dataset = get\_data('credit', profile=True)

```
In [ ]:
         #Data Set Information:
         #This research aimed at the case of customers' default payments in Taiwan a
         #Attribute Information:
         #This research employed a binary variable, default payment (Yes = 1, No = 0),
         #X1: Amount of the given credit (NT dollar): it includes both the individual
         \#X2: Gender (1 = male; 2 = female).
         #X3: Education (1 = graduate school; 2 = university; 3 = high school; 4 = oth
         #X4: Marital status (1 = married; 2 = single; 3 = others).
         #X5: Age (year).
         #X6 - X11: History of past payment. We tracked the past monthly payment record
         #X12-X17: Amount of bill statement (NT dollar). X12 = amount of bill statemen
         #X18-X23: Amount of previous payment (NT dollar). X18 = amount paid in Septem
In [1]:
         import pycaret
         from pycaret.datasets import get data
```

20000	1548	6.5%
30000	1286	5.4%
40000	187	0.8%
50000	2698	11.2%
60000	649	2.7%
70000	588	2.5%
80000	1282	5.3%
90000	512	2.1%

Value	Count	Frequency (%)
1000000	1	< 0.1%
800000	2	< 0.1%
780000	2	< 0.1%
760000	1	< 0.1%
750000	4	< 0.1%
740000	2	< 0.1%
730000	2	< 0.1%
720000	2	< 0.1%
710000	5	< 0.1%
700000	8	< 0.1%

```
In [2]: #check the shape of data
dataset.shape

Out[2]: (24000, 24)

In [3]: data = dataset.sample(frac=0.95, random_state=786)
data_unseen = dataset.drop(data.index)

data.reset_index(inplace=True, drop=True)
data_unseen.reset_index(inplace=True, drop=True)
```

```
print('Data for Modeling: ' + str(data.shape))
         print('Unseen Data For Predictions ' + str(data unseen.shape))
        Data for Modeling: (22800, 24)
        Unseen Data For Predictions (1200, 24)
In [4]:
         from pycaret.classification import *
In [5]:
         exp_clf102 = setup(data = data, target = 'default', session_id=123,
                           normalize = True,
                           transformation = True,
                           ignore low variance = True,
                           remove_multicollinearity = True, multicollinearity_threshole
                           bin_numeric_features = ['LIMIT_BAL', 'AGE'],
                           group features = [['BILL AMT1', 'BILL AMT2', 'BILL AMT3', 'B
                                            ['PAY_AMT1','PAY_AMT2', 'PAY_AMT3', 'PAY_A
                           log_experiment = True, experiment_name = 'credit1')
```

	Description	Value
0	session_id	123
1	Target	default
2	Target Type	Binary
3	Label Encoded	0: 0, 1: 1
4	Original Data	(22800, 24)
5	Missing Values	False
6	Numeric Features	14
7	Categorical Features	9
8	Ordinal Features	False
9	High Cardinality Features	False
10	High Cardinality Method	None
11	Transformed Train Set	(15959, 117)
12	Transformed Test Set	(6841, 117)
13	Shuffle Train-Test	True
14	Stratify Train-Test	False
15	Fold Generator	StratifiedKFold
16	Fold Number	10
17	CPU Jobs	-1
18	Use GPU	False
19	Log Experiment	True
20	Experiment Name	credit1
21	USI	40f5
22	Imputation Type	simple
23	Iterative Imputation Iteration	None
24	Numeric Imputer	mean

