicted')
```

```
plt.ylabel('Truth')  
plt.title('Confusion Matrix')  
plt.show()
```