Assignment # 5: Dimensionality Reduction (DR) and Features Selection (FS) Comparison

Machine Learning II

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In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sb
import math
import warnings
import matplotlib.pyplot as plt
get_ipython().run_line_magic('matplotlib', 'inline')
import cufflinks as cf

import seaborn as sns
from sklearn import preprocessing
#from sklearn.tree import export_graphviz
#import pydot
from IPython.display import Image
#import feature selection modules
from sklearn.feature_selection import mutual_info_classif,RFE,RFECV
from sklearn.feature_selection import mutual_info_regression

#import classification modules
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn import svm
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.ensemble import RandomForestRegressor
#import regression modules
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import PolynomialFeatures
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.ensemble import AdaBoostRegressor
from sklearn.ensemble import VotingRegressor


#import split methods
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.model_selection import RepeatedKFold
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import StratifiedShuffleSplit

#import performance scores
```

```
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
from sklearn.metrics import f1_score
from sklearn.metrics import auc
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
import pandas as pd
import numpy as np
from sklearn import model_selection
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import ElasticNet
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.svm import SVR
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error


from sklearn.neural_network import MLPClassifier
from sklearn.neural_network import MLPRegressor
from sklearn.datasets import make_regression

from math import sqrt
import seaborn as sns

#Stats Libraries
from scipy import stats
import statsmodels.api as sm
from statsmodels.formula.api import ols
import statsmodels.api as sm


# import scaling
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler



warnings.filterwarnings("ignore")
sb.set(color_codes=True, font_scale=1.2)
try:
    from xgboost import XGBClassifier
except:
    print("Failed to import xgboost, make sure you have xgboost installed")
    print("Use following command to install it: pip install xgboost")
    XGBClassifier = None

try:
    import lightgbm as lgb
except:
    print("Failed to import lightgbm, make sure that you have lightgbm installed")
    print("Use following command to install it: conda install -c conda-forge lightgbm")
    lgb = None
```

Part-1: Functions for Features Extraction/Selection for Classification Based Problems

Clssification Algorithms

In [2]:
```
#2) include all classification and regression algorithms
# Classification Algorithms
def XgBoost(trainX, testX, trainY, testY, verbose=True, clf=None):
    if not clf:
        clf = XGBClassifier(random_state=1,learning_rate=0.01)
    clf.fit(trainX,trainY)
    return validationmetrics(clf,testX,testY,verbose=verbose)

def RandomForest(trainX, testX, trainY, testY, verbose=True, clf=None):
    if not clf:
        clf  = RandomForestClassifier()
    clf.fit(trainX , trainY)
    return validationmetrics(clf,testX,testY,verbose=verbose)

def SVM(trainX, testX, trainY, testY, svmtype="SVC", verbose=True, clf=None):
    # for one vs all
    if not clf:
        if svmtype == "Linear":
            clf = svm.LinearSVC()
        else:
            clf = svm.SVC()
    clf.fit(trainX , trainY)
    return validationmetrics(clf,testX,testY,verbose=verbose)

def LogReg(trainX, testX, trainY, testY, verbose=True, clf=None):
    if not clf:
        clf  = LogisticRegression()
    clf.fit(trainX , trainY)
    return validationmetrics(clf,testX,testY,verbose=verbose)


#####################################################################################

# Helper function to provide list of supported algorithms for Classification
def get_supported_algorithms_clf():
    covered_algorithms = [XgBoost,RandomForest,SVM, LogReg]
    return covered_algorithms


#####################################################################################

#Classification Alg Calls
####################################

#Include function for executing ML (classification) without FS.


def run_algorithms_clf(df, label_col, algo_list=get_supported_algorithms_clf(), feature
    """
```

```
    Run Algorithms without FS, REG and CV

    """
    # Lets make a copy of dataframe and work on that to be on safe side
    _df = df.copy()

    if feature_list:
        impftrs = feature_list
        impftrs.append(label_col)
        _df = _df[impftrs]

    _df, trainX, testX, trainY, testY = traintestsplit(_df, 0.3, 91, label_col=label_co
    algo_model_map = {}
    for algo in algo_list:
        print("============ " + algo.__name__ + " ===========")
        res = algo(trainX, testX, trainY, testY)
        algo_model_map[algo.__name__] = res.get("model_obj", None)
        print ("============================== \n")

    return algo_model_map

##########################################################################
# Validation metrics for classification

###############################


# Validation metrics for classification
def validationmetrics(model, testX, testY, verbose=True):
    predictions = model.predict(testX)

    if model.__class__.__module__.startswith('lightgbm'):
        for i in range(0, predictions.shape[0]):
            predictions[i]= 1 if predictions[i] >= 0.5 else 0

    #Accuracy
    accuracy = accuracy_score(testY, predictions)*100

    #Precision
    precision = precision_score(testY, predictions, pos_label=1, labels=[0,1])*100

    #Recall
    recall = recall_score(testY, predictions,pos_label=1,labels=[0,1])*100

    #get FPR (specificity) and TPR (sensitivity)
    fpr , tpr, _ = roc_curve(testY, predictions)

    #AUC
    auc_val = auc(fpr, tpr)

    #F-Score
    f_score = f1_score(testY, predictions)


    if verbose:
        print("Prediction Vector: \n", predictions)
        print("\n Accuracy: \n", accuracy)
        print("\n Precision of event Happening: \n", precision)
        print("\n Recall of event Happening: \n", recall)
        print("\n AUC: \n",auc_val)
        print("\n F-Score:\n", f_score)
```

```
        #confusion Matrix
        print("\n Confusion Matrix: \n", confusion_matrix(testY, predictions,labels=[0,
        #ROC plot

    res_map = {
                "accuracy": accuracy,
                "precision": precision,
                "recall": recall,
                "auc_val": auc_val,
                "f_score": f_score,
                "model_obj": model

            }
    return res_map
```

In [3]:

```
########################################################################
#Helping Function
#######################

#Train Test Split: splitting manually
def traintestsplit(df,split,random=None, label_col=''):
    #make a copy of the label column and store in y
    y = df[label_col].copy()

    #now delete the original
    X = df.drop(label_col,axis=1)

    #manual split
    trainX, testX, trainY, testY= train_test_split(X, y, test_size=split, random_state=
    return X, trainX, testX, trainY, testY

#helper function which only splits into X and y
def XYsplit(df, label_col):
    y = df[label_col].copy()
    X = df.drop(label_col,axis=1)
    return X,y

#Helper Function for Tranformation

#MinMax Transformation
def MinMax_Transformation(df, label_col):
    y = df[label_col].copy()
    X = df.drop(label_col,axis=1)
    scaler = MinMaxScaler()
    scaled_features = MinMaxScaler().fit_transform(X.values)
    df1= pd.DataFrame(scaled_features, index=X.index, columns=X.columns)
    z1=pd.DataFrame(df1)
    z2=pd.DataFrame(y)
    df= pd.concat([z1,z2], axis=1)
    return df
#Standard Transformation
def Standard_Transformation(df, label_col):
    y = df[label_col].copy()
    X = df.drop(label_col,axis=1)
    scaled_features = StandardScaler().fit_transform(X.values)
    df1= pd.DataFrame(scaled_features, index=X.index, columns=X.columns)
    z1=pd.DataFrame(df1)
    z2=pd.DataFrame(y)
    df= pd.concat([z1,z2], axis=1)
    return df
```

```
## Filling Missing Values


def fill_na_interpolate(df, cols_to_interpolate):
    for i in cols_to_interpolate:
        df[i] = df[i].interpolate(method ='linear', limit_direction ='forward')
    return df

def drop_na_rows(df, cols_to_drop_na_rows):
        for i in cols_to_drop_na_rows:
            df = df.drop(df[df[i].isnull()].index)
        return df
```

In [4]:
```
# Load Data
def load_data(file_name):
    def readcsv(file_name):
        return pd.read_csv(file_name)
    def readexcel(file_name):
        return pd.read_excel(file_name)

    func_map = {
        "csv": readcsv,
        "xls": readexcel,
        "xlsx": readexcel,

    }

    # default reader = readcsv
    reader = func_map.get("csv")

    for k,v in func_map.items():
        if file_name.endswith(k):
            reader = v
            break
    return reader(file_name)
```

Function to call LDA, PCA, TSNE, Lasso, Random Forest, XGBoost and Recursive Feature Elemination for Features Selection for Classification Problem

In [5]:
```
#######################################################################################
#Function to call LDA, PCA, TSNE, Lasso, Random Forest, XGBoost and Recursive Feature E
###########################################################
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
from sklearn.feature_selection import SelectFromModel
from sklearn.feature_selection import RFE


######################################################################################

# for Binary Class Classification

##################################

def FE_MLalg_binaryclf(df, label_col, X, Y, trainX, testX, trainY, testY, lda_component
```

```
        pca_components, tnse_components, number_iter, alpha, num_features, learning_

    df1=df.drop(label_col,axis=1)
    ##LDA##

    lda = LinearDiscriminantAnalysis(n_components=lda_components)
    # run an LDA and use it to transform the features
    X_lda = lda.fit(X, Y).transform(X)
    LDA_df = pd.DataFrame(data = X_lda)#, columns = ['X_LDA_1'])
    LDA_df = pd.concat([LDA_df, df[label_col]], axis = 1)
    print('Linear Discriminant Analysis')
    print('Original number of features:', X.shape[1])
    print('Reduced number of features:', X_lda.shape[1])
    print('ML Classification Algorithms Results with LDA FS')
    ML_binary_clf(LDA_df,label_col)
    ##PCA##
    pca = PCA(n_components=pca_components)
    X_pca = pca.fit_transform(X)
    PCA_df = pd.DataFrame(data = X_pca)#, #columns = [b])
    PCA_df = pd.concat([PCA_df, df[label_col]], axis = 1)
    print('PCA Analysis')
    print('Original number of features:', X.shape[1])
    print('Reduced number of features:', X_pca.shape[1])
    print('ML Classification Algorithms Results with PCA FS')
    ML_binary_clf(PCA_df,label_col)
    ##tnse##
    tsne = TSNE(n_components=tnse_components, verbose=0, perplexity=40, n_iter=number_i
    X_tsne = tsne.fit_transform(X)
    TSNE_df = pd.DataFrame(data = X_tsne)#, columns = ['PC1','PC2','PC3','PC4','PC5','P
    TSNE_df = pd.concat([TSNE_df, df[label_col]], axis = 1)
    print('tSNE Analysis')
    print('Original number of features:', X.shape[1])
    print('Reduced number of features:', X_tsne.shape[1])
    print('ML Classification Algorithms Results with tSNE FS')
    ML_binary_clf(TSNE_df,label_col)

    #for Lasoo

    sel_ = SelectFromModel(LogisticRegression(C=alpha, penalty='l1',solver='liblinear')
    #clf = LogisticRegression(C=0.01, penalty='l1',solver='liblinear');
    sel_.fit(X, Y)
    selected_feat = list(X.columns[(sel_.get_support())])
    #pd.Series(X.columns[(sel_.get_support())])
    impftrs_l1 = selected_feat
    impftrs_l11=pd.Series(impftrs_l1)
    impftrs_l1.append(label_col)
    LASSO_df = df[impftrs_l1]
    print('Lasso Analysis')
    print('Selected Features')
    print(impftrs_l11)
    print('ML Classification Algorithms Results with Lasso FS')
    ML_binary_clf(LASSO_df,label_col)

    #for Random Forest calssification
    clf  = RandomForestClassifier(n_estimators=tree, random_state=random)
    clf.fit(trainX, trainY)
    #validationmetrics(clf,testX,testY)
    res_rf = pd.Series(clf.feature_importances_, index=df1.columns.values).sort_values(
    impftrs_rf1=res_rf.head(num_features)
    impftrs_rf=list(impftrs_rf1.keys())
    impftrs_rf.append(label_col)
```

```
    RF_df = df[impftrs_rf]
    print('Random Forest FS Analysis')
    print('Selected Features')
    print(impftrs_rf1)
    print('ML Classification Algorithms Results with Random Forest FS')
    ML_binary_clf(RF_df,label_col)

    #for XGBoost calssification
    clf  = XGBClassifier(random_state=1,learning_rate=learning_rate)
    clf.fit(trainX, trainY)
    res_xgb = pd.Series(clf.feature_importances_, index=df1.columns.values).sort_values
    impftrs_xgb1=res_xgb.head(num_features)
    impftrs_xgb=list(impftrs_xgb1.keys())
    impftrs_xgb.append(label_col)
    XGB_df = df[impftrs_xgb]
    print('Random Forest FS Analysis')
    print('Selected Features')
    print(impftrs_xgb1)
    print('ML Classification Algorithms Results with Random Forest FS')
    ML_binary_clf(XGB_df,label_col)

    ###RFE
    cols = list(X.columns)
    rfe = RFE(estimator=LogisticRegression(), n_features_to_select=num_features)
    # fit RFE
    rfe.fit(trainX, trainY)
    temp = pd.Series(rfe.support_,index = cols)
    selected_features_rfe = temp[temp==True].index
    #print(selected_features_rfe)
    impre=pd.Series(selected_features_rfe)
    impftrs_rfe = list(selected_features_rfe)
    impftrs_rfe.append(label_col)
    print('RFE FS Analysis')
    print('Selected Features')
    print(impre)
    print('ML Classification Algorithms Results with RFE FS')
    RFE_df = df[impftrs_rfe]
    ML_binary_clf(RFE_df,label_col)
    return LDA_df, PCA_df, TSNE_df, LASSO_df, RF_df, XGB_df, RFE_df#res_rf, res_xgb

########################################################################################
#######################################################################################

# for Multi-Class Classification

##################################
def FE_MLalg_multiclf(df, label_col, X, Y, trainX, testX, trainY, testY, lda_components
       pca_components, tnse_components, number_iter, alpha, num_features, learning_

    df1=df.drop(label_col,axis=1)
    ##LDA##

    lda = LinearDiscriminantAnalysis(n_components=lda_components)
    # run an LDA and use it to transform the features
    X_lda = lda.fit(X, Y).transform(X)
    LDA_df = pd.DataFrame(data = X_lda)#, columns = ['X_LDA_1'])
    LDA_df = pd.concat([LDA_df, df[label_col]], axis = 1)
    print('Linear Discriminant Analysis')
    print('Original number of features:', X.shape[1])
    print('Reduced number of features:', X_lda.shape[1])
    print('ML Classification Algorithms Results with LDA FS')
```

```
ML_multiclass_clf(LDA_df,label_col)
##PCA##
pca = PCA(n_components=pca_components)
X_pca = pca.fit_transform(X)
PCA_df = pd.DataFrame(data = X_pca)#, #columns = [b])
PCA_df = pd.concat([PCA_df, df[label_col]], axis = 1)
print('PCA Analysis')
print('Original number of features:', X.shape[1])
print('Reduced number of features:', X_pca.shape[1])
print('ML Classification Algorithms Results with PCA FS')
ML_multiclass_clf(PCA_df,label_col)
##tnse##
tsne = TSNE(n_components=tnse_components, verbose=0, perplexity=40, n_iter=number_i
X_tsne = tsne.fit_transform(X)
TSNE_df = pd.DataFrame(data = X_tsne)#, columns = ['PC1','PC2','PC3','PC4','PC5','P
TSNE_df = pd.concat([TSNE_df, df[label_col]], axis = 1)
print('tSNE Analysis')
print('Original number of features:', X.shape[1])
print('Reduced number of features:', X_tsne.shape[1])
print('ML Classification Algorithms Results with tSNE FS')
ML_multiclass_clf(TSNE_df,label_col)
#for Lasoo

sel_ = SelectFromModel(LogisticRegression(C=alpha, penalty='l1',solver='liblinear')
#clf = LogisticRegression(C=0.01, penalty='l1',solver='liblinear');
sel_.fit(X, Y)
selected_feat = list(X.columns[(sel_.get_support())])
#pd.Series(X.columns[(sel_.get_support())])
impftrs_l1 = selected_feat
impftrs_l11=pd.Series(impftrs_l1)
impftrs_l1.append(label_col)
LASSO_df = df[impftrs_l1]
print('Lasso Analysis')
print('Selected Features')
print(impftrs_l11)
print('ML Classification Algorithms Results with Lasso FS')
ML_multiclass_clf(LASSO_df,label_col)


#for Random Forest calssification
clf  = RandomForestClassifier(n_estimators=tree, random_state=random)
clf.fit(trainX, trainY)
#validationmetrics(clf,testX,testY)
res_rf = pd.Series(clf.feature_importances_, index=df1.columns.values).sort_values(
impftrs_rf1=res_rf.head(num_features)
impftrs_rf=list(impftrs_rf1.keys())
impftrs_rf.append(label_col)
RF_df = df[impftrs_rf]
print('Random Forest FS Analysis')
print('Selected Features')
print(impftrs_rf1)
print('ML Classification Algorithms Results with Random Forest FS')
ML_multiclass_clf(RF_df,label_col)



#for XGBoost calssification
clf  = XGBClassifier(random_state=1,learning_rate=learning_rate)
clf.fit(trainX, trainY)
res_xgb = pd.Series(clf.feature_importances_, index=df1.columns.values).sort_values
impftrs_xgb1=res_xgb.head(num_features)
```

```
    impftrs_xgb=list(impftrs_xgb1.keys())
    impftrs_xgb.append(label_col)
    XGB_df = df[impftrs_xgb]
    print('Random Forest FS Analysis')
    print('Selected Features')
    print(impftrs_xgb1)
    print('ML Classification Algorithms Results with Random Forest FS')
    ML_multiclass_clf(XGB_df,label_col)

