

# **University Institute of Engineering**

# **Department of Computer Science & Engineering**

**Experiment: 3** 

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Branch: Computer Science & Engineering Section/Group:22CSE-212/C

Semester: 1st Date of Performance:09/11/2022

**Subject Name: Disruptive Technology-1** 

**Subject Code: 22ECH-102** 

1. **Aim of the practical:** Explore, visualize, transform and summarize input datasets for building Classificatio/regression/prediction models.

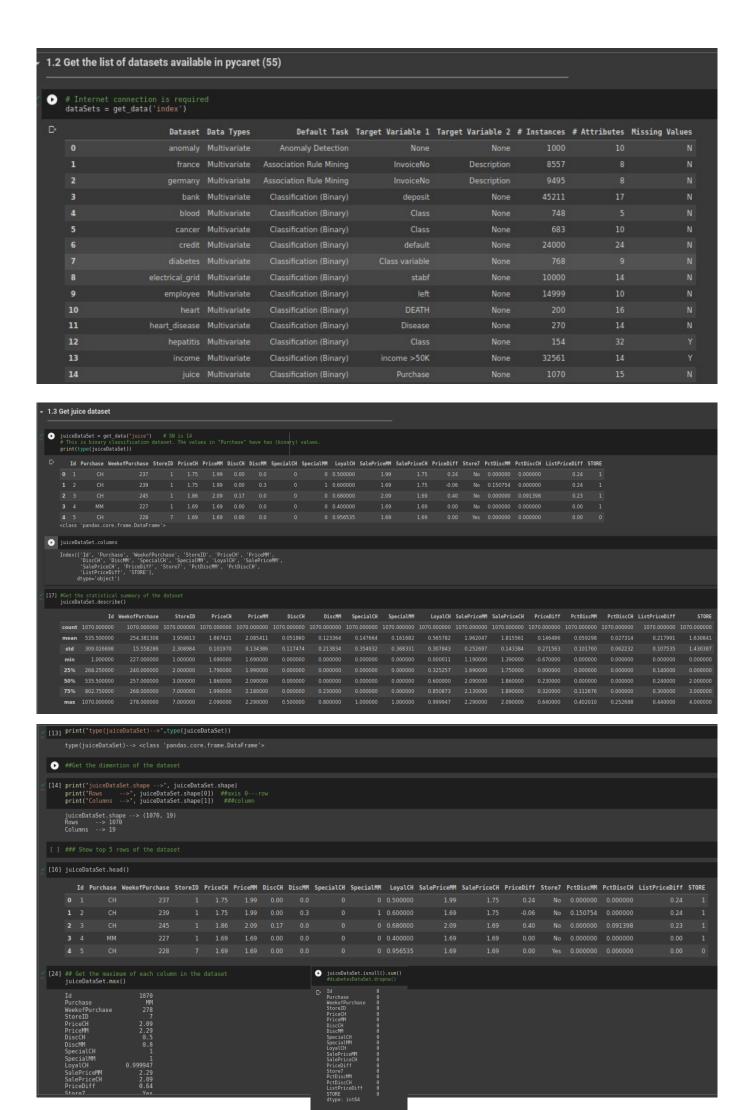
2. **Tool Used:** Google Colaboratory

3. Basic Concept/ Command Description:

- It is a bundle of many Machine Learning algorithms.
- Only three lines of code is required to compare 20 ML models.
- Pycaret is available for:
  - o Classification
  - o Regression
  - o Clustering

## 4. Code:

→ (a) Install Pycaret	
Exclamation sign: It means run it as a shell command rather than a notebook command. This is actually not specific to pip, but really any shell command from the iPython notebook. In computing, a shell is a computer program which exposes an operating system's services to a human user or other program.	
&> <u>/dev/null</u> : <u>/dev/null</u> is the null file. Anything written to it is discarded.	
Together they mean "throw away any error messages".	
Pipi install pycaret &> /dev/null   print ("Pycaret installed sucessfully!!")	
D. Pycaret installed sucessfully!!	
→ (b) Get the version of the pycaret	
[3] ## Utils is a collection of small Python functions and classes which make common patterns shorter and easier. from pycaret.utils import version ()	
'2.3.10'	
- 1. Classification: Basics	
▼ 1.1 Loading Dataset - Loading dataset from pycaret	
<pre>/ [4] from pycaret.datasets import get_data # No output</pre>	
→ 1.2 Get the list of datasets available in pycaret (55)	