	Description	Value
25	Iterative Imputation Numeric Model	None
26	Categorical Imputer	constant
27	Iterative Imputation Categorical Model	None
28	Unknown Categoricals Handling	least_frequent
29	Normalize	True
30	Normalize Method	zscore
31	Transformation	True
32	Transformation Method	yeo-johnson
33	PCA	False
34	PCA Method	None
35	PCA Components	None
36	Ignore Low Variance	True
37	Combine Rare Levels	False
38	Rare Level Threshold	None
39	Numeric Binning	True
40	Remove Outliers	False
41	Outliers Threshold	None
42	Remove Multicollinearity	True
43	Multicollinearity Threshold	0.950000
44	Clustering	False
45	Clustering Iteration	None
46	Polynomial Features	False
47	Polynomial Degree	None
48	Trignometry Features	False
49	Polynomial Threshold	None
50	Group Features	True
51	Feature Selection	False
52	Features Selection Threshold	None
53	Feature Interaction	False
54	Feature Ratio	False
55	Interaction Threshold	None
56	Fix Imbalance	False
57	Fix Imbalance Method	SMOTE

```
In [ ]: top3 = compare_models(n_select = 3)
In [ ]: type(top3)
```

In [12]: print(top3)

[RidgeClassifier(alpha=1.0, class\_weight=None, copy\_X=True, fit\_intercept=True, e,

max\_iter=None, normalize=False, random\_state=123, solver='aut
o',

tol=0.001), LinearDiscriminantAnalysis(n\_components=None, prio
rs=None, shrinkage=None,

In [13]: dt = create\_model('dt', fold = 5)

	Accuracy	AUC	Recall	Prec.	F1	Kappa	мсс
0	0.7284	0.6133	0.4026	0.3844	0.3933	0.2184	0.2185
1	0.7321	0.6182	0.4112	0.3926	0.4017	0.2292	0.2293
2	0.7303	0.6226	0.4269	0.3926	0.4091	0.2347	0.2351
3	0.7356	0.6176	0.4069	0.3978	0.4023	0.2325	0.2326
4	0.7364	0.6151	0.4003	0.3974	0.3989	0.2301	0.2301
Mean	0.7326	0.6173	0.4096	0.3930	0.4010	0.2290	0.2291
SD	0.0031	0.0032	0.0094	0.0048	0.0051	0.0056	0.0057

In [14]: rf = create\_model('rf', round = 2)

	Accuracy	AUC	Recall	Prec.	F1	Kappa	мсс
0	0.81	0.76	0.32	0.61	0.42	0.32	0.34
1	0.82	0.76	0.38	0.66	0.48	0.38	0.41
2	0.82	0.77	0.32	0.67	0.43	0.34	0.38
3	0.82	0.76	0.36	0.65	0.47	0.37	0.39
4	0.82	0.76	0.35	0.66	0.46	0.36	0.39
5	0.83	0.77	0.37	0.69	0.48	0.39	0.41
6	0.82	0.76	0.36	0.66	0.46	0.37	0.39
7	0.82	0.74	0.33	0.69	0.45	0.36	0.39
8	0.81	0.74	0.35	0.62	0.44	0.34	0.36
9	0.82	0.76	0.36	0.65	0.46	0.37	0.39
Mean	0.82	0.76	0.35	0.66	0.46	0.36	0.39
SD	0.01	0.01	0.02	0.03	0.02	0.02	0.02

In [15]: tuned\_rf = tune\_model(rf, optimize = 'AUC')

	Accuracy	AUC	Recall	Prec.	F1	Kappa	МСС
0	0.7513	0.7702	0.6504	0.4522	0.5335	0.3713	0.3827
1	0.7575	0.7687	0.6562	0.4617	0.5420	0.3838	0.3948
2	0.7538	0.7701	0.6447	0.4555	0.5338	0.3732	0.3836
3	0.7393	0.7826	0.6762	0.4378	0.5315	0.3622	0.3786
4	0.7525	0.7948	0.6648	0.4549	0.5402	0.3789	0.3916
5	0.7575	0.7813	0.6590	0.4618	0.5431	0.3849	0.3962
6	0.7262	0.7670	0.6705	0.4209	0.5171	0.3397	0.3577
7	0.7513	0.7500	0.5989	0.4485	0.5129	0.3505	0.3571
8	0.7318	0.7432	0.6246	0.4233	0.5046	0.3300	0.3417
9	0.7254	0.7600	0.6236	0.4141	0.4977	0.3192	0.3318
Mean	0.7447	0.7688	0.6469	0.4431	0.5256	0.3594	0.3716
SD	0.0121	0.0145	0.0231	0.0169	0.0155	0.0222	0.0218