    ###RFE
    cols = list(X.columns)
    rfe = RFE(estimator=LogisticRegression(), n_features_to_select=num_features)
    # fit RFE
    rfe.fit(trainX, trainY)
    temp = pd.Series(rfe.support_,index = cols)
    selected_features_rfe = temp[temp==True].index
    #print(selected_features_rfe)
    impre=pd.Series(selected_features_rfe)
    impftrs_rfe = list(selected_features_rfe)
    impftrs_rfe.append(label_col)
    print('RFE FS Analysis')
    print('Selected Features')
    print(impre)
    print('ML Classification Algorithms Results with RFE FS')
    RFE_df = df[impftrs_rfe]
    ML_multiclass_clf(RFE_df,label_col)
    return LDA_df, PCA_df, TSNE_df, LASSO_df, RF_df, XGB_df, RFE_df#res_rf, res_xgb
```

In [6]:

```
#######################################################################################
#Classification Alg Calls
####################################


#######################################################################################

# for Binary Class Classification

##################################

#Include function for executing ML (classification) with and without FS for binary clas

def ML_binary_clf(df,label_col):
    Y= df[label_col].copy()
    X = df.drop(label_col,axis=1)
    trainX, testX, trainY, testY = train_test_split(X, Y, test_size=0.3, random_state=4
    algorithms = []
    algorithms.append(XGBClassifier(random_state=1,learning_rate=0.01, verbosity = 0,si
    algorithms.append(RandomForestClassifier())
    algorithms.append(svm.SVC())
    algorithms.append(LogisticRegression())
    data1 = []

    for algo in algorithms:
        algo.fit(trainX,trainY)
        Y_pred = algo.predict(testX)
        accuracy = accuracy_score(testY, Y_pred)*100
        precision = precision_score(testY, Y_pred, pos_label=1, labels=[0,1])*100
        #Recall
        recall = recall_score(testY, Y_pred,pos_label=1,labels=[0,1])*100
```

```
        #get FPR (specificity) and TPR (sensitivity)
        fpr , tpr, _ = roc_curve(testY, Y_pred)
        #AUC
        auc_val = auc(fpr, tpr)
        #F-Score
        f_score = f1_score(testY, Y_pred)

        data1.append(({
            'accuracy':accuracy,
            'precision': precision,'recall': recall,
            'auc_val':auc_val,
            'f_score': f_score,
            }))

    results = pd.DataFrame(data=data1, columns=['accuracy',
                                                 'precision','recall','auc_val','f_score
                       index=['XGBoost', 'Random_Forest','SVM', 'LogisticRegression'])
    display(results)
    #print(results)
    return results

#######################################################################################

# for Multiclass Classification

##################################

#Include function for executing ML (classification) with and without FS for Multiclass

def ML_multiclass_clf(df,label_col):
    Y= df[label_col].copy()
    X = df.drop(label_col,axis=1)
    trainX, testX, trainY, testY = train_test_split(X, Y, test_size=0.3, random_state=4
    algorithms = []
    algorithms.append(XGBClassifier(random_state=1,learning_rate=0.01, verbosity = 0,si
    algorithms.append(RandomForestClassifier())
    algorithms.append(svm.SVC())
    algorithms.append(LogisticRegression())
    data1 = []

    for algo in algorithms:
        algo.fit(trainX,trainY)
        Y_pred = algo.predict(testX)
        accuracy = accuracy_score(testY, Y_pred)*100
        precision = precision_score(testY, Y_pred, average='micro')*100
        #Recall
        recall = recall_score(testY, Y_pred, average='micro')*100
        #get FPR (specificity) and TPR (sensitivity)
        #fpr , tpr, _ = roc_curve(testY, Y_pred,sample_weight)
        #AUC
        #auc_val = auc(fpr, tpr)
        #F-Score
        f_score = f1_score(testY, Y_pred,average="macro")

        data1.append(({
            'accuracy':accuracy,
            'precision': precision,'recall': recall,
            #'auc_val':auc_val,
            'f_score': f_score,
            }))
```

```
    results = pd.DataFrame(data=data1, columns=['accuracy',
                                               'precision','recall',#'auc_val',
                                               'f_score'],
                          index=['XGBoost', 'Random_Forest','SVM', 'LogisticRegression'])
    display(results)
    #print(results)
    return results
```

Part-2: Functions for Features Extraction/Selection for Regression Based Problems

Regression Algorithms

In [7]:

```
#Regression Problem Setup

####################################################################################
# Regression Algorithms
def LinearReg(trainX, testX, trainY, testY, verbose=True, clf=None):
    if not clf:
        clf  = LinearRegression()
    clf.fit(trainX , trainY)
    return validationmetrics_reg(clf, testX, testY, verbose=verbose)



def VotingReg(trainX, testX, trainY, testY, verbose=True, clf=None):
    lr = LinearRegression()
    rf = RandomForestRegressor(n_estimators=100)
    sv = SVR(kernel="rbf")
    dt = DecisionTreeRegressor()
    gb = GradientBoostingRegressor()
    ab = AdaBoostRegressor(random_state=0, n_estimators=100)
    if not clf:
        clf = VotingRegressor([('rf', rf), ('dt', dt), ('gb', gb), ('ab', ab)])
    clf.fit(trainX , trainY)
    return validationmetrics_reg(clf, testX, testY, verbose=verbose)


####################################################################################


# Helper function to provide list of supported algorithms for Regression
def get_supported_algorithms_reg():
    covered_algorithms = [LinearReg, VotingReg]
    return covered_algorithms

#ElasticNet, PolynomialReg,
####################################################################################
#Regression Call
####################################

# Helper function to run all algorithms provided in algo_list over given dataframe, wit
# By default it will run all supported algorithms
def run_algorithms_reg(df, label_col, algo_list=get_supported_algorithms_reg(), feature
```

```
    """
    Run Algorithms without FS, REG and CV

    """
    # Lets make a copy of dataframe and work on that to be on safe side
    _df = df.copy()

    if feature_list:
        impftrs = feature_list
        impftrs.append(label_col)
        _df = _df[impftrs]

    _df, trainX, testX, trainY, testY = traintestsplit(_df, 0.2, 91, label_col=label_co
    algo_model_map = {}
    for algo in algo_list:
        print("============ " + algo.__name__ + " ===========")
        res = algo(trainX, testX, trainY, testY)
        algo_model_map[algo.__name__] = res.get("model_obj", None)
        print ("============================== \n")

    return algo_model_map

#######################################################################################
#Validation metrics for Regression algorithms
######################################################
#Validation metrics for Regression algorithms
def validationmetrics_reg(model,testX,testY, verbose=True):
    predictions = model.predict(testX)

    # R-squared
    r2 = r2_score(testY,predictions, multioutput='variance_weighted')

    # Adjusted R-squared
    r2_adjusted = 1-(1-r2)*(testX.shape[0]-1)/(testX.shape[0]-testX.shape[1]-1)
    #MAE
    mae = mean_absolute_error(testY,predictions)
    # MSE
    mse = mean_squared_error(testY,predictions)

    #RMSE
    rmse = math.sqrt(mse)

    if verbose:
        print("R-Squared Value: ", r2)
        print("Adjusted R-Squared: ", r2_adjusted)
        print("MAE: ", mae)
        print("RMSE: ", rmse)
    res_map = {
                "r2": r2,
                "r2_adjusted": r2_adjusted,
                "mae": mae,
                "rmse": rmse,
                "model_obj": model
              }
    return res_map
```

Function to call PCA, TSNE, Random Forest, XGBoost and Recursive Feature Elemination for Features Selection for Regression Problem

In [8]:
```
##########################################################################################
#Function to call LDA, PCA, TSNE, Lasso, Random Forest, XGBoost and Recursive Feature E
############################################################
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
from sklearn.feature_selection import SelectFromModel
from sklearn.feature_selection import RFE
from xgboost import XGBRegressor
#from sklearn.xgboost import XGBRegressor

def FE_MLalg_reg(df, label_col, X, Y, trainX, testX, trainY, testY, lda_components,
           pca_components, tnse_components, number_iter, alpha, num_features, learning_

    df1=df.drop(label_col,axis=1)

    ##PCA##
    pca = PCA(n_components=pca_components)
    X_pca = pca.fit_transform(X)
    PCA_df = pd.DataFrame(data = X_pca)#, #columns = [b])
    PCA_df = pd.concat([PCA_df, df[label_col]], axis = 1)
    print('PCA Analysis')
    print('Original number of features:', X.shape[1])
    print('Reduced number of features:', X_pca.shape[1])
    print('ML Regression Algorithms Results with PCA FS')
    ML_reg(PCA_df,label_col)
    ##tnse##
    tsne = TSNE(n_components=tnse_components, verbose=0, perplexity=40, n_iter=number_i
    X_tsne = tsne.fit_transform(X)
    TSNE_df = pd.DataFrame(data = X_tsne)#, columns = ['PC1','PC2','PC3','PC4','PC5','P
    TSNE_df = pd.concat([TSNE_df, df[label_col]], axis = 1)
    print('tSNE Analysis')
    print('Original number of features:', X.shape[1])
    print('Reduced number of features:', X_tsne.shape[1])
    print('ML Regression Algorithms Results with tSNE FS')
    ML_reg(TSNE_df,label_col)


  #for Random Forest


    clf  = RandomForestRegressor(n_estimators=tree, random_state=random)
    clf.fit(trainX, trainY)
    #validationmetrics(clf,testX,testY)
    res_rf = pd.Series(clf.feature_importances_, index=df1.columns.values).sort_values(
    impftrs_rf1=res_rf.head(num_features)
    impftrs_rf=list(impftrs_rf1.keys())
    impftrs_rf.append(label_col)
    RF_df = df[impftrs_rf]
    print('Random Forest FS Analysis')
    print('Selected Features')
    print(impftrs_rf1)
    print('ML Regression Algorithms Results with Random Forest FS')
    ML_reg(RF_df,label_col)


    #for XGBoost
    clf  = XGBRegressor(random_state=1,learning_rate=learning_rate)
    clf.fit(trainX, trainY)
    #validationmetrics(clf,testX,testY)
```

```
    res_xgb = pd.Series(clf.feature_importances_, index=df1.columns.values).sort_values
    impftrs_xgb1=res_xgb.head(num_features)
    impftrs_xgb=list(impftrs_xgb1.keys())
    impftrs_xgb.append(label_col)
    XGB_df = df[impftrs_xgb]
    print('Random Forest FS Analysis')
    print('Selected Features')
    print(impftrs_xgb1)
    print('ML Regression Algorithms Results with XGB FS')
    ML_reg(XGB_df,label_col)

    ###RFE
    cols = list(X.columns)
    rfe = RFE(estimator=LinearRegression(), n_features_to_select=num_features)
    # fit RFE
    rfe.fit(trainX, trainY)
    temp = pd.Series(rfe.support_,index = cols)
    selected_features_rfe = temp[temp==True].index
    impre=pd.Series(selected_features_rfe)
    impftrs_rfe = list(selected_features_rfe)
    impftrs_rfe.append(label_col)
    print('RFE FS Analysis')
    print('Selected Features')
    print(impre)
    print('ML Regression Algorithms Results with RFE FS')
    RFE_df = df[impftrs_rfe]
    ML_reg(RFE_df,label_col)
    return PCA_df, TSNE_df, RF_df, XGB_df, RFE_df
```

In [9]:

```
#########################################################################################
#Regression Alg Calls
####################################

#Include function for executing ML (classification) with and without FS.
def ML_reg(df,label_col):
    Y= df[label_col].copy()

    #now delete the original
    X = df.drop(label_col,axis=1)

    trainX, testX, trainY, testY = train_test_split(X, Y, test_size=0.3, random_state=4
    r = LinearRegression()
    rf = RandomForestRegressor(n_estimators=100)
    sv = SVR(kernel="rbf")
    dt = DecisionTreeRegressor()
    gb = GradientBoostingRegressor()
    ab = AdaBoostRegressor(random_state=0, n_estimators=100)

    algorithms = []
    algorithms.append(LinearRegression())

    algorithms.append(VotingRegressor([('rf', rf), ('dt', dt), ('gb', gb), ('ab', ab)])

    data1 = []

    for algo in algorithms:
        algo.fit(trainX,trainY)

        Y_pred = algo.predict(testX)
```

```
        r2 = r2_score(testY,Y_pred, multioutput='variance_weighted')

    # Adjusted R-squared
        r2_adjusted = 1-(1-r2)*(testX.shape[0]-1)/(testX.shape[0]-testX.shape[1]-1)
    #MAE
        mae = mean_absolute_error(testY,Y_pred)
    # MSE
        mse = mean_squared_error(testY,Y_pred)

    #RMSE
        rmse = math.sqrt(mse)

        data1.append(({'R-Squared':r2,'Adj-R Squared': r2_adjusted,'MAE': mae,
           'MSE':mse,'RMSE': rmse}))

    results = pd.DataFrame(data=data1, columns=['R-Squared',
                                                 'Adj-R Squared','MAE','MSE','RMSE'],
                       index=['Linear_Regression', 'Voting_Regression'])
    display(results)
    #print(results)
    return results
```

Data Analysis

Classification based Data Analysis

Four different types of datasets are analyzed using four different types of ML algorithms, which are

1. XGBoost
2. Random Forest
3. SVM
4. Logistic Regression

with and without feature extraction/selections. Seven different types of features extraction/selections are considered, which are

1. Linear Discriminant Analysis (LDA)
2. Principal component analysis (PCA)
3. t-distributed stochastic neighbor embedding (t-SNE)
4. Lasso based L1 feature selection -
5. Random Forest based Feature Selection (RF)
6. XGBooset based Feature Selection
7. Recursive Feature Elimination (RFE)

The datasets are

1. Dataset 1: Parkinson's Disease Classification (pd_speech_feature)
2. Dataset 2: Default of Credit Card Clients
3. Dataset 3: MEU-Mobile KSD 2016
4. Dataset 4: Mice Protein Expression (Data_Cortex_Nuclear)

The first two are the binary class, while the latter two are the multi-class classification datasets.

Dataset 1: Parkinson's Disease Classification (pd_speech_feature)

In [11]:
```
FILE_NAME = "pd_speech_features.csv"
LABEL_COL = "class"
df = load_data(FILE_NAME)
display(df.head())
print(df.shape)
print(df.dtypes)
```

ıPeriodPulses	stdDevPeriodPulses	locPctJitter	...	tqwt_kurtosisValue_dec_28	tqwt_kurtosisValue_dec_29
0.008064	0.000087	0.00218	...	1.5620	2.6445
0.008258	0.000073	0.00195	...	1.5589	3.6107
0.008340	0.000060	0.00176	...	1.5643	2.3308
0.010858	0.000183	0.00419	...	3.7805	3.5664
0.008162	0.002669	0.00535	...	6.1727	5.8416

```
(756, 755)
id                              int64
gender                          int64
PPE                           float64
DFA                           float64
RPDE                          float64
                               ...
tqwt_kurtosisValue_dec_33     float64
tqwt_kurtosisValue_dec_34     float64
tqwt_kurtosisValue_dec_35     float64
tqwt_kurtosisValue_dec_36     float64
class                           int64
Length: 755, dtype: object
```

In [12]:
```
#Data X Transformation
#df['id'] = df['id'].astype(int)
label_col='class'
df1=df
df=MinMax_Transformation(df1, label_col)
```

ML Alg witout FE

In [13]:
```
# ML Alg witout FE

label_col='class'
df_cpy=df
res=ML_binary_clf(df_cpy,label_col)
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	85.022026	85.483871	95.783133	0.757604	0.903409

	accuracy	precision	recall	auc_val	f_score
Random_Forest	87.224670	86.631016	97.590361	0.783034	0.917847
SVM	82.378855	80.882353	99.397590	0.677316	0.891892
LogisticRegression	86.343612	85.714286	97.590361	0.766640	0.912676

The results of application of four different ML algorithms on binary classification-based problems show that the Logistic Regression outperform the rest of algorithms in terms of overall accuracy. However, the Random Forest and SVM outperform the others in terms of precision and recall. Overall SVM seems to the best candidate model to predict the class label using the Parkinson's Disease Classification (pd_speech_feature) data set.