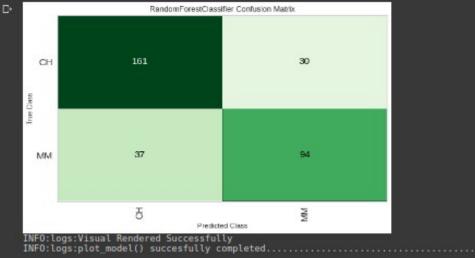


## 3. Classification

If you don't want PyCaret to display the dialogue for confirmation of data types you may pass silent as True within setup to perform a unattended run of experiment.

#### 3.1 Build a single model - "RandomForest"

```
from pycaret.classification import *
#diabetesDataSet = get data("diabetes")
s = setup(data=juiceDataSet, target='Purchase', silent=True)
rfModel = create_model('rf')
plot_model(rfModel, plot='confusion_matrix')
```

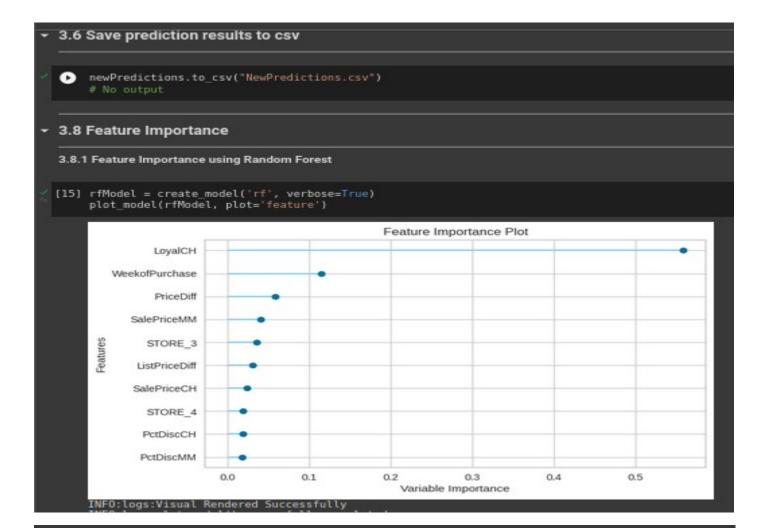


3.3 5	Save	the tra	ined m	nodel																
	sm =	save_mo	del(rfM	lodel, 'rfMode																
			on Pipe	line and Mode		sfully Sa														
3.5 N	Mak	e predi	tion o	n the new da	taset															
Get n	iew	dataset																		
				s from juice ta("juice").i																
		d Purci	ase We	ekofPurchase	StoreID	PriceCH	PriceMM	DiscCH	DiscMM	SpecialCH	SpecialMM	LoyalCH	SalePriceMM	SalePriceCH	PriceDiff	Store7	PctDiscMM	PctDiscCH	ListPriceDiff	STORE
			СН				1.99	0.00				0.500000	1.99	1.75	0.24		0.000000	0.000000	0.24	
			СН			1.75	1.99	0.00	0.3			0.600000	1.69	1.75	-0.06		0.150754	0.000000	0.24	
			СН			1.86		0.17						1.69	0.40			0.091398	0.23	
			ММ			1.69	1.69					0.400000	1.69	1.69			0.000000	0.000000		