In [39]:

```
tuned_rf2 = tune_model(rf, optimize = 'Recall')
```

	Accuracy	AUC	Recall	Prec.	F1	Карра	мсс
0	0.2187	0.5000	1.0000	0.2187	0.3589	0.0000	0.0000
1	0.2187	0.5000	1.0000	0.2187	0.3589	0.0000	0.0000
2	0.2187	0.5000	1.0000	0.2187	0.3589	0.0000	0.0000
3	0.2187	0.5000	1.0000	0.2187	0.3589	0.0000	0.0000
4	0.2187	0.5000	1.0000	0.2187	0.3589	0.0000	0.0000
5	0.2187	0.5000	1.0000	0.2187	0.3589	0.0000	0.0000
6	0.2187	0.5000	1.0000	0.2187	0.3589	0.0000	0.0000
7	0.2187	0.5000	1.0000	0.2187	0.3589	0.0000	0.0000
8	0.2187	0.5000	1.0000	0.2187	0.3589	0.0000	0.0000
9	0.2182	0.5000	1.0000	0.2182	0.3582	0.0000	0.0000
Mean	0.2186	0.5000	1.0000	0.2186	0.3588	0.0000	0.0000
SD	0.0001	0.0000	0.0000	0.0001	0.0002	0.0000	0.0000

In [16]:

```
plot_model(tuned_rf, plot = 'parameter')
```

## **Parameters**

False	bootstrap
0.0	ccp_alpha
balanced_subsample	class_weight
gini	criterion
4	max_depth
sqrt	max_features

<b>Parameters</b>
-------------------

None	max_leaf_nodes
None	max_samples
0.0005	min_impurity_decrease
None	min_impurity_split
3	min_samples_leaf
5	min_samples_split
0.0	min_weight_fraction_leaf
260	n_estimators
-1	n_jobs
False	oob_score
123	random_state
0	verbose
False	warm_start

In [40]:

plot\_model(tuned\_rf2, plot = 'parameter')

- 1	Pa	ra	m	et	6	rs

bootstrap	False
ccp_alpha	0.0
class_weight	balanced
criterion	gini
max_depth	2
max_features	log2
max_leaf_nodes	None
max_samples	None
min_impurity_decrease	0.1
min_impurity_split	None
min_samples_leaf	3
min_samples_split	5
min_weight_fraction_leaf	0.0
n_estimators	10
n_jobs	-1
oob_score	False
random_state	123
verbose	0
warm_start	False

In [20]

# lets create a simple decision tree model that we will use for ensembling

dt = create\_model('dt')

	Accuracy	AUC	Recall	Prec.	F1	Карра	мсс
0	0.7356	0.6225	0.4183	0.4000	0.4090	0.2388	0.2389
1	0.7393	0.6346	0.4413	0.4107	0.4254	0.2571	0.2574
2	0.7343	0.6120	0.3926	0.3926	0.3926	0.2225	0.2225
3	0.7268	0.6175	0.4212	0.3858	0.4027	0.2261	0.2265
4	0.7393	0.6261	0.4183	0.4067	0.4124	0.2450	0.2450
5	0.7256	0.5987	0.3754	0.3732	0.3743	0.1985	0.1985
6	0.7312	0.6155	0.4126	0.3913	0.4017	0.2285	0.2286
7	0.7431	0.6135	0.3840	0.4073	0.3953	0.2324	0.2325
8	0.7318	0.6204	0.4212	0.3941	0.4072	0.2342	0.2344
9	0.7354	0.6260	0.4339	0.4016	0.4171	0.2463	0.2466
Mean	0.7343	0.6187	0.4119	0.3963	0.4038	0.2329	0.2331
SD	0.0053	0.0093	0.0202	0.0108	0.0135	0.0152	0.0152

In [21]:

bagged\_dt = ensemble\_model(dt)