ML Alg with Features Selection (10 Features)

In [19]:
```
## ML Alg with Features Selection (10 Features)
# with Features Selection
label_col='class'
Y= df[label_col].copy()

    #now delete the original
X = df.drop(label_col,axis=1)
X, y=XYsplit(df, label_col)
trainX, testX, trainY, testY = train_test_split(X, Y, test_size=0.3, random_state=42)
df_cpy=df
label_col='class'
lda_components=1
pca_components=10
tsne_components=3
number_iter=300
alpha=0.09
num_features=10
learning_rate=0.2
tree=500



LDA_df, PCA_df, TSNE_df, LASSO_df, RF_df, XGB_df, RFE_df=FE_MLalg_binaryclf(df_cpy, lab
                                                                            testY, lda_compon
                                                                            tnse_components,
                                                                            learning_rate,tre
```

```
Linear Discriminant Analysis
Original number of features: 754
Reduced number of features: 1
ML Classification Algorithms Results with LDA FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	100.0	100.0	100.0	1.0	1.0
Random_Forest	100.0	100.0	100.0	1.0	1.0
SVM	100.0	100.0	100.0	1.0	1.0
LogisticRegression	100.0	100.0	100.0	1.0	1.0

```
PCA Analysis
Original number of features: 754
```

```
Reduced number of features: 10
ML Classification Algorithms Results with PCA FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	83.259912	83.684211	95.783133	0.724817	0.893258
Random_Forest	85.022026	84.020619	98.192771	0.736865	0.905556
SVM	84.140969	83.505155	97.590361	0.725657	0.900000
LogisticRegression	82.819383	82.564103	96.987952	0.706251	0.891967

```
tSNE Analysis
Original number of features: 754
Reduced number of features: 3
ML Classification Algorithms Results with tSNE FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	82.819383	84.699454	93.373494	0.737359	0.888252
Random_Forest	84.140969	86.111111	93.373494	0.761949	0.895954
SVM	81.057269	80.000000	98.795181	0.657910	0.884097
LogisticRegression	71.365639	72.645740	97.590361	0.487952	0.832905

```
Lasso Analysis
Selected Features
0                          gender
1                             DFA
2               mean_MFCC_2nd_coef
3              std_6th_delta_delta
4              std_8th_delta_delta
5              std_9th_delta_delta
6     tqwt_entropy_shannon_dec_16
7         tqwt_entropy_log_dec_12
8         tqwt_entropy_log_dec_26
9         tqwt_entropy_log_dec_34
10        tqwt_entropy_log_dec_35
11           tqwt_maxValue_dec_11
12      tqwt_kurtosisValue_dec_36
dtype: object
ML Classification Algorithms Results with Lasso FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	81.057269	85.549133	89.156627	0.740865	0.873156
Random_Forest	85.462555	85.945946	95.783133	0.765801	0.905983
SVM	86.343612	85.340314	98.192771	0.761456	0.913165
LogisticRegression	82.819383	82.564103	96.987952	0.706251	0.891967

```
Random Forest FS Analysis
Selected Features
std_delta_delta_log_energy    1.554695
std_delta_log_energy          1.266033
std_6th_delta_delta           0.918244
std_7th_delta_delta           0.904587
std_9th_delta_delta           0.901225
tqwt_TKEO_mean_dec_12         0.881834
tqwt_TKEO_std_dec_12          0.821213
mean_MFCC_2nd_coef            0.779943
std_Log_energy                0.719549
```

```
std_6th_delta                 0.657631
dtype: float64
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	82.378855	83.510638	94.578313	0.718793	0.887006
Random_Forest	81.497797	84.065934	92.168675	0.723138	0.879310
SVM	79.295154	79.310345	96.987952	0.640677	0.872629
LogisticRegression	77.092511	78.217822	95.180723	0.615248	0.858696

```
Random Forest FS Analysis
Selected Features
tqwt_TKEO_std_dec_13            6.956244
std_delta_delta_log_energy      2.836820
tqwt_entropy_log_dec_18         2.747715
tqwt_entropy_log_dec_12         2.729622
tqwt_entropy_shannon_dec_13     2.071369
app_LT_TKEO_mean_3_coef         2.023748
tqwt_entropy_shannon_dec_33     1.961154
tqwt_TKEO_std_dec_11            1.951341
tqwt_minValue_dec_9             1.867691
minIntensity                    1.691795
dtype: float32
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	79.295154	84.795322	87.349398	0.723632	0.860534
Random_Forest	85.903084	86.413043	95.783133	0.773998	0.908571
SVM	78.854626	77.830189	99.397590	0.611742	0.873016
LogisticRegression	78.414097	78.260870	97.590361	0.619099	0.868633

```
RFE FS Analysis
Selected Features
0                 mean_2nd_delta
1     std_delta_delta_log_energy
2              std_6th_delta_delta
3              std_7th_delta_delta
4              std_9th_delta_delta
5        tqwt_entropy_log_dec_26
6        tqwt_entropy_log_dec_33
7           tqwt_maxValue_dec_11
8           tqwt_maxValue_dec_25
9     tqwt_kurtosisValue_dec_36
dtype: object
ML Classification Algorithms Results with RFE FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	83.700441	87.283237	90.963855	0.774491	0.890855
Random_Forest	83.700441	86.033520	92.771084	0.758937	0.892754
SVM	84.140969	84.946237	95.180723	0.746395	0.897727
LogisticRegression	83.259912	84.042553	95.180723	0.730002	0.892655

Here seven different techniques are used to perform dimensionality reduction on high-dimensional data. Many different feature selection and feature extraction methods have been used. All these methods aim to remove redundant and irrelevant features so that classification of new instances will be more accurate. The methods are

1. Linear Discriminant Analysis (LDA)
2. Principal component analysis (PCA)
3. t-distributed stochastic neighbor embedding (t-SNE)
4. Lasso based L1 feature selection -
5. Random Forest based Feature Selection (RF)
6. XGBooset based Feature Selection
7. Recursive Feature Elimination (RFE)

The selected features are used as features to predict the class label using four different Machine Learning algorithms, which are

1. XGBoost,
2. Random forest
3. SVM
4. Logistic Regression (LR)

The results show that with the application of reducing the features the performance falls a bit in comparison to the using original whole features set. However, there does not seem a significant reduction in the performance in terms of accuracy, precision, and recall. The fall in performance is less than 1% if we extract about 10 of the features and use them in the analysis.

The comparison across various features extraction and selection methods indicates that LDA outperform the rest of six features extractions/selection methods as it has the highest accuracy, precision, and recall. PCA is on the second number in terms of performance. It shows that the features variation is almost captured by the single LDA factor and about 10 PCA based factors. More than 95% of the variation is captured by these factors. Lasso, Random Forest, RFE and XGBoost based methods have almost performance as the result of four ML based algorithms is almost similar across these three features selection-based methods.

The t-SNE based feature selection methods seems the worst among the seven methods. However, the accuracy is about 78% along with the reasonable precision and accuracy. Comparison across Machine Learning algorithms show that the Random Forest and SVM are the best and come up with almost same amount of accuracy and precision.

ML Alg with Features Selection (15 Features)

In [20]:
```
## ML Alg with Features Selection (15 Features)
# with Features Selection
label_col='class'
Y= df[label_col].copy()

    #now delete the original
X = df.drop(label_col,axis=1)
X, y=XYsplit(df, label_col)
trainX, testX, trainY, testY = train_test_split(X, Y, test_size=0.3, random_state=42)
df_cpy=df
label_col='class'
```

```
lda_components=1
pca_components=15
tnse_components=3
number_iter=300
alpha=0.12
num_features=15
learning_rate=0.2
tree=500



LDA_df, PCA_df, TSNE_df, LASSO_df, RF_df, XGB_df, RFE_df=FE_MLalg_binaryclf(df_cpy, lab
                                                                         testY, lda_compon
                                                                         tnse_components,
                                                                         learning_rate,tre
```

```
Linear Discriminant Analysis
Original number of features: 754
Reduced number of features: 1
ML Classification Algorithms Results with LDA FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	100.0	100.0	100.0	1.0	1.0
Random_Forest	100.0	100.0	100.0	1.0	1.0
SVM	100.0	100.0	100.0	1.0	1.0
LogisticRegression	100.0	100.0	100.0	1.0	1.0

```
PCA Analysis
Original number of features: 754
Reduced number of features: 15
ML Classification Algorithms Results with PCA FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	83.259912	83.684211	95.783133	0.724817	0.893258
Random_Forest	84.581498	83.937824	97.590361	0.733853	0.902507
SVM	85.022026	84.020619	98.192771	0.736865	0.905556
LogisticRegression	82.819383	82.564103	96.987952	0.706251	0.891967

```
tSNE Analysis
Original number of features: 754
Reduced number of features: 3
ML Classification Algorithms Results with tSNE FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	83.259912	84.408602	94.578313	0.735187	0.892045
Random_Forest	85.462555	85.185185	96.987952	0.755432	0.907042
SVM	77.092511	76.388889	99.397590	0.578955	0.863874
LogisticRegression	72.246696	72.888889	98.795181	0.493976	0.838875

```
Lasso Analysis
Selected Features
0                          gender
1                             DFA
2               mean_MFCC_2nd_coef
```

```
3             std_6th_delta_delta
4             std_8th_delta_delta
5             std_9th_delta_delta
6     tqwt_entropy_shannon_dec_16
7     tqwt_entropy_shannon_dec_17
8         tqwt_entropy_log_dec_12
9         tqwt_entropy_log_dec_26
10        tqwt_entropy_log_dec_34
11        tqwt_entropy_log_dec_35
12           tqwt_maxValue_dec_11
13      tqwt_kurtosisValue_dec_28
14      tqwt_kurtosisValue_dec_36
dtype: object
ML Classification Algorithms Results with Lasso FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	81.497797	84.444444	91.566265	0.728323	0.878613
Random_Forest	84.581498	85.026738	95.783133	0.749407	0.900850
SVM	82.819383	82.233503	97.590361	0.701067	0.892562
LogisticRegression	84.140969	83.163265	98.192771	0.720472	0.900552

```
Random Forest FS Analysis
Selected Features
std_delta_delta_log_energy     1.627607
std_delta_log_energy           1.599640
std_6th_delta_delta            0.934900
std_7th_delta                  0.861546
std_9th_delta_delta            0.794993
tqwt_entropy_shannon_dec_12    0.775695
mean_MFCC_2nd_coef             0.727541
tqwt_TKEO_mean_dec_12          0.721502
tqwt_TKEO_std_dec_12           0.691918
std_7th_delta_delta            0.657989
std_Log_energy                 0.633259
std_10th_delta_delta           0.630228
tqwt_entropy_log_dec_12        0.620777
std_8th_delta_delta            0.576910
tqwt_TKEO_std_dec_11           0.559679
dtype: float64
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	83.700441	85.635359	93.373494	0.753753	0.893372
Random_Forest	83.259912	84.042553	95.180723	0.730002	0.892655
SVM	81.057269	80.597015	97.590361	0.668280	0.882834
LogisticRegression	79.295154	79.899497	95.783133	0.651047	0.871233

```
Random Forest FS Analysis
Selected Features
tqwt_TKEO_std_dec_13           6.956244
std_delta_delta_log_energy     2.836820
tqwt_entropy_log_dec_18        2.747715
tqwt_entropy_log_dec_12        2.729622
tqwt_entropy_shannon_dec_13    2.071369
app_LT_TKEO_mean_3_coef        2.023748
tqwt_entropy_shannon_dec_33    1.961154
tqwt_TKEO_std_dec_11           1.951341
tqwt_minValue_dec_9            1.867691
```

```
minIntensity                   1.691795
tqwt_meanValue_dec_31          1.661849
app_det_TKEO_mean_4_coef       1.609059
mean_4th_delta_delta           1.539960
tqwt_maxValue_dec_21           1.503230
tqwt_entropy_shannon_dec_18    1.322190
dtype: float32
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	79.295154	84.795322	87.349398	0.723632	0.860534
Random_Forest	84.140969	84.210526	96.385542	0.736026	0.898876
SVM	80.616740	79.901961	98.192771	0.654898	0.881081
LogisticRegression	79.735683	79.702970	96.987952	0.648874	0.875000

```
RFE FS Analysis
Selected Features
0              mean_MFCC_1st_coef
1                  mean_2nd_delta
2                  std_10th_delta
3      std_delta_delta_log_energy
4             std_6th_delta_delta
5             std_7th_delta_delta
6             std_9th_delta_delta
7         tqwt_entropy_log_dec_26
8         tqwt_entropy_log_dec_33
9             tqwt_stdValue_dec_6
10           tqwt_maxValue_dec_11
11           tqwt_maxValue_dec_25
12      tqwt_kurtosisValue_dec_28
13      tqwt_kurtosisValue_dec_33
14      tqwt_kurtosisValue_dec_36
dtype: object
ML Classification Algorithms Results with RFE FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	84.581498	86.187845	93.975904	0.764961	0.899135
Random_Forest	85.022026	84.020619	98.192771	0.736865	0.905556
SVM	85.462555	85.185185	96.987952	0.755432	0.907042
LogisticRegression	83.700441	83.419689	96.987952	0.722645	0.896936

Here we increase the number of extracted features from 10 to 15. The results show that there is no significant improvement in the performance. The results seem almost indicial to the one obtained in case of using the 10 features. The performance of LDA is best, followed by PCA. The RF, XGBoost, Lasso and RFE have almost same performance. t-SNE seems to be worst. Across the ML algorithms the SVM and RF outperform the others in terms of accuracy and precision.

ML Alg with Features Selection (5 Features)

In [24]:
```
## ML Alg with Features Selection (5 Features)
# with Features Selection
label_col='class'
Y= df[label_col].copy()
```

```
    #now delete the original
X = df.drop(label_col,axis=1)
X, y=XYsplit(df, label_col)
trainX, testX, trainY, testY = train_test_split(X, Y, test_size=0.3, random_state=42)
df_cpy=df
label_col='class'
lda_components=1
pca_components=5
tnse_components=2
number_iter=300
alpha=0.04
num_features=5
learning_rate=0.2
tree=500



LDA_df, PCA_df, TSNE_df, LASSO_df, RF_df, XGB_df, RFE_df=FE_MLalg_binaryclf(df_cpy, lab
                                                                        testY, lda_compon
                                                                        tnse_components,
                                                                        learning_rate,tre
```

```
Linear Discriminant Analysis
Original number of features: 754
Reduced number of features: 1
ML Classification Algorithms Results with LDA FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	100.0	100.0	100.0	1.0	1.0
Random_Forest	100.0	100.0	100.0	1.0	1.0
SVM	100.0	100.0	100.0	1.0	1.0
LogisticRegression	100.0	100.0	100.0	1.0	1.0

```
PCA Analysis
Original number of features: 754
Reduced number of features: 5
ML Classification Algorithms Results with PCA FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	77.533040	80.104712	92.168675	0.649368	0.857143
Random_Forest	82.378855	83.510638	94.578313	0.718793	0.887006
SVM	81.938326	82.383420	95.783133	0.700227	0.885794
LogisticRegression	81.938326	82.051282	96.385542	0.695042	0.886427

```
tSNE Analysis
Original number of features: 754
Reduced number of features: 2
ML Classification Algorithms Results with tSNE FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	83.259912	83.333333	96.385542	0.719633	0.893855
Random_Forest	88.986784	88.950276	96.987952	0.821005	0.927954
SVM	80.616740	81.443299	95.180723	0.680822	0.877778
LogisticRegression	80.616740	81.443299	95.180723	0.680822	0.877778

```
Lasso Analysis
Selected Features
0                    gender
1          mean_MFCC_2nd_coef
2         std_8th_delta_delta
3     tqwt_entropy_log_dec_26
4        tqwt_minValue_dec_11
dtype: object
ML Classification Algorithms Results with Lasso FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	78.414097	80.000000	93.975904	0.650207	0.864266
Random_Forest	82.819383	83.597884	95.180723	0.721805	0.890141
SVM	81.497797	80.693069	98.192771	0.671292	0.885870
LogisticRegression	82.819383	81.592040	98.795181	0.690697	0.893733

```
Random Forest FS Analysis
Selected Features
std_delta_delta_log_energy    1.715591
std_delta_log_energy          1.257408
std_7th_delta_delta           1.177634
mean_MFCC_2nd_coef            0.816525
std_9th_delta_delta           0.814052
dtype: float64
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	79.295154	81.481481	92.771084	0.676970	0.867606
Random_Forest	79.735683	82.258065	92.168675	0.690352	0.869318
SVM	77.973568	79.000000	95.180723	0.631641	0.863388
LogisticRegression	77.973568	78.155340	96.987952	0.616087	0.865591

```
Random Forest FS Analysis
Selected Features
tqwt_TKEO_std_dec_13           6.956244
std_delta_delta_log_energy     2.836820
tqwt_entropy_log_dec_18        2.747715
tqwt_entropy_log_dec_12        2.729622
tqwt_entropy_shannon_dec_13    2.071369
dtype: float32
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	81.938326	84.530387	92.168675	0.731335	0.881844
Random_Forest	84.140969	84.946237	95.180723	0.746395	0.897727
SVM	80.176211	79.802956	97.590361	0.651886	0.878049
LogisticRegression	75.770925	75.342466	99.397590	0.554365	0.857143

```
RFE FS Analysis
Selected Features
0           std_6th_delta_delta
1           std_9th_delta_delta
2       tqwt_entropy_log_dec_26
3          tqwt_maxValue_dec_11
4    tqwt_kurtosisValue_dec_36
```

```
dtype: object
ML Classification Algorithms Results with RFE FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	78.854626	82.065217	90.963855	0.684327	0.862857
Random_Forest	81.057269	83.606557	92.168675	0.714942	0.876791
SVM	82.819383	82.564103	96.987952	0.706251	0.891967
LogisticRegression	81.057269	80.904523	96.987952	0.673464	0.882192

Here we decrease the number of extracted features from 10 to 5. The results show that there is no significant loss in the performance. The results seem almost indicial to the one obtained in case of using the 10 features. There seems to be about 2% loss in terms of accuracy and precision by reducing the number of extracted features.

The performance of LDA is best, followed by PCA. The RF, XGBoost, Lasso and RFE have almost same performance. t-SNE seems to be worst. Across the ML algorithms the SVM and RF outperform the others in terms of accuracy and precision.

In [ ]:

Dataset 2: Default of Credit Card Clients

In [25]:

```
FILE_NAME = "default of credit card clients.csv"
LABEL_COL = "default payment next month"
df = load_data(FILE_NAME)
#df=pd.read_csv('C:\\Users\\waliullah\\Desktop\\MLii\\Assignment4\\pd_speech_features1.
display(df.head())
print(df.shape)
print(df.dtypes)
```

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	...	BILL_AMT4	E
0	1	20000	2	2	1	24	2	2	-1	-1	...	0	
1	2	120000	2	2	2	26	-1	2	0	0	...	3272	
2	3	90000	2	2	2	34	0	0	0	0	...	14331	
3	4	50000	2	2	1	37	0	0	0	0	...	28314	
4	5	50000	1	2	1	57	-1	0	-1	0	...	20940	

5 rows × 25 columns

```
(30000, 25)
ID                          int64
LIMIT_BAL                   int64
SEX                         int64
EDUCATION                   int64
MARRIAGE                    int64
AGE                         int64
```

```
PAY_0                         int64
PAY_2                         int64
PAY_3                         int64
PAY_4                         int64
PAY_5                         int64
PAY_6                         int64
BILL_AMT1                     int64
BILL_AMT2                     int64
BILL_AMT3                     int64
BILL_AMT4                     int64
BILL_AMT5                     int64
BILL_AMT6                     int64
PAY_AMT1                      int64
PAY_AMT2                      int64
PAY_AMT3                      int64
PAY_AMT4                      int64
PAY_AMT5                      int64
PAY_AMT6                      int64
default payment next month    int64
dtype: object
```

In [26]:
```
df.isnull().sum()
```

Out[26]:
```
ID                            0
LIMIT_BAL                     0
SEX                           0
EDUCATION                     0
MARRIAGE                      0
AGE                           0
PAY_0                         0
PAY_2                         0
PAY_3                         0
PAY_4                         0
PAY_5                         0
PAY_6                         0
BILL_AMT1                     0
BILL_AMT2                     0
BILL_AMT3                     0
BILL_AMT4                     0
BILL_AMT5                     0
BILL_AMT6                     0
PAY_AMT1                      0
PAY_AMT2                      0
PAY_AMT3                      0
PAY_AMT4                      0
PAY_AMT5                      0
PAY_AMT6                      0
default payment next month    0
dtype: int64
```

In [27]:
```
df.columns
```

Out[27]:
```
Index(['ID', 'LIMIT_BAL', 'SEX', 'EDUCATION', 'MARRIAGE', 'AGE', 'PAY_0',
       'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6', 'BILL_AMT1', 'BILL_AMT2',
       'BILL_AMT3', 'BILL_AMT4', 'BILL_AMT5', 'BILL_AMT6', 'PAY_AMT1',
       'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6',
       'default payment next month'],
      dtype='object')
```

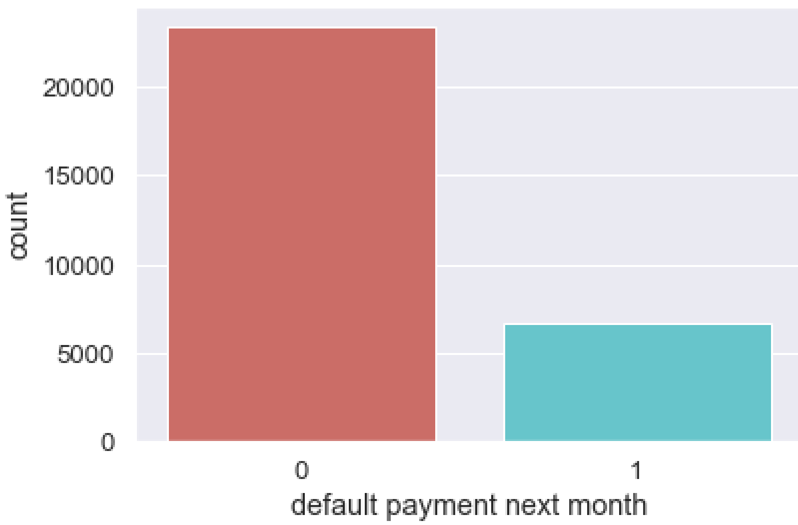
In [28]:
```
#dropping unncessary columns
df.drop('ID', inplace=True, axis=1)
```

In [29]:
```
#Data X Transformation
```

```
label_col='default payment next month'
df1=df
df=MinMax_Transformation(df1, label_col)
```

In [30]:
```
import seaborn as sns
import matplotlib.pyplot as plt
sns.countplot(x='default payment next month', data=df, palette='hls')
plt.show()

count_no_sub = len(df[df['default payment next month']==0])
count_sub = len(df[df['default payment next month']==1])
pct_of_no_sub = count_no_sub/(count_no_sub+count_sub)
print("percentage of non default is", pct_of_no_sub*100)
pct_of_sub = count_sub/(count_no_sub+count_sub)
print("percentage of defauld is", pct_of_sub*100)
```




```
percentage of non default is 77.88000000000001
percentage of defauld is 22.12
```

ML Alg witout FE

In [31]:
```
# ML Alg witout FE

label_col='default payment next month'
df_cpy=df
res=ML_binary_clf(df_cpy,label_col)
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	81.955556	66.279070	34.897959	0.649774	0.457219
Random_Forest	81.277778	62.008734	36.224490	0.650228	0.457327
SVM	81.733333	67.211329	31.479592	0.636020	0.428770
LogisticRegression	80.822222	68.111455	22.448980	0.597614	0.337682

Using the default of credit card clients dataset, the results of application of four different ML algorithms on binary classification based problems show that all four ML based algorithms have almost similar performance in terms of accuracy. However, the RF seems the best in terms of recall and Logistic Regression in terms of precision.

ML Alg with Features Selection (10 Features)

In [32]:
```
## ML Alg with Features Selection (10 Features)
# with Features Selection
label_col='default payment next month'
Y= df[label_col].copy()

    #now delete the original
X = df.drop(label_col,axis=1)
X, y=XYsplit(df, label_col)
trainX, testX, trainY, testY = train_test_split(X, Y, test_size=0.3, random_state=42)
df_cpy=df
label_col='default payment next month'
lda_components=1
pca_components=10
tnse_components=3
number_iter=300
alpha=0.09
num_features=10
learning_rate=0.11
tree=500



LDA_df, PCA_df, TSNE_df, LASSO_df, RF_df, XGB_df, RFE_df=FE_MLalg_binaryclf(df_cpy, lab
                                                                              testY, lda_compon
                                                                              tnse_components,
                                                                              learning_rate,tre
```

```
Linear Discriminant Analysis
Original number of features: 23
Reduced number of features: 1
ML Classification Algorithms Results with LDA FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	81.511111	63.285458	35.969388	0.650799	0.458686
Random_Forest	71.677778	35.012723	35.102041	0.584814	0.350573
SVM	81.544444	63.778802	35.306122	0.648619	0.454516
LogisticRegression	80.900000	67.438495	23.775510	0.602897	0.351565

```
PCA Analysis
Original number of features: 23
Reduced number of features: 10
ML Classification Algorithms Results with PCA FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	81.544444	64.197531	34.489796	0.645673	0.448722
Random_Forest	80.688889	59.487179	35.510204	0.643886	0.444728
SVM	81.866667	66.237624	34.132653	0.646445	0.450505
LogisticRegression	80.788889	67.962675	22.295918	0.596849	0.335766

```
tSNE Analysis
Original number of features: 23
Reduced number of features: 3
ML Classification Algorithms Results with tSNE FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	79.822222	57.982262	26.683673	0.606501	0.365479
Random_Forest	77.966667	49.031171	29.693878	0.605501	0.369876
SVM	79.866667	61.280488	20.510204	0.584511	0.307339
LogisticRegression	78.222222	0.000000	0.000000	0.500000	0.000000

```
Lasso Analysis
Selected Features
0     LIMIT_BAL
1           SEX
2     EDUCATION
3      MARRIAGE
4           AGE
5         PAY_0
6         PAY_2
7         PAY_3
8         PAY_4
9         PAY_5
10    BILL_AMT1
dtype: object
ML Classification Algorithms Results with Lasso FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	81.977778	66.344294	35.000000	0.650284	0.458250
Random_Forest	80.711111	59.256198	36.581633	0.647894	0.452366
SVM	81.755556	66.425620	32.806122	0.640948	0.439208
LogisticRegression	80.944444	68.817204	22.857143	0.599868	0.343164

```
Random Forest FS Analysis
Selected Features
PAY_0        9.780214
AGE          6.612790
BILL_AMT1    5.992291
LIMIT_BAL    5.940480
BILL_AMT2    5.420082
BILL_AMT3    5.167654
PAY_AMT1     5.068900
BILL_AMT6    4.961940
BILL_AMT4    4.952818
BILL_AMT5    4.923184
dtype: float64
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	82.100000	67.751780	33.979592	0.647384	0.452599
Random_Forest	80.955556	61.141304	34.438776	0.641725	0.440601
SVM	81.966667	68.996618	31.224490	0.636591	0.429926
LogisticRegression	80.977778	68.289086	23.622449	0.602842	0.351024

```
Random Forest FS Analysis
Selected Features
PAY_0        40.389748
PAY_2        19.445076
PAY_3         3.913856
```

```
PAY_4        3.842141
PAY_6        2.536490
PAY_AMT3     2.087170
PAY_5        2.028392
LIMIT_BAL    2.019863
BILL_AMT1    1.938453
PAY_AMT2     1.926965
dtype: float32
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	82.155556	66.889313	35.765306	0.654182	0.466090
Random_Forest	80.344444	57.757920	36.275510	0.644446	0.445628
SVM	82.166667	67.050913	35.612245	0.653700	0.465178
LogisticRegression	80.600000	68.013468	20.612245	0.589567	0.316366

```
RFE FS Analysis
Selected Features
0        PAY_0
1        PAY_2
2        PAY_3
3    BILL_AMT1
4     PAY_AMT1
5     PAY_AMT2
6     PAY_AMT3
7     PAY_AMT4
8     PAY_AMT5
9     PAY_AMT6
dtype: object
ML Classification Algorithms Results with RFE FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	82.188889	68.497409	33.724490	0.647032	0.451966
Random_Forest	81.066667	61.678832	34.489796	0.642619	0.442408
SVM	82.055556	69.230769	31.683673	0.638816	0.434722
LogisticRegression	80.488889	68.545455	19.234694	0.583887	0.300398

Here we have used seven different feature selection and feature extraction methods to evaluate their performance in predicting the label of binary class based classification. All these methods aim to remove redundant and irrelevant features so that classification of new instances will be more accurate.

The methods are Linear Discriminant Analysis (LDA), Principal component analysis (PCA), t-distributed stochastic neighbor embedding (t-SNE), Lasso based L1 feature selection, Random Forest based Feature Selection (RF), XGBooset based Feature Selection and Recursive Feature Elimination (RFE). The selected features are used as features to predict the class label using four different Machine Learning algorithms, which are XGBoost, Random forest, SVM and Logistic Regression (LR).

The results show that with the application of reducing the features the performance falls a bit in comparison to the using original whole features set. However, there does not seem a significant reduction in the performance in terms of accuracy, precision, and recall. The fall in performance is less than 2% if we extract about 10 of the features and use them in the analysis.

The comparison across various features extraction and selection methods indicates that LDA and PCA outperform the rest of five features extractions/selection methods as it has the highest accuracy, precision, and recall. Lasso, Random Forest, RFE and XGBoost based methods have almost performance as the result of four ML based algorithms is almost similar across these three feature selection based methods. The t-SNE based feature selection methods seems the worst among the seven methods.

Comparison across Machine Learning algorithms show that the Random Forest and SVM are the best and come up with almost same amount of accuracy and precision.

ML Alg with Features Selection (15 Features)

In [35]:
```
## ML Alg with Features Selection (15 Features)
# with Features Selection
label_col='default payment next month'
Y= df[label_col].copy()

    #now delete the original
X = df.drop(label_col,axis=1)
X, y=XYsplit(df, label_col)
trainX, testX, trainY, testY = train_test_split(X, Y, test_size=0.3, random_state=42)
df_cpy=df
label_col='default payment next month'


lda_components=1
pca_components=15
tnse_components=3
number_iter=300
alpha=0.13
num_features=15
learning_rate=0.2
tree=500




LDA_df, PCA_df, TSNE_df, LASSO_df, RF_df, XGB_df, RFE_df=FE_MLalg_binaryclf(df_cpy, lab
                                                                         testY, lda_compon
                                                                         tnse_components,
                                                                         learning_rate,tre
```

```
Linear Discriminant Analysis
Original number of features: 23
Reduced number of features: 1
ML Classification Algorithms Results with LDA FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	81.511111	63.285458	35.969388	0.650799	0.458686
Random_Forest	71.666667	35.010163	35.153061	0.584927	0.350815
SVM	81.544444	63.778802	35.306122	0.648619	0.454516

	accuracy	precision	recall	auc_val	f_score
LogisticRegression	80.900000	67.438495	23.775510	0.602897	0.351565

```
PCA Analysis
Original number of features: 23
Reduced number of features: 15
ML Classification Algorithms Results with PCA FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	81.411111	63.324048	34.795918	0.645926	0.449127
Random_Forest	81.088889	61.538462	35.102041	0.644970	0.447044
SVM	81.800000	66.841004	32.602041	0.640496	0.438272
LogisticRegression	80.811111	68.118196	22.346939	0.597175	0.336535

```
tSNE Analysis
Original number of features: 23
Reduced number of features: 3
ML Classification Algorithms Results with tSNE FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	79.855556	58.556461	25.663265	0.603032	0.356864
Random_Forest	78.200000	49.917763	30.969388	0.611594	0.382242
SVM	79.733333	62.639405	17.193878	0.571694	0.269816
LogisticRegression	78.222222	0.000000	0.000000	0.500000	0.000000

```
Lasso Analysis
Selected Features
0     LIMIT_BAL
1           SEX
2     EDUCATION
3      MARRIAGE
4           AGE
5         PAY_0
6         PAY_2
7         PAY_3
8         PAY_4
9         PAY_5
10        PAY_6
11    BILL_AMT1
12     PAY_AMT5
dtype: object
ML Classification Algorithms Results with Lasso FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	82.088889	66.827853	35.255102	0.651915	0.461590
Random_Forest	81.088889	61.101549	36.224490	0.649020	0.454837
SVM	81.700000	66.702241	31.887755	0.637280	0.431481
LogisticRegression	80.933333	68.885449	22.704082	0.599245	0.341520

```
Random Forest FS Analysis
Selected Features
PAY_0        9.490055
AGE          6.608469
BILL_AMT1    6.003876
```

```
LIMIT_BAL    5.968637
BILL_AMT2    5.448427
PAY_AMT1     5.136433
BILL_AMT3    5.087672
BILL_AMT6    5.006599
BILL_AMT5    4.963241
BILL_AMT4    4.946628
PAY_AMT2     4.792054
PAY_2        4.774453
PAY_AMT3     4.604046
PAY_AMT6     4.553079
PAY_AMT4     4.327158
dtype: float64
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	81.944444	67.179487	33.418367	0.644365	0.446337
Random_Forest	81.244444	62.078153	35.663265	0.647990	0.453014
SVM	81.966667	69.390104	30.765306	0.634934	0.426299
LogisticRegression	80.700000	67.897271	21.581633	0.593704	0.327526

```
Random Forest FS Analysis
Selected Features
PAY_0        36.845131
PAY_2        19.932110
PAY_3         3.998759
PAY_4         3.669531
PAY_6         2.756535
PAY_AMT3      2.313308
BILL_AMT1     2.235609
PAY_5         2.134971
LIMIT_BAL     2.051992
BILL_AMT2     1.975180
PAY_AMT2      1.971158
EDUCATION     1.963886
PAY_AMT1      1.945929
PAY_AMT6      1.779573
BILL_AMT3     1.777691
dtype: float32
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	81.933333	66.276803	34.693878	0.648896	0.455459
Random_Forest	81.300000	61.929371	36.683673	0.652026	0.460750
SVM	82.066667	67.510121	34.030612	0.647355	0.452510
LogisticRegression	80.644444	67.986799	21.020408	0.591324	0.321122

```
RFE FS Analysis
Selected Features
0     LIMIT_BAL
1     EDUCATION
2           AGE
3         PAY_0
4         PAY_2
5         PAY_3
6         PAY_4
7     BILL_AMT1
8     BILL_AMT3
```

```
9       PAY_AMT1
10      PAY_AMT2
11      PAY_AMT3
12      PAY_AMT4
13      PAY_AMT5
14      PAY_AMT6
dtype: object
ML Classification Algorithms Results with RFE FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	82.155556	67.878788	34.285714	0.648843	0.455593
Random_Forest	81.388889	62.489045	36.377551	0.651490	0.459852
SVM	81.933333	68.152174	31.989796	0.639139	0.435417
LogisticRegression	80.733333	67.993631	21.785714	0.594653	0.329985

Here we increase the number of extracted features from 10 to 15. The results show that there is no significant improvement in the performance. The results seem almost indicial to the one obtained in case of using the 10 features. The performance of LDA is best, followed by PCA. The RF, XGBoost, Lasso and RFE have almost same performance. t-SNE seems to be worst. Across the ML algorithms the SVM and RF outperform the others in terms of accuracy and precision.