#### Make prediction on new dataset

[13] newPredictions = predict\_model(rfModel, data = newDataSet) newPredictions

				cy AUC	Recall P	rec. Fl	Карра	мсс												
Rand	iom Forest	Classifier		0 1.0																
Id	Purchase	WeekofPu	ırchase	StoreID	PriceCH	PriceMM	DiscCH	DiscMM	SpecialCH	SpecialMM	SalePriceMM	SalePriceCH	PriceDiff	Store7	PctDiscMM	PctDiscCH	ListPriceDiff	STORE	Label	Score
					1.75	1.99					1.99		0.24		0.000000	0.000000	0.24		MM	0.63
	СН				1.75	1.99	0.00	0.3			1.69	1.75	-0.06		0.150754	0.000000	0.24		CH	0.90
					1.86		0.17					1.69	0.40			0.091398	0.23			
	MM				1.69	1.69					1.69	1.69			0.000000	0.000000			MM	
					1.69	1.69					1.69	1.69								
					1.69	1.99					1.99	1.69	0.30		0.000000		0.30			0.91
					1.69	1.99		0.4				1.69	-0.10		0.201005		0.30			
	СН				1.75	1.99		0.4			1.59	1.75	-0.16		0.201005	0.000000	0.24		CH	0.73
						1.99		0.4			1.59		-0.16		0.201005		0.24			1.00
	CH				1.75	1.99		0.4			1.59	1.75	-0.16		0.201005	0.000000	0.24		CH	0.99
	× 21 colum																			



#### 1.4 Parameter setting for all classification models

- Train/Test division
- Sampling
- Normalization
- Transformation
- · PCA (Dimention Reduction)
- Handaling of Outliers
- Feature Selection
- from pycaret.classification import \*
  s = setup(data=juiceDataSet, target='Purchase', silent=True)

C+		Description	Value
	0	session_id	2083
	1	Target	Purchase
	2	Target Type	Binary
	3	Label Encoded	CH: 0, MM: 1
	4	Original Data	(1070, 19)
	5	Missing Values	False
	6	Numeric Features	13
	7	Categorical Features	5
	8	Ordinal Features	False
	9	High Cardinality Features	False

#### 1.5 Run and compare the Model Performance



	Model	Accuracy	AUC	Recall	Prec.	F1	Карра	мсс	TT (Sec)
ridge	Ridge Classifier	0.8383	0.0000	0.7908	0.8013	0.7931	0.6608	0.6641	0.026
lda	Linear Discriminant Analysis	0.8343	0.8986	0.7874	0.7949	0.7881	0.6525	0.6560	0.034
Ir	Logistic Regression	0.8302	0.8982	0.7638	0.8005	0.7788	0.6417	0.6452	0.918
gbc	Gradient Boosting Classifier	0.8142	0.8943	0.7570	0.7725	0.7613	0.6097	0.6135	0.255
ada	Ada Boost Classifier	0.8061	0.8802	0.7329	0.7736	0.7483	0.5914	0.5965	0.229
lightgbm	Light Gradient Boosting Machine	0.7981	0.8766	0.7434	0.7503	0.7443	0.5779	0.5807	0.256
rf	Random Forest Classifier	0.7889	0.8701	0.7332	0.7339	0.7316	0.5579	0.5601	0.678
dt	Decision Tree Classifier	0.7781	0.7707	0.7089	0.7335	0.7157	0.5343	0.5395	0.034
nb	Naive Bayes	0.7647	0.8334	0.7634	0.6799	0.7169	0.5172	0.5227	0.027
et	Extra Trees Classifier	0.7608	0.8410	0.7098	0.6929	0.6977	0.5004	0.5048	0.502
knn	K Neighbors Classifier	0.7126	0.7448	0.5933	0.6572	0.6192	0.3899	0.3948	0.157
svm	SVM - Linear Kernel	0.6373	0.0000	0.3336	0.4274	0.3259	0.1787	0.1985	0.033
dummy	Dummy Classifier	0.6056	0.5000	0.0000	0.0000	0.0000	0.0000	0.0000	0.039
qda	Quadratic Discriminant Analysis	0.4854	0.5133	0.6420	0.3666	0.4577	0.0246	0.0220	0.054

# 2. Classification: Advance - 1

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#### 2.1 Model Performance using data "Normalization"

Normalization is a technique often applied as part of data preparation for machine learning. The goal of normalization is to change the values of numeric columns in the dataset to use a common scale, without distorting differences in the ranges of values or losing information.