	Accuracy	AUC	Recall	Prec.	F1	Kappa	мсс
0	0.8064	0.7300	0.3238	0.6075	0.4224	0.3189	0.3417
1	0.8152	0.7289	0.3725	0.6311	0.4685	0.3655	0.3841
2	0.8102	0.7341	0.3209	0.6292	0.4250	0.3254	0.3519
3	0.8095	0.7394	0.3266	0.6230	0.4286	0.3274	0.3520
4	0.8051	0.7262	0.3152	0.6044	0.4143	0.3110	0.3348
5	0.8114	0.7368	0.3524	0.6212	0.4497	0.3462	0.3665
6	0.7964	0.7279	0.3095	0.5625	0.3993	0.2889	0.3076
7	0.8145	0.7235	0.3181	0.6568	0.4286	0.3335	0.3648
8	0.8008	0.7073	0.3095	0.5838	0.4045	0.2982	0.3198
9	0.8144	0.7223	0.3764	0.6238	0.4695	0.3653	0.3824
Mean	0.8084	0.7276	0.3325	0.6143	0.4310	0.3280	0.3506
SD	0.0059	0.0085	0.0240	0.0251	0.0231	0.0244	0.0239

In [22]:

# check the parameters of bagged\_dt
print(bagged\_dt)

e,

min\_impurity\_split=Non

af=0.0,

min\_samples\_leaf=1,
min\_samples\_split=2,
min\_weight\_fraction\_le

presort='deprecated',
random\_state=123,
splitter='best'),

bootstrap=True, bootstrap\_features=False, max\_features=1.0,
max\_samples=1.0, n\_estimators=10, n\_jobs=None,
oob\_score=False, random\_state=123, verbose=0,
warm\_start=False)

In [23]:

boosted\_dt = ensemble\_model(dt, method = 'Boosting')

	Accuracy	AUC	Recall	Prec.	F1	Kappa	мсс
0	0.7563	0.6397	0.3610	0.4315	0.3931	0.2422	0.2437
1	0.7701	0.6684	0.3668	0.4672	0.4109	0.2706	0.2737
2	0.7832	0.6625	0.3123	0.5070	0.3865	0.2638	0.2752
3	0.7694	0.6478	0.2894	0.4570	0.3544	0.2226	0.2312
4	0.7788	0.7193	0.4241	0.4933	0.4561	0.3183	0.3197
5	0.7569	0.6793	0.4011	0.4389	0.4192	0.2658	0.2663
6	0.7732	0.6685	0.3696	0.4760	0.4161	0.2781	0.2816
7	0.7826	0.6933	0.3152	0.5046	0.3880	0.2643	0.2751
8	0.7638	0.6917	0.3524	0.4489	0.3949	0.2507	0.2536
9	0.7925	0.6843	0.3448	0.5381	0.4203	0.3012	0.3123
Mean	0.7727	0.6755	0.3537	0.4762	0.4040	0.2678	0.2732
SD	0.0112	0.0222	0.0388	0.0324	0.0257	0.0261	0.0262

In [24]:

bagged\_dt2 = ensemble\_model(dt, n\_estimators=50)

	Accuracy	AUC	Recall	Prec.	F1	Карра	мсс
0	0.8120	0.7460	0.3496	0.6256	0.4485	0.3460	0.3673
1	0.8195	0.7563	0.3840	0.6473	0.4820	0.3813	0.4004
2	0.8102	0.7550	0.3352	0.6223	0.4358	0.3337	0.3569
3	0.8120	0.7462	0.3467	0.6269	0.4465	0.3444	0.3663
4	0.8189	0.7587	0.3553	0.6596	0.4618	0.3645	0.3898
5	0.8195	0.7638	0.3610	0.6597	0.4667	0.3691	0.3934
6	0.7995	0.7505	0.3295	0.5721	0.4182	0.3075	0.3246
7	0.8214	0.7359	0.3467	0.6798	0.4592	0.3655	0.3952
8	0.8108	0.7445	0.3324	0.6270	0.4345	0.3335	0.3577
9	0.8226	0.7588	0.3879	0.6585	0.4882	0.3895	0.4095
Mean	0.8147	0.7516	0.3528	0.6379	0.4541	0.3535	0.3761
SD	0.0067	0.0080	0.0191	0.0286	0.0207	0.0237	0.0247