ML Alg with Features Selection (5 Features)

In [36]:

```
## ML Alg with Features Selection (5 Features)
# with Features Selection
label_col='default payment next month'
Y= df[label_col].copy()

    #now delete the original
X = df.drop(label_col,axis=1)
X, y=XYsplit(df, label_col)
trainX, testX, trainY, testY = train_test_split(X, Y, test_size=0.3, random_state=42)
df_cpy=df
label_col='default payment next month'
lda_components=1
pca_components=5
tnse_components=3
number_iter=300
alpha=0.02
num_features=5
learning_rate=0.11
tree=500



LDA_df, PCA_df, TSNE_df, LASSO_df, RF_df, XGB_df, RFE_df=FE_MLalg_binaryclf(df_cpy, lab
                                                                           testY, lda_compon
                                                                           tnse_components,
                                                                           learning_rate,tre
```

```
Linear Discriminant Analysis
Original number of features: 23
Reduced number of features: 1
ML Classification Algorithms Results with LDA FS
```

	accuracy	precision	recall	auc_val	f_score

	accuracy	precision	recall	auc_val	f_score
XGBoost	81.511111	63.285458	35.969388	0.650799	0.458686
Random_Forest	71.688889	35.045778	35.153061	0.585069	0.350993
SVM	81.544444	63.778802	35.306122	0.648619	0.454516
LogisticRegression	80.900000	67.438495	23.775510	0.602897	0.351565

```
PCA Analysis
Original number of features: 23
Reduced number of features: 5
ML Classification Algorithms Results with PCA FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	80.155556	59.334764	28.214286	0.614154	0.382434
Random_Forest	78.433333	50.852018	28.928571	0.605722	0.368780
SVM	79.911111	61.875000	20.204082	0.583691	0.304615
LogisticRegression	79.433333	63.260341	13.265306	0.555602	0.219317

```
tSNE Analysis
Original number of features: 23
Reduced number of features: 3
ML Classification Algorithms Results with tSNE FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	79.655556	60.254372	19.336735	0.578928	0.292777
Random_Forest	78.255556	50.126582	30.306122	0.609556	0.377742
SVM	79.355556	61.333333	14.081633	0.558050	0.229046
LogisticRegression	78.222222	0.000000	0.000000	0.500000	0.000000

```
Lasso Analysis
Selected Features
0    LIMIT_BAL
1          SEX
2     MARRIAGE
3        PAY_0
4        PAY_2
5        PAY_3
dtype: object
ML Classification Algorithms Results with Lasso FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	81.766667	64.177778	36.836735	0.655562	0.468071
Random_Forest	79.700000	55.500414	34.234694	0.632963	0.423477
SVM	81.866667	66.532258	33.673469	0.644788	0.447154
LogisticRegression	80.833333	68.740032	21.989796	0.596029	0.333204

```
Random Forest FS Analysis
Selected Features
PAY_0        9.660216
AGE          6.625396
BILL_AMT1    6.004315
LIMIT_BAL    5.957170
```

```
BILL_AMT2    5.385281
dtype: float64
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	82.100000	67.934224	33.724490	0.646463	0.450733
Random_Forest	80.100000	57.000829	35.102041	0.638649	0.434481
SVM	81.977778	68.988764	31.326531	0.637030	0.430877
LogisticRegression	80.933333	67.941176	23.571429	0.602374	0.350000

```
Random Forest FS Analysis
Selected Features
PAY_0    40.389748
PAY_2    19.445076
PAY_3     3.913856
PAY_4     3.842141
PAY_6     2.536490
dtype: float32
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	82.100000	66.991237	35.102041	0.651433	0.460663
Random_Forest	81.644444	64.285714	35.357143	0.649442	0.456221
SVM	82.044444	66.829746	34.846939	0.650158	0.458082
LogisticRegression	80.811111	69.846678	20.918367	0.592021	0.321947

```
RFE FS Analysis
Selected Features
0        PAY_0
1        PAY_3
2    BILL_AMT1
3     PAY_AMT1
4     PAY_AMT2
dtype: object
ML Classification Algorithms Results with RFE FS
```

	accuracy	precision	recall	auc_val	f_score
XGBoost	81.933333	66.971545	33.622449	0.645030	0.447690
Random_Forest	79.855556	56.160939	34.183673	0.633773	0.424992
SVM	81.966667	68.784838	31.479592	0.637512	0.431922
LogisticRegression	80.544444	69.034608	19.336735	0.584610	0.302112

Here we decrease the number of extracted features from 10 to 5. The results show that there is significant loss in the performance. There seems to be about 10% loss in terms of accuracy and precision by reducing the number of extracted features.

The performance of RF, XGBoost, Lasso and RFE is best and have almost same precision and recall. The t-SNE seems to be worst. The LDA and PCA are on the second number. The Across the ML algorithms the SVM and XGBoost outperform the others in terms of accuracy and precision.

Dataset 3: MEU-Mobile KSD 2016

In [37]:
```
FILE_NAME = "MEU-Mobile KSD 2016.csv"
LABEL_COL = "Subject"
df = load_data(FILE_NAME)
#df=pd.read_csv('C:\\Users\\waliullah\\Desktop\\MLii\\Assignment4\\pd_speech_features1.
display(df.head())
print(df.shape)
print(df.dtypes)
```

	Subject	Hold .	Hold t	Hold i	Hold e	Hold Shift	Hold 5	Hold Shift.1	Hold Caps	Hold r	...	Size Caps	Size r	Size (
0	1	89	92	64	85	123	82	70	101	84	...	0.225806	0.225806	0.32258
1	1	90	88	99	83	123	101	81	94	88	...	0.225806	0.225806	0.32258
2	1	87	90	83	65	79	73	96	62	64	...	0.225806	0.193548	0.29032
3	1	71	81	62	72	83	94	89	104	73	...	0.225806	0.225806	0.25806
4	1	89	72	82	82	62	89	68	88	69	...	0.290323	0.225806	0.32258

5 rows × 72 columns

```
(2856, 72)
Subject          int64
Hold .           int64
Hold t           int64
Hold i           int64
Hold e           int64
                ...  
Size l         float64
Size Enter     float64
AvH            float64
AvP            float64
AvA            float64
Length: 72, dtype: object
```

In [38]:
```
df.isnull().sum()
```

Out[38]:
```
Subject       0
Hold .        0
Hold t        0
Hold i        0
Hold e        0
             ..
Size l        0
Size Enter    0
AvH           0
AvP           0
AvA           0
Length: 72, dtype: int64
```

In [39]:
```
#Data X Transformation

label_col='Subject'
df1=df
df=MinMax_Transformation(df1, label_col)
```

ML Alg witout FE

In [40]:
```
# ML Alg witout FE

label_col='Subject'
df_cpy=df
res=ML_multiclass_clf(df_cpy,label_col)
```

	accuracy	precision	recall	f_score
XGBoost	80.046674	80.046674	80.046674	0.799470
Random_Forest	92.532089	92.532089	92.532089	0.923526
SVM	65.810968	65.810968	65.810968	0.661108
LogisticRegression	63.360560	63.360560	63.360560	0.621503

The results of application of four different ML algorithms on binary classification based problems show that the Logistic Regression outperform the rest of algorithms in terms of overall accuracy. However, the Random Forest and SVM outperform the others in terms of precision and recall. Overall SVM seems to the best candidate model to predict the class label.

ML Alg with Features Selection (10 Features)

In [43]:
```
## ML Alg with Features Selection (10 Features)
# with Features Selection
label_col='Subject'
Y= df[label_col].copy()

    #now delete the original
X = df.drop(label_col,axis=1)
X, y=XYsplit(df, label_col)
trainX, testX, trainY, testY = train_test_split(X, Y, test_size=0.3, random_state=42)
df_cpy=df
label_col='Subject'
lda_components=10
pca_components=10
tnse_components=2
number_iter=300
alpha=0.08
num_features=10
learning_rate=0.11
tree=500



LDA_df, PCA_df, TSNE_df, LASSO_df, RF_df, XGB_df, RFE_df=FE_MLalg_multiclf(df_cpy, labe
                                                                        testY, lda_compon
                                                                        tnse_components,
                                                                        learning_rate,tre
```

```
Linear Discriminant Analysis
Original number of features: 71
Reduced number of features: 10
ML Classification Algorithms Results with LDA FS
```

	accuracy	precision	recall	f_score
XGBoost	64.527421	64.527421	64.527421	0.648757
Random_Forest	69.194866	69.194866	69.194866	0.690707

	accuracy	precision	recall	f_score
SVM	72.695449	72.695449	72.695449	0.727117
LogisticRegression	71.878646	71.878646	71.878646	0.714027

```
PCA Analysis
Original number of features: 71
Reduced number of features: 10
ML Classification Algorithms Results with PCA FS
```

	accuracy	precision	recall	f_score
XGBoost	38.739790	38.739790	38.739790	0.383714
Random_Forest	40.956826	40.956826	40.956826	0.411112
SVM	44.807468	44.807468	44.807468	0.450687
LogisticRegression	34.189032	34.189032	34.189032	0.315241

```
tSNE Analysis
Original number of features: 71
Reduced number of features: 2
ML Classification Algorithms Results with tSNE FS
```

	accuracy	precision	recall	f_score
XGBoost	42.007001	42.007001	42.007001	0.407491
Random_Forest	39.789965	39.789965	39.789965	0.400129
SVM	37.922987	37.922987	37.922987	0.339422
LogisticRegression	34.072345	34.072345	34.072345	0.311169

```
Lasso Analysis
Selected Features
0             Hold n
1         DD l.Enter
2         UD l.Enter
3         Pressure i
4     Pressure Shift
5      Pressure Caps
6         Pressure a
7     Pressure Enter
8         Size Enter
9                AvH
10               AvP
11               AvA
dtype: object
ML Classification Algorithms Results with Lasso FS
```

	accuracy	precision	recall	f_score
XGBoost	55.075846	55.075846	55.075846	0.550616
Random_Forest	60.443407	60.443407	60.443407	0.602819
SVM	40.140023	40.140023	40.140023	0.395887
LogisticRegression	24.037340	24.037340	24.037340	0.214336

```
Random Forest FS Analysis
Selected Features
AvH          4.916028
AvA          4.177554
```

```
AvP           3.211048
DD Caps.r     2.292841
UD Caps.r     2.261405
DD n.l        2.124383
DD i.e        2.119492
UD o.a        2.082335
DD r.o        2.077077
DD a.n        2.066744
dtype: float64
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	f_score
XGBoost	70.945158	70.945158	70.945158	0.706772
Random_Forest	79.929988	79.929988	79.929988	0.794846
SVM	40.840140	40.840140	40.840140	0.395113
LogisticRegression	15.285881	15.285881	15.285881	0.107135

```
Random Forest FS Analysis
Selected Features
AvA            4.575877
AvP            3.722332
AvH            3.702333
Hold a         3.174852
UD o.a         2.982936
UD Caps.r      2.793411
UD l.Enter     2.596567
DD i.e         2.554679
DD a.n         2.436496
DD l.Enter     2.382475
dtype: float32
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	f_score
XGBoost	70.711785	70.711785	70.711785	0.707320
Random_Forest	77.129522	77.129522	77.129522	0.768139
SVM	44.574096	44.574096	44.574096	0.440592
LogisticRegression	20.303384	20.303384	20.303384	0.164201

```
RFE FS Analysis
Selected Features
0    Hold Shift
1        Hold r
2        Hold o
3        Hold a
4        Hold n
5        Size t
6     Size Caps
7           AvH
8           AvP
9           AvA
dtype: object
ML Classification Algorithms Results with RFE FS
```

	accuracy	precision	recall	f_score
XGBoost	48.424737	48.424737	48.424737	0.482316
Random_Forest	52.742124	52.742124	52.742124	0.518647

	accuracy	precision	recall	f_score
SVM	52.508751	52.508751	52.508751	0.523213
LogisticRegression	36.172695	36.172695	36.172695	0.323474

The results show that with the application of reducing the features the performance falls a bit in comparison to the using original whole features set. However, there does not seem a significant reduction in the performance in terms of accuracy, precision, and recall. The comparison across various features extraction and selection methods indicates that XGBoost is the best among other in terms of accuracy, precision, and recall. The Random Forest, Lasso and RFE have almost same performance. Comparison across Machine Learning algorithms show that the Random Forest and SVM are the best and come up with almost same amount of accuracy and precision.

ML Alg with Features Selection (15 Features)

In [46]:
```
## ML Alg with Features Selection (15 Features)
# with Features Selection
label_col='Subject'
Y= df[label_col].copy()

    #now delete the original
X = df.drop(label_col,axis=1)
X, y=XYsplit(df, label_col)
trainX, testX, trainY, testY = train_test_split(X, Y, test_size=0.3, random_state=42)
df_cpy=df
label_col='Subject'

lda_components=15
pca_components=15
tnse_components=3
number_iter=300
alpha=0.09
num_features=15
learning_rate=0.2
tree=500



LDA_df, PCA_df, TSNE_df, LASSO_df, RF_df, XGB_df, RFE_df=FE_MLalg_multiclf(df_cpy, labe
                                                                             testY, lda_compon
                                                                             tnse_components,
                                                                             learning_rate,tre
```

```
Linear Discriminant Analysis
Original number of features: 71
Reduced number of features: 15
ML Classification Algorithms Results with LDA FS
```

	accuracy	precision	recall	f_score
XGBoost	66.394399	66.394399	66.394399	0.667496
Random_Forest	74.445741	74.445741	74.445741	0.740460
SVM	78.179697	78.179697	78.179697	0.783387
LogisticRegression	74.795799	74.795799	74.795799	0.746934

```
PCA Analysis
Original number of features: 71
Reduced number of features: 15
ML Classification Algorithms Results with PCA FS
```

	accuracy	precision	recall	f_score
XGBoost	41.306884	41.306884	41.306884	0.411303
Random_Forest	45.507585	45.507585	45.507585	0.452068
SVM	49.824971	49.824971	49.824971	0.501480
LogisticRegression	41.306884	41.306884	41.306884	0.396551

```
tSNE Analysis
Original number of features: 71
Reduced number of features: 3
ML Classification Algorithms Results with tSNE FS
```

	accuracy	precision	recall	f_score
XGBoost	40.723454	40.723454	40.723454	0.401170
Random_Forest	45.390898	45.390898	45.390898	0.448111
SVM	41.773629	41.773629	41.773629	0.396889
LogisticRegression	37.339557	37.339557	37.339557	0.348440

```
Lasso Analysis
Selected Features
0             Hold a
1             Hold n
2         DD l.Enter
3         UD l.Enter
4         Pressure t
5         Pressure i
6         Pressure e
7     Pressure Shift
8         Pressure 5
9      Pressure Caps
10        Pressure a
11        Pressure n
12    Pressure Enter
13        Size Enter
14               AvH
15               AvP
16               AvA
dtype: object
ML Classification Algorithms Results with Lasso FS
```

	accuracy	precision	recall	f_score
XGBoost	57.759627	57.759627	57.759627	0.577401
Random_Forest	68.611435	68.611435	68.611435	0.683938
SVM	42.940490	42.940490	42.940490	0.430936
LogisticRegression	29.171529	29.171529	29.171529	0.268206

```
Random Forest FS Analysis
Selected Features
AvH           4.957346
AvA           4.248136
AvP           3.157856
```

```
UD Caps.r     2.378671
DD Caps.r     2.212318
UD o.a        2.129665
UD i.e        2.111589
DD r.o        2.092234
UD r.o        2.081059
UD l.Enter    2.068374
UD n.l        2.057585
DD i.e        2.048154
DD o.a        2.030265
DD l.Enter    1.998818
DD n.l        1.984026
dtype: float64
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	f_score
XGBoost	71.295216	71.295216	71.295216	0.713631
Random_Forest	80.746791	80.746791	80.746791	0.805154
SVM	43.640607	43.640607	43.640607	0.428145
LogisticRegression	17.736289	17.736289	17.736289	0.130179

```
Random Forest FS Analysis
Selected Features
AvA           5.136408
AvP           3.866963
AvH           3.818790
Hold a        3.076774
DD i.e        3.059487
UD o.a        2.944897
Hold i        2.796641
UD l.Enter    2.637264
DD a.n        2.500731
DD l.Enter    2.393451
UD Caps.r     2.367267
UD 5.Shift    2.284286
UD ..t        2.272466
UD i.e        2.192970
DD r.o        2.115121
dtype: float32
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	f_score
XGBoost	74.562427	74.562427	74.562427	0.748526
Random_Forest	83.897316	83.897316	83.897316	0.838085
SVM	49.474912	49.474912	49.474912	0.496377
LogisticRegression	23.337223	23.337223	23.337223	0.193001

```
RFE FS Analysis
Selected Features
0         Hold Shift
1             Hold 5
2          Hold Caps
3             Hold r
4             Hold o
5             Hold a
6             Hold n
7     Pressure Enter
8             Size t
```

```
9             Size 5
10      Size Shift.1
11         Size Caps
12               AvH
13               AvP
14               AvA
dtype: object
ML Classification Algorithms Results with RFE FS
```

	accuracy	precision	recall	f_score
XGBoost	50.641774	50.641774	50.641774	0.507750
Random_Forest	56.359393	56.359393	56.359393	0.559250
SVM	54.842474	54.842474	54.842474	0.551712
LogisticRegression	42.123687	42.123687	42.123687	0.391796

Here we increase the number of extracted features from 10 to 15. The results show that there is significant improvement in the performance. The comparison across various features extraction and selection methods indicates that XGBoost is the best among other in terms of accuracy, precision, and recall. The Random Forest, Lasso and RFE have almost same performance. Comparison across Machine Learning algorithms show that the Random Forest and SVM are the best and come up with almost same amount of accuracy and precision.

ML Alg with Features Selection (5 Features)

In [50]:

```
## ML Alg with Features Selection (5 Features)
# with Features Selection
label_col='Subject'
Y= df[label_col].copy()

    #now delete the original
X = df.drop(label_col,axis=1)
X, y=XYsplit(df, label_col)
trainX, testX, trainY, testY = train_test_split(X, Y, test_size=0.3, random_state=42)
df_cpy=df
label_col='Subject'
lda_components=5
pca_components=5
tnse_components=3
number_iter=300
alpha=0.075
num_features=5
learning_rate=0.2
tree=500



LDA_df, PCA_df, TSNE_df, LASSO_df, RF_df, XGB_df, RFE_df=FE_MLalg_multiclf(df_cpy, labe
                                                                            testY, lda_compon
                                                                            tnse_components,
                                                                            learning_rate,tre
```

```
Linear Discriminant Analysis
Original number of features: 71
Reduced number of features: 5
ML Classification Algorithms Results with LDA FS
```

	accuracy	precision	recall	f_score
XGBoost	53.792299	53.792299	53.792299	0.538903
Random_Forest	57.292882	57.292882	57.292882	0.573543
SVM	58.576429	58.576429	58.576429	0.590635
LogisticRegression	58.693116	58.693116	58.693116	0.584300

```
PCA Analysis
Original number of features: 71
Reduced number of features: 5
ML Classification Algorithms Results with PCA FS
```

	accuracy	precision	recall	f_score
XGBoost	36.522754	36.522754	36.522754	0.367239
Random_Forest	38.039673	38.039673	38.039673	0.385261
SVM	38.506418	38.506418	38.506418	0.383862
LogisticRegression	28.471412	28.471412	28.471412	0.254364

```
tSNE Analysis
Original number of features: 71
Reduced number of features: 3
ML Classification Algorithms Results with tSNE FS
```

	accuracy	precision	recall	f_score
XGBoost	41.190198	41.190198	41.190198	0.402263
Random_Forest	44.690782	44.690782	44.690782	0.432833
SVM	40.490082	40.490082	40.490082	0.373976
LogisticRegression	36.056009	36.056009	36.056009	0.333316

```
Lasso Analysis
Selected Features
0        Pressure i
1    Pressure Enter
2               AvH
3               AvP
4               AvA
dtype: object
ML Classification Algorithms Results with Lasso FS
```

	accuracy	precision	recall	f_score
XGBoost	44.457410	44.457410	44.457410	0.441165
Random_Forest	42.590432	42.590432	42.590432	0.419519
SVM	38.739790	38.739790	38.739790	0.380073
LogisticRegression	14.002334	14.002334	14.002334	0.100749

```
Random Forest FS Analysis
Selected Features
AvH           4.906460
AvA           4.207526
AvP           3.066363
DD Caps.r     2.391286
UD Caps.r     2.244847
```

```
dtype: float64
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	f_score
XGBoost	51.808635	51.808635	51.808635	0.515525
Random_Forest	51.808635	51.808635	51.808635	0.512267
SVM	36.756126	36.756126	36.756126	0.357797
LogisticRegression	12.252042	12.252042	12.252042	0.076307

```
Random Forest FS Analysis
Selected Features
AvA       5.136408
AvP       3.866963
AvH       3.818790
Hold a    3.076774
DD i.e    3.059487
dtype: float32
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	f_score
XGBoost	55.192532	55.192532	55.192532	0.544369
Random_Forest	57.642940	57.642940	57.642940	0.569610
SVM	43.757293	43.757293	43.757293	0.427112
LogisticRegression	16.569428	16.569428	16.569428	0.120883

```
RFE FS Analysis
Selected Features
0    Hold a
1    Hold n
2       AvH
3       AvP
4       AvA
dtype: object
ML Classification Algorithms Results with RFE FS
```

	accuracy	precision	recall	f_score
XGBoost	43.290548	43.290548	43.290548	0.427565
Random_Forest	42.590432	42.590432	42.590432	0.427569
SVM	45.040840	45.040840	45.040840	0.443440
LogisticRegression	20.536756	20.536756	20.536756	0.156517

Here we decrease the number of extracted features from 10 to 5. The results show that there is significant loss in the performance. There seems to be about 10% loss in terms of accuracy and precision by reducing the number of extracted features. The performance of RF, XGBoost, is best and have almost same precision and recall. The t-SNE seems to be worst. The Lasso and RFE seems to the second best and the LDA and PCA are on the third number. The Across the ML algorithms the SVM and XGBoost outperform the others in terms of accuracy and precision.

In [ ]:

```

```

Dataset 4: Mice Protein Expression (Data_Cortex_Nuclear)

In [51]:
```
FILE_NAME = "Data_Cortex_Nuclear.csv"
LABEL_COL = "class"
df = load_data(FILE_NAME)
#df=pd.read_csv('C:\\Users\\waliullah\\Desktop\\MLii\\Assignment4\\pd_speech_features1.
display(df.head())
print(df.shape)
print(df.dtypes)
```

	MouseID	DYRK1A_N	ITSN1_N	BDNF_N	NR1_N	NR2A_N	pAKT_N	pBRAF_N	pCAMKII_N	pCRE
0	309_1	0.503644	0.747193	0.430175	2.816329	5.990152	0.218830	0.177565	2.373744	0.232
1	309_2	0.514617	0.689064	0.411770	2.789514	5.685038	0.211636	0.172817	2.292150	0.226
2	309_3	0.509183	0.730247	0.418309	2.687201	5.622059	0.209011	0.175722	2.283337	0.230
3	309_4	0.442107	0.617076	0.358626	2.466947	4.979503	0.222886	0.176463	2.152301	0.207
4	309_5	0.434940	0.617430	0.358802	2.365785	4.718679	0.213106	0.173627	2.134014	0.192

5 rows × 82 columns

```
(1080, 82)
MouseID       object
DYRK1A_N     float64
ITSN1_N      float64
BDNF_N       float64
NR1_N        float64
               ...
CaNA_N       float64
Genotype      object
Treatment     object
Behavior      object
class         object
Length: 82, dtype: object
```

In [52]:
```
df.columns
```

Out[52]:
```
Index(['MouseID', 'DYRK1A_N', 'ITSN1_N', 'BDNF_N', 'NR1_N', 'NR2A_N', 'pAKT_N',
       'pBRAF_N', 'pCAMKII_N', 'pCREB_N', 'pELK_N', 'pERK_N', 'pJNK_N',
       'PKCA_N', 'pMEK_N', 'pNR1_N', 'pNR2A_N', 'pNR2B_N', 'pPKCAB_N',
       'pRSK_N', 'AKT_N', 'BRAF_N', 'CAMKII_N', 'CREB_N', 'ELK_N', 'ERK_N',
       'GSK3B_N', 'JNK_N', 'MEK_N', 'TRKA_N', 'RSK_N', 'APP_N', 'Bcatenin_N',
       'SOD1_N', 'MTOR_N', 'P38_N', 'pMTOR_N', 'DSCR1_N', 'AMPKA_N', 'NR2B_N',
       'pNUMB_N', 'RAPTOR_N', 'TIAM1_N', 'pP70S6_N', 'NUMB_N', 'P70S6_N',
       'pGSK3B_N', 'pPKCG_N', 'CDK5_N', 'S6_N', 'ADARB1_N', 'AcetylH3K9_N',
       'RRP1_N', 'BAX_N', 'ARC_N', 'ERBB4_N', 'nNOS_N', 'Tau_N', 'GFAP_N',
```

```
       'GluR3_N', 'GluR4_N', 'IL1B_N', 'P3525_N', 'pCASP9_N', 'PSD95_N',
       'SNCA_N', 'Ubiquitin_N', 'pGSK3B_Tyr216_N', 'SHH_N', 'BAD_N', 'BCL2_N',
       'pS6_N', 'pCFOS_N', 'SYP_N', 'H3AcK18_N', 'EGR1_N', 'H3MeK4_N',
       'CaNA_N', 'Genotype', 'Treatment', 'Behavior', 'class'],
      dtype='object')
```

In [53]:

```
df.drop('MouseID', inplace=True, axis=1)



df.isnull().sum()
```

Out[53]:

```
DYRK1A_N     3
ITSN1_N      3
BDNF_N       3
NR1_N        3
NR2A_N       3
            ..
CaNA_N       0
Genotype     0
Treatment    0
Behavior     0
class        0
Length: 81, dtype: int64
```

In [54]:

```
cols_to_interpolate=['DYRK1A_N', 'ITSN1_N', 'BDNF_N', 'NR1_N', 'NR2A_N', 'pAKT_N', 'pBR
                     'pCAMKII_N', 'pCREB_N', 'pELK_N', 'pERK_N', 'pJNK_N', 'PKCA_N',
                     'pMEK_N', 'pNR1_N', 'pNR2A_N', 'pNR2B_N', 'pPKCAB_N', 'pRSK_N', 'A
                     'BRAF_N', 'CAMKII_N', 'CREB_N', 'ELK_N', 'ERK_N', 'GSK3B_N', 'JNK_
                     'MEK_N', 'TRKA_N', 'RSK_N', 'APP_N', 'Bcatenin_N', 'SOD1_N', 'MTOR
                     'P38_N', 'pMTOR_N', 'DSCR1_N', 'AMPKA_N', 'NR2B_N', 'pNUMB_N',
                     'RAPTOR_N', 'TIAM1_N', 'pP70S6_N', 'NUMB_N', 'P70S6_N', 'pGSK3B_N'
                     'pPKCG_N', 'CDK5_N', 'S6_N', 'ADARB1_N', 'AcetylH3K9_N', 'RRP1_N',
                     'BAX_N', 'ARC_N', 'ERBB4_N', 'nNOS_N', 'Tau_N', 'GFAP_N', 'GluR3_N
                     'GluR4_N', 'IL1B_N', 'P3525_N', 'pCASP9_N', 'PSD95_N', 'SNCA_N',
                     'Ubiquitin_N', 'pGSK3B_Tyr216_N', 'SHH_N', 'BAD_N', 'BCL2_N', 'pS6
                     'pCFOS_N', 'SYP_N', 'H3AcK18_N', 'EGR1_N', 'H3MeK4_N']

df=fill_na_interpolate(df, cols_to_interpolate)
```

In [55]:

```
df = df.dropna()
df.reset_index(drop=True, inplace=True)

df.isnull().sum()
```

Out[55]:

```
DYRK1A_N     0
ITSN1_N      0
BDNF_N       0
NR1_N        0
NR2A_N       0
            ..
CaNA_N       0
Genotype     0
Treatment    0
Behavior     0
class        0
Length: 81, dtype: int64
```

In [56]:

```
#label encoding
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

```
df['Genotype']=le.fit_transform(df['Genotype'])
df['Treatment']=le.fit_transform(df['Treatment'])
df['Behavior']=le.fit_transform(df['Behavior'])
df['class']=le.fit_transform(df['class'])

df
```

Out[56]:

	DYRK1A_N	ITSN1_N	BDNF_N	NR1_N	NR2A_N	pAKT_N	pBRAF_N	pCAMKII_N	pCREB_N	
0	0.743118	0.862653	0.377742	2.735757	6.067570	0.219049	0.185338	2.277492	0.194465	2
1	0.711480	0.807054	0.351591	2.546888	5.595574	0.199170	0.165975	2.118811	0.174689	2
2	0.704633	0.802537	0.350110	2.467733	5.548400	0.205323	0.165058	2.107281	0.171401	1
3	0.677359	0.770235	0.356397	2.563223	4.975196	0.228087	0.186498	2.259045	0.190974	2
4	0.591572	0.678768	0.312480	2.164182	4.313938	0.195786	0.161102	1.975689	0.161912	1
...	...	...	...	...	...	...	...	...	...	
1060	0.254860	0.463591	0.254860	2.092082	2.600035	0.211736	0.171262	2.483740	0.207317	1
1061	0.272198	0.474163	0.251638	2.161390	2.801492	0.251274	0.182496	2.512737	0.216339	1
1062	0.228700	0.395179	0.234118	1.733184	2.220852	0.220665	0.161435	1.989723	0.185164	0
1063	0.221242	0.412894	0.243974	1.876347	2.384088	0.208897	0.173623	2.086028	0.192044	0
1064	0.302626	0.461059	0.256564	2.092790	2.594348	0.251001	0.191811	2.361816	0.223632	1

1065 rows × 81 columns

In [57]:

```
#Data X Transformation

label_col='class'
df1=df
df=MinMax_Transformation(df1, label_col)
df['Genotype'] = df['Genotype'].astype(int)
df['Treatment'] = df['Treatment'].astype(int)
df['Behavior'] = df['Behavior'].astype(int)
df
```

Out[57]:

	DYRK1A_N	ITSN1_N	BDNF_N	NR1_N	NR2A_N	pAKT_N	pBRAF_N	pCAMKII_N	pCREB_N	
0	0.252122	0.261865	0.687370	0.578919	0.641960	0.327466	0.479384	0.152530	0.422121	0
1	0.238778	0.238279	0.618907	0.501093	0.571983	0.285687	0.402859	0.126602	0.319885	0
2	0.235891	0.236363	0.615032	0.468476	0.564989	0.298618	0.399234	0.124718	0.302888	0
3	0.224388	0.222660	0.631490	0.507824	0.480007	0.346460	0.483968	0.149516	0.404071	0
4	0.188207	0.183858	0.516517	0.343393	0.381971	0.278575	0.383600	0.103216	0.253835	0
...	...	...	...	...	...	...	...	...	...	
1060	0.046197	0.092577	0.365672	0.313684	0.127872	0.312096	0.423753	0.186230	0.488562	0
1061	0.053509	0.097062	0.357235	0.342243	0.157739	0.395191	0.468154	0.190968	0.535204	0
1062	0.035163	0.063556	0.311370	0.165795	0.071655	0.330863	0.384915	0.105509	0.374040	0

	DYRK1A_N	ITSN1_N	BDNF_N	NR1_N	NR2A_N	pAKT_N	pBRAF_N	pCAMKII_N	pCREB_N	
1063	0.032018	0.071071	0.337173	0.224787	0.095856	0.306129	0.433086	0.121245	0.409605	0
1064	0.066342	0.091503	0.370133	0.313976	0.127028	0.394619	0.504969	0.166308	0.572903	0

1065 rows × 81 columns

ML Alg witout FE

In [58]:
```
# ML Alg witout FE

label_col='class'
df_cpy=df
res=ML_multiclass_clf(df_cpy,label_col)
```

	accuracy	precision	recall	f_score
XGBoost	96.25	96.25	96.25	0.957755
Random_Forest	100.00	100.00	100.00	1.000000
SVM	100.00	100.00	100.00	1.000000
LogisticRegression	100.00	100.00	100.00	1.000000

The results of application of four different ML algorithms on binary classification based problems show that the Logistic Regression, Random Forest and SVM are 100% accurate in terms of all three accuracy criteria. The XGBoost seems a bit worse than the other three.