## Commonly used techniques: clipping, log scaling, z-score, minmax, maxabs, robust
s = setup(data=juiceDataSet, target='Purchase', normalize = True, normalize\_method = 'zscore', silent=True)
cm = compare\_models()

	Model	Accuracy	AUC	Recall	Prec.	F1	Карра	МСС	TT (Sec)
ridge	Ridge Classifier	0.8261	0.0000	0.7557	0.8060	0.7787	0.6358	0.6380	0.018
lda	Linear Discriminant Analysis	0.8221	0.8893	0.7559	0.7967	0.7749	0.6281	0.6296	0.020
lr	Logistic Regression	0.8208	0.8907	0.7491	0.7990	0.7721	0.6248	0.6268	0.054
gbc	Gradient Boosting Classifier	0.8140	0.8902	0.7523	0.7819	0.7648	0.6114	0.6137	0.255
ada	Ada Boost Classifier	0.8020	0.8732	0.7225	0.7772	0.7457	0.5842	0.5883	0.172
rf	Random Forest Classifier	0.7915	0.8707	0.7495	0.7413	0.7436	0.5681	0.5700	0.671
lightgbm	Light Gradient Boosting Machine	0.7913	0.8727	0.7391	0.7520	0.7417	0.5671	0.5712	0.089
knn	K Neighbors Classifier	0.7901	0.8451	0.7066	0.7613	0.7316	0.5599	0.5621	0.147
dt	Decision Tree Classifier	0.7739	0.7711	0.7259	0.7214	0.7226	0.5319	0.5331	0.018
et	Extra Trees Classifier	0.7674	0.8346	0.7133	0.7184	0.7134	0.5179	0.5205	0.599
nb	Naive Bayes	0.7566	0.8290	0.7625	0.6784	0.7168	0.5049	0.5092	0.018
svm	SVM - Linear Kernel	0.7566	0.0000	0.6918	0.7110	0.6860	0.4899	0.5032	0.020
qda	Quadratic Discriminant Analysis	0.6244	0.6128	0.4863	0.4435	0.4405	0.1990	0.2079	0.027
dummy	Dummy Classifier	0.5949	0.5000	0.0000	0.0000	0.0000	0.0000	0.0000	0.023

#### 2.2 Model Performance using "Feature Selection"

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Feature Selection is one of the core concepts in machine learning which hugely impacts the performance of your model. The data features that you use to train your machine learning models have a huge influence on the performance you can achieve. The goal of feature selection in machine learning is to find the best set of features that allows one to build useful models of studied phenomena. Threshold used for feature selection (including newly created polynomial features). A higher value will result in a higher feature space. It is recommended to do multiple trials with different values of feature\_selection\_threshold.

s = setup(data=juiceDataSet, target='Purchase', feature\_selection = True, feature\_selection\_threshold = 0.6, silent=True) cm = compare\_models()

		Model	Accuracy	AUC	Recall	Prec.	F1	Карра	мсс	тτ	(Sec)
	lr	Logistic Regression	0.8274	0.8985	0.7268	0.7955	0.7582	0.6248	0.6274		0.106
ri	idge	Ridge Classifier	0.8234	0.0000	0.7304	0.7863	0.7554	0.6178	0.6205		0.024
	lda	Linear Discriminant Analysis	0.8207	0.8990	0.7339	0.7775	0.7525	0.6126	0.6154		0.022
ē	ada	Ada Boost Classifier	0.8088	0.8878	0.6990	0.7764	0.7325	0.5847	0.5896		0.133
9	gbc	Gradient Boosting Classifier	0.8047	0.8913	0.7339	0.7454	0.7357	0.5814	0.5851		0.142
	rf	Random Forest Classifier	0.7900	0.8641	0.7342	0.7155	0.7224	0.5539	0.5563		0.556
ligh	ntgbm	Light Gradient Boosting Machine	0.7821	0.8724	0.7057	0.7200	0.7087	0.5351	0.5390		0.068
•	qda	Quadratic Discriminant Analysis	0.7807	0.8492	0.8264	0.6734	0.7411	0.5550	0.5647		0.037
	nb	Naive Bayes	0.7754	0.8439	0.7555	0.6850	0.7164	0.5316	0.5358		0.016
	dt	Decision Tree Classifier	0.7742	0.7650	0.6952	0.7134	0.6994	0.5191	0.5236		0.023
	et	Extra Trees Classifier	0.7701	0.8324	0.6956	0.6970	0.6948	0.5105	0.5119		0.476
	knn	K Neighbors Classifier	0.7380	0.7768	0.5691	0.6896	0.6208	0.4239	0.4304		0.136
du	ımmy	Dummy Classifier	0.6217	0.5000	0.0000	0.0000	0.0000	0.0000	0.0000		0.014
s	vm	SVM - Linear Kernel	0.5737	0.0000	0.2000	0.0760	0.1101	0.0000	0.0000		0.026

### 2.3 Model Performance using "Outlier Removal"

Sometimes a dataset can contain extreme values that are outside the range of what is expected and unlike the other data. These are called outliers and often machine learning modeling and model skill in general can be improved by understanding and even removing these outlier values, outliers\_threshold = 0.05 is the default value.