In [25]:

# train individual models to blend

```
lightgbm = create model('lightgbm', verbose = False)
          dt = create_model('dt', verbose = False)
          lr = create model('lr', verbose = False)# train individual models to blend
In [26]:
          # blend individual models
          blend soft = blend models(estimator list = [lightgbm, dt, lr], method = 'soft
                           AUC
                                                              MCC
                Accuracy
                                Recall
                                        Prec.
                                                  F1 Kappa
             0
                  0.7776
                         0.7415 0.3868
                                       0.4891 0.4320 0.2960 0.2992
                         0.7477 0.3668
                                       0.5845 0.4507 0.3393 0.3529
                  0.8045
             2
                  0.8033 0.7394 0.3381
                                       0.5871 0.4291 0.3205 0.3383
             3
                  0.7920
                        0.7533 0.3467
                                       0.5378 0.4216
                                                      0.3019
                                                             0.3127
             4
                  0.7976
                         0.7724
                                0.3381
                                       0.5619
                                              0.4222
                                                     0.3086
                                                            0.3232
             5
                  0.7675  0.7464  0.3438  0.4580  0.3928  0.2526
             6
                  0.7726
                        0.7364 0.3754
                                       0.4746
                                              0.4192 0.2802 0.2832
                  7
             8
                  0.7945  0.7368  0.3381  0.5488  0.4184
                                                     0.3021 0.3152
                  0.7981
                         0.7376 0.3678
                                      0.5565 0.4429
                                                     0.3258 0.3363
                  0.7884
                         0.7447
                                0.3537
                                       0.5282
                                              0.4225
                                                      0.2991
          Mean
                                                            0.3088
            SD
                  0.0129
                         0.0107
                                0.0178 0.0452
                                              0.0172 0.0258 0.0296
In [27]:
          # blend individual models
          blend_hard = blend_models(estimator_list = [lightgbm, dt, lr], method = 'hard
                Accuracy
                           AUC
                                Recall
                                        Prec.
                                                  F1
                                                     Kappa
                                                              MCC
             0
                  0.8139 0.0000 0.2980 0.6667
                                              0.4119
                                                     0.3200 0.3567
                  0.8233 0.0000
                                0.3181
                                        0.7161 0.4405 0.3535 0.3947
             2
                  0.8102 0.0000 0.2693 0.6620 0.3829 0.2935 0.3352
             3
                  0.8114 0.0000 0.2779 0.6644
                                              0.3919
                                                      0.3019 0.3422
             4
                  0.8177  0.0000  0.2865  0.7042  0.4073
                                                      0.3215
                                                             0.3671
             5
                  0.8133 0.0000 0.2837
                                       0.6735 0.3992
                                                     0.3097 0.3505
             6
                  0.8158
                        0.0000
                                0.3152 0.6667 0.4280
                                                     0.3346 0.3680
                  0.8108 0.0000 0.2607
                                       0.6741 0.3760 0.2893 0.3349
             8
                  0.8139 0.0000 0.2693
                                       0.6912 0.3876
                                                     0.3020 0.3489
                  0.3164 0.3524
          Mean
                  0.8143 0.0000
                                0.2875
                                       0.6779
                                              0.4034
                                                      0.3143
                                                             0.3551
                  0.0037 0.0000
                                0.0183
                                       0.0183
            SD
                                               0.0191
                                                      0.0185
                                                             0.0171
In [28]:
          # blend top3 models from compare models
          blender top3 = blend models(top3)
                           AUC
                                Recall
                                                              MCC
                Accuracy
                                        Prec.
                                                     Kappa
```