ML Alg with Features Selection (10 Features)

In [65]:
```
## ML Alg with Features Selection (10 Features)
# with Features Selection
label_col='class'
Y= df[label_col].copy()

    #now delete the original
X = df.drop(label_col,axis=1)
X, y=XYsplit(df, label_col)
trainX, testX, trainY, testY = train_test_split(X, Y, test_size=0.3, random_state=42)
df_cpy=df
label_col='class'
lda_components=4
pca_components=10
tnse_components=2
number_iter=300
alpha=0.34
num_features=10
learning_rate=0.11
tree=500



LDA_df, PCA_df, TSNE_df, LASSO_df, RF_df, XGB_df, RFE_df=FE_MLalg_multiclf(df_cpy, labe
                                                                  testY, lda_compon
```

```
tnse_components,
learning_rate,tre
```

```
Linear Discriminant Analysis
Original number of features: 80
Reduced number of features: 4
ML Classification Algorithms Results with LDA FS
```

	accuracy	precision	recall	f_score
XGBoost	94.3750	94.3750	94.3750	0.947147
Random_Forest	95.9375	95.9375	95.9375	0.963728
SVM	96.5625	96.5625	96.5625	0.968279
LogisticRegression	96.2500	96.2500	96.2500	0.965575

```
PCA Analysis
Original number of features: 80
Reduced number of features: 10
ML Classification Algorithms Results with PCA FS
```

	accuracy	precision	recall	f_score
XGBoost	99.6875	99.6875	99.6875	0.996323
Random_Forest	100.0000	100.0000	100.0000	1.000000
SVM	100.0000	100.0000	100.0000	1.000000
LogisticRegression	100.0000	100.0000	100.0000	1.000000

```
tSNE Analysis
Original number of features: 80
Reduced number of features: 2
ML Classification Algorithms Results with tSNE FS
```

	accuracy	precision	recall	f_score
XGBoost	99.0625	99.0625	99.0625	0.989954
Random_Forest	100.0000	100.0000	100.0000	1.000000
SVM	100.0000	100.0000	100.0000	1.000000
LogisticRegression	100.0000	100.0000	100.0000	1.000000

```
Lasso Analysis
Selected Features
0        TRKA_N
1       pNUMB_N
2       pPKCG_N
3         ARC_N
4       GluR3_N
5         pS6_N
6        CaNA_N
7      Genotype
8     Treatment
9      Behavior
dtype: object
ML Classification Algorithms Results with Lasso FS
```

	accuracy	precision	recall	f_score
XGBoost	99.375	99.375	99.375	0.993168
Random_Forest	100.000	100.000	100.000	1.000000

	accuracy	precision	recall	f_score
SVM	100.000	100.000	100.000	1.000000
LogisticRegression	100.000	100.000	100.000	1.000000

```
Random Forest FS Analysis
Selected Features
Treatment      10.848080
Genotype       10.138145
SOD1_N          4.985803
Behavior        4.379229
pPKCG_N         3.336739
pERK_N          3.137252
CaNA_N          2.485933
DYRK1A_N        2.324298
Ubiquitin_N     2.204098
ITSN1_N         2.175839
dtype: float64
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	f_score
XGBoost	99.6875	99.6875	99.6875	0.996657
Random_Forest	100.0000	100.0000	100.0000	1.000000
SVM	100.0000	100.0000	100.0000	1.000000
LogisticRegression	100.0000	100.0000	100.0000	1.000000

```
Random Forest FS Analysis
Selected Features
BCL2_N      6.802333
SYP_N       6.678327
CaNA_N      5.958408
pMTOR_N     5.213238
BRAF_N      5.147465
SHH_N       4.613681
pPKCG_N     4.305129
pPKCAB_N    4.104352
Genotype    4.089956
P38_N       3.583378
dtype: float32
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	f_score
XGBoost	92.8125	92.8125	92.8125	0.927607
Random_Forest	97.5000	97.5000	97.5000	0.974229
SVM	89.6875	89.6875	89.6875	0.898465
LogisticRegression	70.0000	70.0000	70.0000	0.687640

```
RFE FS Analysis
Selected Features
0         SOD1_N
1        pPKCG_N
2           S6_N
3          ARC_N
4    Ubiquitin_N
5          pS6_N
6         CaNA_N
7       Genotype
```

```
8      Treatment
9       Behavior
dtype: object
ML Classification Algorithms Results with RFE FS
```

	accuracy	precision	recall	f_score
XGBoost	99.375	99.375	99.375	0.991859
Random_Forest	100.000	100.000	100.000	1.000000
SVM	100.000	100.000	100.000	1.000000
LogisticRegression	100.000	100.000	100.000	1.000000

Here I have used seven different feature selection and feature extraction methods to evaluate their performance in predicting the label of binary class based classification. All these methods aim to remove redundant and irrelevant features so that classification of new instances will be more accurate. The methods are Linear Discriminant Analysis (LDA), Principal component analysis (PCA), t-distributed stochastic neighbor embedding (t-SNE), Lasso based L1 feature selection, Random Forest based Feature Selection (RF), XGBooset based Feature Selection and Recursive Feature Elimination (RFE). The selected features are used as features to predict the class label using four different Machine Learning algorithms, which are XGBoost, Random forest, SVM and Logistic Regression (LR).

The results show that with the application of reducing the features the performance falls a bit in comparison to the using original whole features set. However, there does not seem a significant reduction in the performance in terms of accuracy, precision, and recall. The comparison across various features extraction and selection methods indicates that PCA, Lasso, Random Forest, XGBoost and RFE have 100% accuracy, precision, and recall. The LDA and t-NSE seems a bit worse than the other five features' extractions methods.

The Logistic Regression, Random Forest and SVM are 100% accurate in terms of all three accuracy criterias. The XGBoost seems a bit worse than the other three.

ML Alg with Features Selection (15 Features)

In [75]:
```
## ML Alg with Features Selection (15 Features)
# with Features Selection
label_col='class'
Y= df[label_col].copy()

#now delete the original
X = df.drop(label_col,axis=1)
X, y=XYsplit(df, label_col)
trainX, testX, trainY, testY = train_test_split(X, Y, test_size=0.3, random_state=42)
df_cpy=df
label_col='class'
lda_components=6
pca_components=15
tnse_components=3
number_iter=300
alpha=2.9
num_features=15
learning_rate=0.2
```

```
tree=500




LDA_df, PCA_df, TSNE_df, LASSO_df, RF_df, XGB_df, RFE_df=FE_MLalg_multiclf(df_cpy, labe
                                                                        testY, lda_compon
                                                                        tnse_components,
                                                                        learning_rate,tre
```

```
Linear Discriminant Analysis
Original number of features: 80
Reduced number of features: 6
ML Classification Algorithms Results with LDA FS
```

	accuracy	precision	recall	f_score
XGBoost	95.6250	95.6250	95.6250	0.955941
Random_Forest	99.6875	99.6875	99.6875	0.997275
SVM	98.4375	98.4375	98.4375	0.985125
LogisticRegression	99.6875	99.6875	99.6875	0.997275

```
PCA Analysis
Original number of features: 80
Reduced number of features: 15
ML Classification Algorithms Results with PCA FS
```

	accuracy	precision	recall	f_score
XGBoost	99.375	99.375	99.375	0.993053
Random_Forest	100.000	100.000	100.000	1.000000
SVM	100.000	100.000	100.000	1.000000
LogisticRegression	100.000	100.000	100.000	1.000000

```
tSNE Analysis
Original number of features: 80
Reduced number of features: 3
ML Classification Algorithms Results with tSNE FS
```

	accuracy	precision	recall	f_score
XGBoost	98.75	98.75	98.75	0.987383
Random_Forest	100.00	100.00	100.00	1.000000
SVM	100.00	100.00	100.00	1.000000
LogisticRegression	100.00	100.00	100.00	1.000000

```
Lasso Analysis
Selected Features
0        pJNK_N
1        pRSK_N
2        TRKA_N
3        MTOR_N
4       pMTOR_N
5       pNUMB_N
6       pPKCG_N
7         ARC_N
8       GluR3_N
9         pS6_N
```

```
10       CaNA_N
11     Genotype
12    Treatment
13     Behavior
dtype: object
ML Classification Algorithms Results with Lasso FS
```

	accuracy	precision	recall	f_score
XGBoost	99.6875	99.6875	99.6875	0.996803
Random_Forest	100.0000	100.0000	100.0000	1.000000
SVM	100.0000	100.0000	100.0000	1.000000
LogisticRegression	100.0000	100.0000	100.0000	1.000000

```
Random Forest FS Analysis
Selected Features
Treatment      10.297912
Genotype       10.150235
SOD1_N          4.884909
Behavior        4.166230
pPKCG_N         3.298503
pERK_N          3.256558
CaNA_N          2.681118
Ubiquitin_N     2.394434
DYRK1A_N        2.181614
pS6_N           2.071384
ARC_N           2.071313
APP_N           1.992916
pCAMKII_N       1.960053
pP70S6_N        1.909159
Tau_N           1.847798
dtype: float64
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	f_score
XGBoost	99.0625	99.0625	99.0625	0.988911
Random_Forest	100.0000	100.0000	100.0000	1.000000
SVM	100.0000	100.0000	100.0000	1.000000
LogisticRegression	100.0000	100.0000	100.0000	1.000000

```
Random Forest FS Analysis
Selected Features
BCL2_N       7.402934
SYP_N        5.787881
pMTOR_N      4.930232
CaNA_N       4.924162
AMPKA_N      4.638332
BRAF_N       4.386397
Genotype     4.286679
pAKT_N       4.221324
SHH_N        4.167904
pPKCG_N      3.801099
pPKCAB_N     3.720124
pP70S6_N     3.638589
P38_N        3.526210
Treatment    2.999167
Behavior     2.669520
dtype: float32
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	f_score
XGBoost	98.125	98.125	98.125	0.979176
Random_Forest	100.000	100.000	100.000	1.000000
SVM	100.000	100.000	100.000	1.000000
LogisticRegression	100.000	100.000	100.000	1.000000

```
RFE FS Analysis
Selected Features
0        pCAMKII_N
1         pPKCAB_N
2           SOD1_N
3          pNUMB_N
4         pP70S6_N
5          pPKCG_N
6             S6_N
7         ADARB1_N
8            ARC_N
9       Ubiquitin_N
10           pS6_N
11          CaNA_N
12        Genotype
13       Treatment
14        Behavior
dtype: object
ML Classification Algorithms Results with RFE FS
```

	accuracy	precision	recall	f_score
XGBoost	97.8125	97.8125	97.8125	0.973755
Random_Forest	100.0000	100.0000	100.0000	1.000000
SVM	100.0000	100.0000	100.0000	1.000000
LogisticRegression	100.0000	100.0000	100.0000	1.000000

Here we increase the number of extracted features from 10 to 15. The results show that with the application of reducing the features the performance falls a bit in comparison to the using original whole features set. However, there does not seem a significant reduction in the performance in terms of accuracy, precision, and recall. The comparison across various features extraction and selection methods indicates that PCA, Lasso, Random Forest, XGBoost and RFE have 100% accuracy, precision, and recall. The LDA and t-NSE seems a bit worse than the other five features' extractions methods.

The Logistic Regression, Random Forest and SVM are 100% accurate in terms of all three accuracy criterias. The XGBoost seems a bit worse than the other three.

ML Alg with Features Selection (5 Features)

In [80]:

```
## ML Alg with Features Selection (5 Features)
# with Features Selection
label_col='class'
Y= df[label_col].copy()

    #now delete the original
X = df.drop(label_col,axis=1)
```

```
X, y=XYsplit(df, label_col)
trainX, testX, trainY, testY = train_test_split(X, Y, test_size=0.3, random_state=42)
df_cpy=df
label_col='class'
lda_components=3
pca_components=5
tnse_components=2
number_iter=300
alpha=0.06
num_features=5
learning_rate=0.2
tree=500



LDA_df, PCA_df, TSNE_df, LASSO_df, RF_df, XGB_df, RFE_df=FE_MLalg_multiclf(df_cpy, labe
                                                                     testY, lda_compon
                                                                     tnse_components,
                                                                     learning_rate,tre
```

```
Linear Discriminant Analysis
Original number of features: 80
Reduced number of features: 3
ML Classification Algorithms Results with LDA FS
```

	accuracy	precision	recall	f_score
XGBoost	90.3125	90.3125	90.3125	0.909834
Random_Forest	91.8750	91.8750	91.8750	0.924770
SVM	90.3125	90.3125	90.3125	0.909771
LogisticRegression	90.9375	90.9375	90.9375	0.915788

```
PCA Analysis
Original number of features: 80
Reduced number of features: 5
ML Classification Algorithms Results with PCA FS
```

	accuracy	precision	recall	f_score
XGBoost	100.0	100.0	100.0	1.0
Random_Forest	100.0	100.0	100.0	1.0
SVM	100.0	100.0	100.0	1.0
LogisticRegression	100.0	100.0	100.0	1.0

```
tSNE Analysis
Original number of features: 80
Reduced number of features: 2
ML Classification Algorithms Results with tSNE FS
```

	accuracy	precision	recall	f_score
XGBoost	99.0625	99.0625	99.0625	0.990391
Random_Forest	100.0000	100.0000	100.0000	1.000000
SVM	100.0000	100.0000	100.0000	1.000000
LogisticRegression	100.0000	100.0000	100.0000	1.000000

```
Lasso Analysis
```

```
Selected Features
0        ARC_N
1       CaNA_N
2     Genotype
3    Treatment
4     Behavior
dtype: object
ML Classification Algorithms Results with Lasso FS
```

	accuracy	precision	recall	f_score
XGBoost	99.6875	99.6875	99.6875	0.997113
Random_Forest	100.0000	100.0000	100.0000	1.000000
SVM	100.0000	100.0000	100.0000	1.000000
LogisticRegression	100.0000	100.0000	100.0000	1.000000

```
Random Forest FS Analysis
Selected Features
Treatment    10.573620
Genotype      9.953548
SOD1_N        4.869929
Behavior      4.029964
pERK_N        3.466682
dtype: float64
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	f_score
XGBoost	99.0625	99.0625	99.0625	0.991188
Random_Forest	100.0000	100.0000	100.0000	1.000000
SVM	100.0000	100.0000	100.0000	1.000000
LogisticRegression	100.0000	100.0000	100.0000	1.000000

```
Random Forest FS Analysis
Selected Features
BCL2_N     7.402934
SYP_N      5.787881
pMTOR_N    4.930232
CaNA_N     4.924162
AMPKA_N    4.638332
dtype: float32
ML Classification Algorithms Results with Random Forest FS
```

	accuracy	precision	recall	f_score
XGBoost	63.750	63.750	63.750	0.628457
Random_Forest	68.750	68.750	68.750	0.679964
SVM	55.625	55.625	55.625	0.534460
LogisticRegression	41.875	41.875	41.875	0.391129

```
RFE FS Analysis
Selected Features
0        pS6_N
1       CaNA_N
2     Genotype
3    Treatment
4     Behavior
```

```
dtype: object
ML Classification Algorithms Results with RFE FS
```

	accuracy	precision	recall	f_score
XGBoost	99.6875	99.6875	99.6875	0.997113
Random_Forest	100.0000	100.0000	100.0000	1.000000
SVM	100.0000	100.0000	100.0000	1.000000
LogisticRegression	100.0000	100.0000	100.0000	1.000000

Here we decrease the number of extracted features from 10 to 15. The results show that with the application of reducing the features the performance falls a bit in comparison to the using original whole features set. However, there does not seem a significant reduction in the performance in terms of accuracy, precision, and recall. The comparison across various features extraction and selection methods indicates that PCA, Lasso, Random Forest, XGBoost and RFE have 100% accuracy, precision, and recall. The LDA and t-NSE seems a bit worse than the other five features' extractions methods.

The Logistic Regression, Random Forest and SVM are 100% accurate in terms of all three accuracy criteria. The XGBoost seems a bit worse than the other three.

Summary of Classification based Problem

Seven different techniques to perform dimensionality reduction on high-dimensional data. All these methods aim to remove redundant and irrelevant features so that classification of new instances will be more accurate. The methods are Linear Discriminant Analysis (LDA), Principal component analysis (PCA), t-distributed stochastic neighbor embedding (t-SNE), Lasso based L1 feature selection, Random Forest based Feature Selection (RF), XGBooset based Feature Selection and Recursive Feature Elimination (RFE). The selected features are used as features to predict the class label using four different Machine Learning algorithms, which are XGBoost, Random forest, SVM and Logistic Regression (LR).

The results show that with the application of reducing the features the performance falls a bit in comparison to the using original whole features set. However, there does not seem a significant reduction in the performance in terms of accuracy, precision, and recall. The fall in performance is less than 1% if we extract about 10 of the features and use them in the analysis.

The comparison across various features extraction and selection methods indicates that XGBoost and Random Forest features selections methods outperform the other five methods. The Lasso and recursive features elimination (RFE) methods seems the second best. However, the LDA and PCA based methods outperform the former seven methods if the features are highly correlated, whereas the former four methods outperform the LDA and PCA based methods if the degree of correlation is low among the features. The t-SNE seems the worst performing features extraction methods.

By increasing the feature number, the accuracy and precision improve, while the performance of ML algorithms fall by decreasing the number of features. Overall, it seems that if the features are highly correlated then there is no significant fall in the performance by decreasing the number of factors or features. It is about 2 to 3%. However, if the degree of correlation is low then there is significant reduction in accuracy and precision scores in case of reduction in the number of features or factors. Comparison across Machine Learning algorithms show that the Random Forest and SVM are the best and come up with almost same amount of accuracy and precision.

Regression based Data Analysis

The train.csv dataset which contains 81 features extracted from 21263 superconductors along with the critical temperature is analyzed using two different types of ML algorithms, which are

1. Linear Regression Model
2. Voting Regression

with and without feature extraction/selections. Six different types of features extraction/selections are considered, which are

1. Principal component analysis (PCA)
2. t-distributed stochastic neighbor embedding (t-SNE)
3. Lasso based L1 feature selection -
4. Random Forest based Feature Selection (RF)
5. XGBooset based Feature Selection
6. Recursive Feature Elimination (RFE)

The dataset is

Dataset 5: Superconductivty Data Set (train)

The dependent variable (label) is "critical_temp".

Dataset 5: Superconductivty Data Set (train)

In [81]:

```
FILE_NAME = "train.csv"
LABEL_COL = "critical_temp"
df = load_data(FILE_NAME)
#df=pd.read_csv('C:\\Users\\waliullah\\Desktop\\MLii\\Assignment4\\pd_speech_features1.
display(df.head())
print(df.shape)
print(df.dtypes)
```

	number_of_elements	mean_atomic_mass	wtd_mean_atomic_mass	gmean_atomic_mass	wtd_gmean_ato
0	4	88.944468	57.862692	66.361592	
1	5	92.729214	58.518416	73.132787	
2	4	88.944468	57.885242	66.361592	
3	4	88.944468	57.873967	66.361592	
4	4	88.944468	57.840143	66.361592	

5 rows × 82 columns

```
(21263, 82)
number_of_elements        int64
mean_atomic_mass        float64
wtd_mean_atomic_mass    float64
gmean_atomic_mass       float64
wtd_gmean_atomic_mass   float64
                          ...
range_Valence             int64
wtd_range_Valence       float64
std_Valence             float64
wtd_std_Valence         float64
critical_temp           float64
Length: 82, dtype: object
```

In [82]:
```
#Data X Transformation

label_col='critical_temp'
df1=df
df=MinMax_Transformation(df1, label_col)
```

ML Alg witout FE for Regression

In [83]:
```
label_col='critical_temp'
df_cpy=df
res_clf=ML_reg(df_cpy,label_col)
```

	R-Squared	Adj-R Squared	MAE	MSE	RMSE
Linear_Regression	0.728144	0.724647	13.424387	315.542302	17.763510
Voting_Regression	0.885481	0.884008	8.432079	132.921198	11.529146

The results of application of two different ML algorithms on regression based problems dataset show that the Voting Regression outperform the simple Linear Regression (MLR) model in terms of all accuracy features. The R-Squared as well as RMSE of Voting Regression is significantly lower than the Linear Regression based model.

ML Alg with Features Selection (10 Features)

In [84]:
```
label_col='critical_temp'
Y= df[label_col].copy()