[13] s = setup(data=juiceDataSet, target='Purchase', remove\_outliers = True, outliers| threshold = 0.05, silent=True)
 cm = compare\_models()

	Model	Accuracy	AUC	Recall	Prec.	F1	Карра	МСС	TT (Sec)
ridge	Ridge Classifier	0.8352	0.0000	0.7757	0.8039	0.7875	0.6530	0.6556	0.016
lda	Linear Discriminant Analysis	0.8352	0.9014	0.7793	0.8010	0.7882	0.6534	0.6556	0.022
gbc	Gradient Boosting Classifier	0.8324	0.9044	0.7757	0.7971	0.7846	0.6475	0.6496	0.146
lr	Logistic Regression	0.8268	0.9012	0.7509	0.8014	0.7728	0.6332	0.6367	0.140
lightgbm	Light Gradient Boosting Machine	0.8268	0.8872	0.7687	0.7910	0.7782	0.6361	0.6380	0.098
ada	Ada Boost Classifier	0.8225	0.8881	0.7546	0.7903	0.7697	0.6258	0.6284	0.127
rf	Random Forest Classifier	0.8070	0.8834	0.7405	0.7675	0.7520	0.5942	0.5964	0.528
et	Extra Trees Classifier	0.7803	0.8453	0.7085	0.7318	0.7162	0.5375	0.5411	0.475
dt	Decision Tree Classifier	0.7676	0.7634	0.6911	0.7165	0.7005	0.5112	0.5144	0.047
nb	Naive Bayes	0.7592	0.8388	0.7613	0.6778	0.7132	0.5071	0.5147	0.018
knn	K Neighbors Classifier	0.7183	0.7914	0.5956	0.6611	0.6241	0.4004	0.4034	0.121
dummy	Dummy Classifier	0.6028	0.5000	0.0000	0.0000	0.0000	0.0000	0.0000	0.018
svm	SVM - Linear Kernel	0.5239	0.0000	0.4000	0.1606	0.2291	0.0000	0.0000	0.023
qda	Quadratic Discriminant Analysis	0.4437	0.5222	0.9071	0.4177	0.5657	0.0422	0.0427	0.020

## 2.4 Model Performance using "Transformation"

Data transformation is the process in which you take data from its raw, siloed and normalized source state and transform it into data that's joined together, dimensionally modeled, de-normalized, and ready for analysis

[14] s = setup(data=juiceDataSet, target='Purchase', transformation = True, transformation\_method = 'yeo-johnson', silent=True)
 cm = compare\_models()

	Model	Accuracy	AUC	Recall	Prec.	F1	Карра	мсс	TT (Sec)
lr	Logistic Regression	0.8223	0.8933	0.7659	0.7839	0.7732	0.6273	0.6292	0.034
ridge	Ridge Classifier	0.8089	0.0000	0.7623	0.7606	0.7592	0.6012	0.6036	0.017
lda	Linear Discriminant Analysis	0.8075	0.8922	0.7623	0.7580	0.7579	0.5986	0.6011	0.021
gbc	Gradient Boosting Classifier	0.8022	0.8950	0.7383	0.7615	0.7479	0.5852	0.5873	0.151
ada	Ada Boost Classifier	0.7995	0.8783	0.7141	0.7638	0.7357	0.5747	0.5778	0.131
svm	SVM - Linear Kernel	0.7914	0.0000	0.7420	0.7430	0.7359	0.5647	0.5720	0.022
lightgbm	Light Gradient Boosting Machine	0.7834	0.8756	0.7177	0.7324	0.7234	0.5456	0.5472	0.072
rf	Random Forest Classifier	0.7808	0.8560	0.7216	0.7242	0.7220	0.5413	0.5422	0.516
knn	K Neighbors Classifier	0.7755	0.8399	0.6976	0.7287	0.7102	0.5274	0.5304	0.122
dt	Decision Tree Classifier	0.7688	0.7678	0.7110	0.7066	0.7066	0.5162	0.5182	0.019
et	Extra Trees Classifier	0.7595	0.8171	0.6870	0.6975	0.6906	0.4941	0.4953	0.468
nb	Naive Bayes	0.7527	0.8317	0.7621	0.6691	0.7096	0.4969	0.5031	0.020
qda	Quadratic Discriminant Analysis	0.6954	0.7612	0.7255	0.6275	0.6518	0.3940	0.4027	0.017
dummy	Dummy Classifier	0.6070	0.5000	0.0000	0.0000	0.0000	0.0000	0.0000	0.016