	Accuracy	AUC	Recall	Prec.	F1	Kappa	мсс
0	0.8189	0.0000	0.3582	0.6579	0.4638	0.3661	0.3906
1	0.8315	0.0000	0.3897	0.7083	0.5028	0.4114	0.4381
2	0.8214	0.0000	0.3410	0.6839	0.4551	0.3623	0.3937
3	0.8296	0.0000	0.3754	0.7081	0.4906	0.3997	0.4288
4	0.8221	0.0000	0.3582	0.6757	0.4682	0.3732	0.4003
5	0.8321	0.0000	0.4011	0.7035	0.5109	0.4186	0.4427
6	0.8221	0.0000	0.3610	0.6738	0.4701	0.3747	0.4011
7	0.8277	0.0000	0.3553	0.7126	0.4742	0.3847	0.4180
8	0.8202	0.0000	0.3553	0.6667	0.4636	0.3674	0.3936
9	0.8245	0.0000	0.3793	0.6735	0.4853	0.3893	0.4126
Mean	0.8250	0.0000	0.3674	0.6864	0.4785	0.3847	0.4120
SD	0.0046	0.0000	0.0174	0.0189	0.0174	0.0187	0.0182

In [29]:

print(blender top3.estimators )

[RidgeClassifier(alpha=1.0, class\_weight=None, copy\_X=True, fit\_intercept=True,

max\_iter=None, normalize=False, random\_state=123, solver='aut
o',

tol=0.001), LinearDiscriminantAnalysis(n\_components=None, prio rs=None, shrinkage=None,

In [30]:

stack\_soft = stack\_models(top3)

	Accuracy	AUC	Recall	Prec.	F1	Kappa	мсс
0	0.7870	0.7003	0.0802	0.5957	0.1414	0.0944	0.1589
1	0.7888	0.7038	0.0888	0.6200	0.1554	0.1064	0.1746
2	0.7857	0.6954	0.0860	0.5660	0.1493	0.0972	0.1558
3	0.7838	0.7146	0.0860	0.5357	0.1481	0.0933	0.1463
4	0.7957	0.7281	0.1117	0.7091	0.1931	0.1420	0.2241
5	0.7895	0.7057	0.0831	0.6444	0.1472	0.1024	0.1755
6	0.7926	0.7204	0.0917	0.6957	0.1620	0.1171	0.1988
7	0.7882	0.7138	0.0602	0.6774	0.1105	0.0776	0.1562
8	0.7926	0.7135	0.0946	0.6875	0.1662	0.1197	0.1997
9	0.7875	0.7018	0.0805	0.5957	0.1418	0.0948	0.1593

	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
Mean	0.7891	0.7097	0.0863	0.6327	0.1515	0.1045	0.1749
SD	0.0034	0.0096	0.0123	0.0563	0.0200	0.0170	0.0238

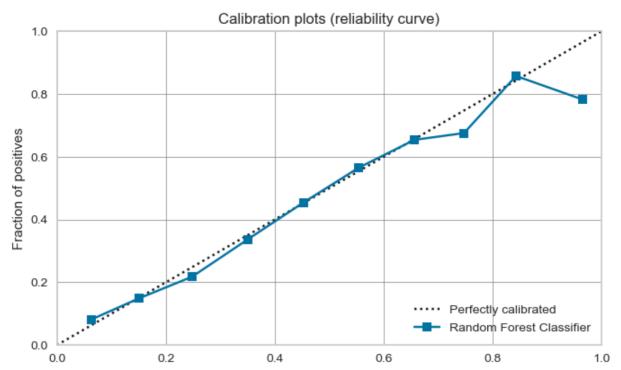
```
In [31]:
    xgboost = create_model('xgboost')
    stack_soft2 = stack_models(top3, meta_model=xgboost)
```