    #now delete the original
X = df.drop(label_col,axis=1)
X, y=XYsplit(df, label_col)
trainX, testX, trainY, testY = train_test_split(X, Y, test_size=0.3, random_state=42)
df_cpy=df
label_col='critical_temp'
lda_components=1
pca_components=10
tnse_components=3
number_iter=300
alpha=0.1
num_features=10
learning_rate=0.11
tree=100
```

```
PCA_df, TSNE_df, RF_df, XGB_df, RFE_df=FE_MLalg_reg(df_cpy, label_col, X, Y, trainX, te
                                                                        testY, lda_compon
                                                                        tnse_components,
                                                                        learning_rate,tre
```

```
PCA Analysis
Original number of features: 81
Reduced number of features: 10
ML Regression Algorithms Results with PCA FS
```

	R-Squared	Adj-R Squared	MAE	MSE	RMSE
Linear_Regression	0.562418	0.561731	17.864704	507.899573	22.536627
Voting_Regression	0.861160	0.860942	9.129162	161.150507	12.694507

```
tSNE Analysis
Original number of features: 81
Reduced number of features: 3
ML Regression Algorithms Results with tSNE FS
```

	R-Squared	Adj-R Squared	MAE	MSE	RMSE
Linear_Regression	0.183261	0.182876	25.428252	947.985724	30.789377
Voting_Regression	0.820394	0.820310	11.311081	208.467788	14.438414

```
Random Forest FS Analysis
Selected Features
range_ThermalConductivity          54.017313
wtd_gmean_ThermalConductivity      12.375299
std_atomic_mass                     2.978458
wtd_gmean_Valence                   2.110215
gmean_ElectronAffinity              1.095040
wtd_entropy_ThermalConductivity     1.085876
wtd_std_ElectronAffinity            1.072624
mean_Density                        1.035698
wtd_mean_ThermalConductivity        1.004299
wtd_std_Valence                     0.969976
dtype: float64
ML Regression Algorithms Results with Random Forest FS
```

	R-Squared	Adj-R Squared	MAE	MSE	RMSE
Linear_Regression	0.632902	0.632326	16.143617	426.089041	20.641924
Voting_Regression	0.883109	0.882925	7.901371	135.674834	11.647954

```
Random Forest FS Analysis
Selected Features
range_ThermalConductivity        65.199738
wtd_gmean_ThermalConductivity     9.434132
range_atomic_radius               2.499496
std_atomic_mass                   1.860079
gmean_ElectronAffinity            1.329480
wtd_gmean_Valence                 1.308799
wtd_std_ElectronAffinity          1.205467
std_Density                       1.095559
entropy_ThermalConductivity       0.850869
wtd_mean_ThermalConductivity      0.718418
dtype: float32
ML Regression Algorithms Results with XGB FS
```

	R-Squared	Adj-R Squared	MAE	MSE	RMSE
Linear_Regression	0.609084	0.608470	16.448230	453.734879	21.301053

	R-Squared	Adj-R Squared	MAE	MSE	RMSE
Voting_Regression	0.883078	0.882894	7.994346	135.711307	11.649520

```
RFE FS Analysis
Selected Features
0            mean_atomic_mass
1        wtd_mean_atomic_mass
2           gmean_atomic_mass
3       wtd_gmean_atomic_mass
4                   range_fie
5                     std_fie
6      wtd_mean_atomic_radius
7     wtd_gmean_atomic_radius
8      range_ElectronAffinity
9        std_ElectronAffinity
dtype: object
ML Regression Algorithms Results with RFE FS
```

	R-Squared	Adj-R Squared	MAE	MSE	RMSE
Linear_Regression	0.575665	0.574999	17.043138	492.523626	22.192873
Voting_Regression	0.859899	0.859679	9.142508	162.614691	12.752047

Here six different techniques to perform dimensionality reduction on high-dimensional data are used. All these methods aim to remove redundant and irrelevant features so that prediction of new instances will be more accurate. The methods are as discussed above. The selected features are then used as features to predict the dependent variable using two different Machine Learning algorithms, which are Simple Linear Regression and Voting Regression.

The results show that with the application of reducing the features the performance falls a bit in comparison to the using original whole features set. However, there does not seem a significant reduction in the performance in terms of R-Squared, MAE and RMSE. The fall in performance is less than 1% if we extract about 10 of the features and use them in the analysis. The comparison across various features extraction and selection methods indicates that Random Forest and XGBoost based features selection methods outperform the rest of four features extractions/selection methods. PCA is on the second number in terms of performance. It shows that the features variation is almost captured by the 10 PCA based factors. More than 95% of the variation is captured by these factors. The Recursive Features Elimination (RFE) method is better than t-SNE and worse than the rest.

The t-SNE based feature selection methods seems the worst among the seven methods. Comparison across Machine Learning algorithms show that the Voting Regression performance is significantly higher than the Simple Linear Regression in terms of all accuracy-based measures.

ML Alg with Features Selection (15 Features)

In [85]:
```
label_col='critical_temp'
Y= df[label_col].copy()

    #now delete the original
X = df.drop(label_col,axis=1)
X, y=XYsplit(df, label_col)
trainX, testX, trainY, testY = train_test_split(X, Y, test_size=0.3, random_state=42)
df_cpy=df
```

```
label_col='critical_temp'
lda_components=1
pca_components=15
tnse_components=3
number_iter=300
alpha=0.1
num_features=15
learning_rate=0.11
tree=100



PCA_df, TSNE_df, RF_df, XGB_df, RFE_df=FE_MLalg_reg(df_cpy, label_col, X, Y, trainX, te
                                                                        testY, lda_compon
                                                                        tnse_components,
                                                                        learning_rate,tre
```

```
PCA Analysis
Original number of features: 81
Reduced number of features: 15
ML Regression Algorithms Results with PCA FS
```

	R-Squared	Adj-R Squared	MAE	MSE	RMSE
Linear_Regression	0.592454	0.591493	17.071546	473.037201	21.749418
Voting_Regression	0.865492	0.865174	8.948377	156.123414	12.494936

```
tSNE Analysis
Original number of features: 81
Reduced number of features: 3
ML Regression Algorithms Results with tSNE FS
```

	R-Squared	Adj-R Squared	MAE	MSE	RMSE
Linear_Regression	0.139690	0.139285	26.80537	998.558447	31.599975
Voting_Regression	0.821379	0.821295	11.37378	207.324562	14.398769

```
Random Forest FS Analysis
Selected Features
range_ThermalConductivity          54.086594
wtd_gmean_ThermalConductivity      12.335965
std_atomic_mass                     2.798113
wtd_gmean_Valence                   2.112463
wtd_entropy_ThermalConductivity     1.247609
gmean_ElectronAffinity              1.162652
wtd_mean_Valence                    1.161541
wtd_mean_ThermalConductivity        1.144356
wtd_std_ElectronAffinity            1.036688
mean_Density                        1.024929
wtd_range_Valence                   0.925496
wtd_std_Valence                     0.831315
wtd_std_ThermalConductivity         0.789226
wtd_range_atomic_mass               0.728244
wtd_std_atomic_mass                 0.725744
dtype: float64
ML Regression Algorithms Results with Random Forest FS
```

	R-Squared	Adj-R Squared	MAE	MSE	RMSE
Linear_Regression	0.642355	0.641512	15.912456	415.116588	20.374410
Voting_Regression	0.879530	0.879246	8.437743	139.828539	11.824912

```
Random Forest FS Analysis
```

```
Selected Features
range_ThermalConductivity         65.199738
wtd_gmean_ThermalConductivity      9.434132
range_atomic_radius                2.499496
std_atomic_mass                    1.860079
gmean_ElectronAffinity             1.329480
wtd_gmean_Valence                  1.308799
wtd_std_ElectronAffinity           1.205467
std_Density                        1.095559
entropy_ThermalConductivity        0.850869
wtd_mean_ThermalConductivity       0.718418
gmean_Density                      0.658043
mean_Density                       0.605342
wtd_entropy_ThermalConductivity    0.593412
wtd_range_Valence                  0.484002
wtd_std_Valence                    0.483726
dtype: float32
ML Regression Algorithms Results with XGB FS
```

	R-Squared	Adj-R Squared	MAE	MSE	RMSE
Linear_Regression	0.641539	0.640694	15.846617	416.063579	20.397637
Voting_Regression	0.883834	0.883560	8.135824	134.833584	11.611786

```
RFE FS Analysis
Selected Features
0              mean_atomic_mass
1          wtd_mean_atomic_mass
2             gmean_atomic_mass
3         wtd_gmean_atomic_mass
4                      mean_fie
5                     gmean_fie
6                     range_fie
7                       std_fie
8         wtd_mean_atomic_radius
9        wtd_gmean_atomic_radius
10     wtd_mean_ElectronAffinity
11    wtd_gmean_ElectronAffinity
12        range_ElectronAffinity
13          std_ElectronAffinity
14      wtd_std_ElectronAffinity
dtype: object
ML Regression Algorithms Results with RFE FS
```

	R-Squared	Adj-R Squared	MAE	MSE	RMSE
Linear_Regression	0.619751	0.618855	16.181259	441.353160	21.008407
Voting_Regression	0.859787	0.859456	9.645784	162.744755	12.757145

Here we increase the number of extracted features from 10 to 15. The results show that there is no significant improvement in the performance. The results seem almost indicial to the one obtained in case of using the 10 features. The performance of Random Forest and XGBoost based methods is best, followed by PCA. The RFE have almost same performance. The t-SNE seems to be worst. Across the ML algorithms the Voting Regression outperform the others in terms of R-Squared and RMSE.

ML Alg with Features Selection (5 Features)

In [86]:
```
label_col='critical_temp'
Y= df[label_col].copy()
```

```
    #now delete the original
X = df.drop(label_col,axis=1)
X, y=XYsplit(df, label_col)
trainX, testX, trainY, testY = train_test_split(X, Y, test_size=0.3, random_state=42)
df_cpy=df
label_col='critical_temp'
lda_components=1
pca_components=5
tnse_components=2
number_iter=300
alpha=0.081
num_features=5
learning_rate=0.11
tree=100



PCA_df, TSNE_df, RF_df, XGB_df, RFE_df=FE_MLalg_reg(df_cpy, label_col, X, Y, trainX, te
                                                                      testY, lda_compon
                                                                      tnse_components,
                                                                      learning_rate,tre
```

```
PCA Analysis
Original number of features: 81
Reduced number of features: 5
ML Regression Algorithms Results with PCA FS
```

	R-Squared	Adj-R Squared	MAE	MSE	RMSE
Linear_Regression	0.539144	0.538782	18.051610	534.913502	23.128197
Voting_Regression	0.853307	0.853192	9.175283	170.266058	13.048604

```
tSNE Analysis
Original number of features: 81
Reduced number of features: 2
ML Regression Algorithms Results with tSNE FS
```

	R-Squared	Adj-R Squared	MAE	MSE	RMSE
Linear_Regression	0.213889	0.213642	24.342085	912.435650	30.206550
Voting_Regression	0.825559	0.825504	10.329002	202.473082	14.229304

```
Random Forest FS Analysis
Selected Features
range_ThermalConductivity         54.023765
wtd_gmean_ThermalConductivity     12.427331
std_atomic_mass                    2.703324
wtd_gmean_Valence                  2.223437
wtd_entropy_ThermalConductivity    1.164621
dtype: float64
ML Regression Algorithms Results with Random Forest FS
```

	R-Squared	Adj-R Squared	MAE	MSE	RMSE
Linear_Regression	0.506603	0.506216	19.040107	572.684102	23.930819
Voting_Regression	0.869080	0.868977	8.746272	151.958721	12.327154

```
Random Forest FS Analysis
Selected Features
range_ThermalConductivity       65.199738
wtd_gmean_ThermalConductivity    9.434132
```

```
range_atomic_radius            2.499496
std_atomic_mass                1.860079
gmean_ElectronAffinity         1.329480
dtype: float32
ML Regression Algorithms Results with XGB FS
```

	R-Squared	Adj-R Squared	MAE	MSE	RMSE
Linear_Regression	0.548013	0.547658	18.293333	524.619482	22.904573
Voting_Regression	0.858007	0.857896	8.782716	164.810201	12.837843

```
RFE FS Analysis
Selected Features
0       wtd_mean_atomic_mass
1          gmean_atomic_mass
2      wtd_gmean_atomic_mass
3     wtd_mean_atomic_radius
4    wtd_gmean_atomic_radius
dtype: object
ML Regression Algorithms Results with RFE FS
```

	R-Squared	Adj-R Squared	MAE	MSE	RMSE
Linear_Regression	0.436126	0.435684	19.451419	654.486144	25.582927
Voting_Regression	0.793599	0.793437	10.964460	239.568869	15.478012

Here we decrease the number of extracted features from 10 to 5. The results show that there is no significant loss in the performance. The results seem almost indicial to the one obtained in case of using the 10 features. There seems to be about 4% loss in terms of Adjusted R-Squared by reducing the number of extracted features. The performance of Random Forest and XGBoost is best, followed by PCA.

Summary of Regression based Problem Analysis

Six different techniques to perform dimensionality reduction on high-dimensional data are used. The methods are as discussed above. The selected features are then used as features to predict the dependent variable using two different Machine Learning algorithms, which are Simple Linear Regression and Voting Regression.

The results show that with the application of reducing the features the performance falls a bit in comparison to the using original whole features set. However, there does not seem a significant reduction in the performance in terms of R-Squared, MAE and RMSE. The fall in performance is less than 1% if we extract about 10 of the features and use them in the analysis. The comparison across various features extraction and selection methods indicates that Random Forest and XGBoost based features selection methods outperform the rest of four features extractions/selection methods. PCA is on the second number in terms of performance. It shows that the features variation is almost captured by the 10 PCA based factors. More than 95% of the variation is captured by these factors. The Recursive Features Elimination (RFE) method is better than t-SNE and worse than the rest.

The t-SNE based feature selection methods seems the worst among the seven methods.

Comparison across Machine Learning algorithms show that the Voting Regression performance is significantly higher than the Simple Linear Regression in terms of all accuracy-based measures.

Overall Summary

Seven different techniques to perform dimensionality reduction on high-dimensional data. Many different feature selection and feature extraction methods have been used. All these methods aim to remove redundant and irrelevant features so that classification of new instances will be more accurate. The methods are

1. Linear Discriminant Analysis (LDA)
2. Principal component analysis (PCA)
3. t-distributed stochastic neighbor embedding (t-SNE)
4. Lasso based L1 feature selection -
5. Random Forest based Feature Selection (RF)
6. XGBooset based Feature Selection
7. Recursive Feature Elimination (RFE)

The selected features are used as features to predict the class label using four different Machine Learning algorithms, which are

1. XGBoost,
2. Random forest
3. SVM
4. Logistic Regression (LR)

while used in regression based scenario with

1. Simple Linear Regression
2. Voting Regression

The results show that with the application of reducing the features the performance falls a bit in comparison to the using original whole features set. However, there does not seem a significant reduction in the performance in terms of accuracy, precision, and recall. The fall in performance is less than 1% if we extract about 10 of the features and use them in the analysis.

How does the classification performance compare across the 7 DR/FS methods?

The comparison across various features extraction and selection methods indicates that XGBoost and Random Forest features selections methods outperform the other five methods. The Lasso and recursive features elimination (RFE) methods seems the second best. However, the LDA and PCA based methods outperform the former seven methods if the features are highly correlated, whereas the former four methods outperform the LDA and PCA based methods if the degree of correlation is low among the features. The t-SNE seems the worst performing features extraction methods.

Comparison across Machine Learning algorithms show that the Random Forest and SVM are the best and come up with almost same amount of accuracy and precision.

How does the regression performance compare across the 7 DR/FS methods?

The results show that with the application of reducing the features the performance falls a bit in comparison to the using original whole features set. However, there does not seem a significant reduction in the performance in terms of R-Squared, MAE and RMSE. The fall in performance is less than 1% if we extract about 10 of the features and use them in the analysis. The comparison across various features extraction and selection methods indicates that Random Forest and XGBoost based features selection methods outperform the rest of four features extractions/selection methods. PCA is on the second number in terms of performance. It shows that the features variation is almost captured by the 10 PCA based factors. More than 95% of the variation is captured by these factors. The Recursive Features Elimination (RFE) method is better than t-SNE and worse than the rest.

Comparison across Machine Learning algorithms show that the Voting Regression performance is significantly higher than the Simple Linear Regression in terms of all accuracy-based measures.

What is the effect of increasing or decreasing the total number of your desired features on the classification and regression performance?

By increasing the feature number, the accuracy and precision improve, while the performance of ML algorithms fall by decreasing the number of features. Overall, it seems that if the features are highly correlated then there is no significant fall in the performance by decreasing the number of factors or features. It is about 2 to 3%. However, if the degree of correlation is low then there is significant reduction in accuracy and precision scores in case of reduction in the number of features or factors.

In [ ]:

```

```