## ▼ 2.5 Model Performance using "PCA"

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An important machine learning method for dimensionality reduction is called Principal Component Analysis. It is a method that uses simple matrix operations from linear algebra and statistics to calculate a projection of the original data into the same number or fewer dimensions.

s = setup(data=juiceDataSet, target='Purchase', pca = True, pca\_method = 'linear', silent=True)
cm = compare\_models()

	Model	Accuracy	AUC	Recall	Prec.	F1	Карра	МСС	TT (Sec)
knn	K Neighbors Classifier	0.6657	0.6808	0.4690	0.5898	0.5183	0.2686	0.2749	0.122
dt	Decision Tree Classifier	0.6629	0.6371	0.5345	0.5702	0.5495	0.2813	0.2832	0.018
rf	Random Forest Classifier	0.6616	0.6922	0.5345	0.5680	0.5483	0.2788	0.2808	0.528
et	Extra Trees Classifier	0.6616	0.6484	0.5345	0.5695	0.5490	0.2792	0.2813	0.470
lightgbm	Light Gradient Boosting Machine	0.6457	0.6455	0.4276	0.5622	0.4807	0.2208	0.2280	0.050
gbc	Gradient Boosting Classifier	0.6430	0.6502	0.3621	0.5676	0.4341	0.1947	0.2083	0.089
ada	Ada Boost Classifier	0.6390	0.6324	0.3379	0.5665	0.4159	0.1800	0.1954	0.109
ridge	Ridge Classifier	0.6136	0.0000	0.0138	0.1400	0.0247	0.0088	0.0216	0.017
dummy	Dummy Classifier	0.6123	0.5000	0.0000	0.0000	0.0000	0.0000	0.0000	0.016
lr	Logistic Regression	0.6056	0.5686	0.0138	0.0900	0.0239	-0.0069	-0.0126	0.038
lda	Linear Discriminant Analysis	0.6043	0.5686	0.0138	0.0833	0.0235	-0.0094	-0.0166	0.016
nb	Naive Bayes	0.6030	0.5672	0.0931	0.4411	0.1499	0.0228	0.0434	0.017
qda	Quadratic Discriminant Analysis	0.6030	0.5672	0.0931	0.4411	0.1499	0.0228	0.0434	0.016
svm	SVM - Linear Kernel	0.5627	0.0000	0.3276	0.3501	0.3291	0.0426	0.0435	0.021

## 2.6 Model Performance using "Outlier Removal" + "Normalization"

[17] s = setup(data=juiceDataSet, target='Purchase', remove\_outliers = True, outliers | threshold = 0.05, normalize = True, normalize\_method = 'zscore', silent=True) cm = compare\_models()

	Model	Accuracy	AUC	Recall	Prec.	F1	Карра	MCC	TT (Sec)
lr	Logistic Regression	0.8169	0.8916	0.7521	0.7757	0.7625	0.6137	0.6152	0.034
ridge	Ridge Classifier	0.8141	0.0000	0.7591	0.7667	0.7616	0.6094	0.6107	0.019
lda	Linear Discriminant Analysis	0.8141	0.8927	0.7591	0.7676	0.7616	0.6094	0.6113	0.022
gbc	Gradient Boosting Classifier	0.8127	0.8801	0.7488	0.7705	0.7561	0.6047	0.6082	0.151
ada	Ada Boost Classifier	0.8014	0.8697	0.7234	0.7604	0.7389	0.5793	0.5819	0.111
rf	Random Forest Classifier	0.7887	0.8491	0.7017	0.7494	0.7185	0.5510	0.5564	0.516
knn	K Neighbors Classifier	0.7817	0.8349	0.6803	0.7464	0.7067	0.5345	0.5398	0.117
lightgbm	Light Gradient Boosting Machine	0.7789	0.8697	0.7093	0.7250	0.7129	0.5339	0.5376	0.066
nb	Naive Bayes	0.7535	0.8243	0.7735	0.6595	0.7106	0.4986	0.5051	0.018
et	Extra Trees Classifier	0.7521	0.8175	0.6660	0.6896	0.6714	0.4745	0.4782	0.523
svm	SVM - Linear Kernel	0.7507	0.0000	0.6827	0.6934	0.6712	0.4737	0.4848	0.017
dt	Decision Tree Classifier	0.7423	0.7324	0.6733	0.6740	0.6700	0.4594	0.4623	0.019
qda	Quadratic Discriminant Analysis	0.6451	0.6828	0.5193	0.5144	0.4745	0.2408	0.2645	0.023
dummy	Dummy Classifier	0.6085	0.5000	0.0000	0.0000	0.0000	0.0000	0.0000	0.019

#### 2.7 Model Performance using "Outlier Removal" + "Normalization" + "Transformation"

[18] s = setup(data=juiceDataSet, target='Purchase', remove\_outliers = True, outliers threshold = 0.05, normalize = True, normalize\_method = 'zscore', transformation = True, transformation\_method = 'yeo-johnson', silent=True)
cm = compare\_models()

	Model	Accuracy	AUC	Recall	Prec.	F1	Карра	MCC	TT (Sec)
lda	Linear Discriminant Analysis	0.8296	0.8940	0.7821	0.7771	0.7773	0.6396	0.6420	
ridge	Ridge Classifier	0.8282	0.0000	0.7784	0.7764	0.7753	0.6364	0.6386	0.041
	Logistic Regression	0.8268	0.8958	0.7525	0.7883	0.7679	0.6300	0.6325	0.034
ada	Ada Boost Classifier	0.8141	0.8852	0.7378	0.7675	0.7504	0.6026	0.6047	0.125
gbc	Gradient Boosting Classifier	0.8085	0.8801	0.7343	0.7586	0.7439	0.5912	0.5936	0.150
knn	K Neighbors Classifier	0.7972	0.8390	0.6971	0.7556	0.7222	0.5633	0.5671	0.120
lightgbm	Light Gradient Boosting Machine	0.7930	0.8575	0.7452	0.7229	0.7324	0.5638	0.5656	0.062
rf	Random Forest Classifier	0.7845	0.8578	0.7011	0.7262	0.7099	0.5392	0.5424	0.518
qda	Quadratic Discriminant Analysis	0.7718	0.8376	0.7602	0.6812	0.7178	0.5275	0.5304	
et	Extra Trees Classifier	0.7690	0.8190	0.6754	0.7095	0.6873	0.5053	0.5099	0.483
nb	Naive Bayes	0.7606	0.8379	0.7452	0.6710	0.7045	0.5048	0.5084	0.017
dt	Decision Tree Classifier	0.7592	0.7454	0.6602	0.6972	0.6743	0.4841	0.4881	0.021
svm	SVM - Linear Kernel	0.7592		0.7597	0.6650	0.6959	0.4998	0.5145	0.022
dummy	Dummy Classifier	0.6183	0.5000	0.0000	0.0000	0.0000	0.0000	0.0000	0.014



# **University Institute of Engineering**

# **Department of Computer Science & Engineering**

# **Evaluation Grid (To be filled by Faculty):**

Sr. No.	Parameters	Marks Obtained	Maximum Marks
1.	Worksheet completion including writinglearning objectives/Outcomes. (To be submitted at the end of the day)		10
2.	Post Lab Quiz Result.		5
3.	Student Engagement in Simulation/Demonstration/Perform ance and Controls/Pre-Lab Questions.	A	5
	Signature of Faculty (with Date):	Total Marks Obtained:	20