	Accuracy	AUC	Recall	Prec.	F1	Карра	мсс
0	0.8051	0.7575	0.3410	0.5950	0.4335	0.3262	0.3446
1	0.8195	0.7630	0.3926	0.6432	0.4875	0.3857	0.4031
2	0.8177	0.7569	0.3410	0.6611	0.4499	0.3537	0.3816
3	0.8208	0.7722	0.3868	0.6522	0.4856	0.3856	0.4049
4	0.8108	0.7650	0.3524	0.6181	0.4489	0.3449	0.3647
5	0.8152	0.7540	0.3553	0.6392	0.4567	0.3561	0.3784
6	0.8145	0.7554	0.3696	0.6293	0.4657	0.3625	0.3813
7	0.8183	0.7530	0.3295	0.6725	0.4423	0.3486	0.3803
8	0.8114	0.7438	0.3467	0.6237	0.4457	0.3430	0.3645
9	0.8157	0.7358	0.3649	0.6350	0.4635	0.3619	0.3821
Mean	0.8149	0.7557	0.3580	0.6369	0.4579	0.3568	0.3786
SD	0.0045	0.0098	0.0194	0.0212	0.0169	0.0175	0.0169

```
In [32]:
    rf = create_model('rf')
```

	Accuracy	AUC	Recall	Prec.	F1	Карра	мсс
0	0.8070	0.7557	0.3181	0.6133	0.4189	0.3168	0.3414
1	0.8221	0.7599	0.3754	0.6650	0.4799	0.3824	0.4052
2	0.8177	0.7652	0.3209	0.6747	0.4350	0.3422	0.3759
3	0.8189	0.7578	0.3639	0.6546	0.4678	0.3692	0.3923
4	0.8189	0.7572	0.3524	0.6613	0.4598	0.3630	0.3889
5	0.8258	0.7748	0.3668	0.6919	0.4794	0.3864	0.4145
6	0.8189	0.7593	0.3582	0.6579	0.4638	0.3661	0.3906
7	0.8221	0.7438	0.3324	0.6946	0.4496	0.3589	0.3936
8	0.8102	0.7433	0.3467	0.6173	0.4440	0.3403	0.3609
9	0.8188	0.7559	0.3592	0.6545	0.4638	0.3657	0.3896
Mean	0.8180	0.7573	0.3494	0.6585	0.4562	0.3591	0.3853
SD	0.0053	0.0087	0.0186	0.0255	0.0184	0.0198	0.0201

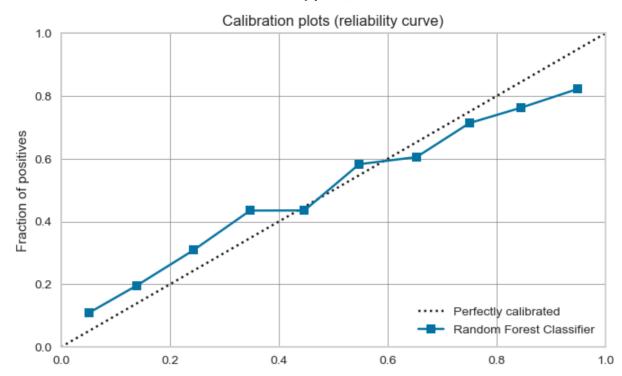
```
In [33]: plot_model(rf, plot='calibration')
```



In [34]: calibrated\_rf = calibrate\_model(rf)

	Accuracy	AUC	Recall	Prec.	F1	Kappa	мсс
0	0.8058	0.7653	0.3009	0.6140	0.4038	0.3037	0.3313
1	0.8315	0.7657	0.3725	0.7222	0.4915	0.4026	0.4343
2	0.8189	0.7693	0.3095	0.6923	0.4277	0.3383	0.3771
3	0.8258	0.7650	0.3668	0.6919	0.4794	0.3864	0.4145
4	0.8170	0.7708	0.3324	0.6629	0.4427	0.3474	0.3771
5	0.8252	0.7759	0.3610	0.6923	0.4746	0.3819	0.4111
6	0.8183	0.7689	0.3295	0.6725	0.4423	0.3486	0.3803
7	0.8271	0.7506	0.3352	0.7267	0.4588	0.3721	0.4117
8	0.8152	0.7524	0.3295	0.6534	0.4381	0.3416	0.3703
9	0.8201	0.7642	0.3420	0.6723	0.4533	0.3590	0.3885
Mean	0.8205	0.7648	0.3379	0.6801	0.4512	0.3582	0.3896
SD	0.0069	0.0074	0.0222	0.0314	0.0248	0.0272	0.0278

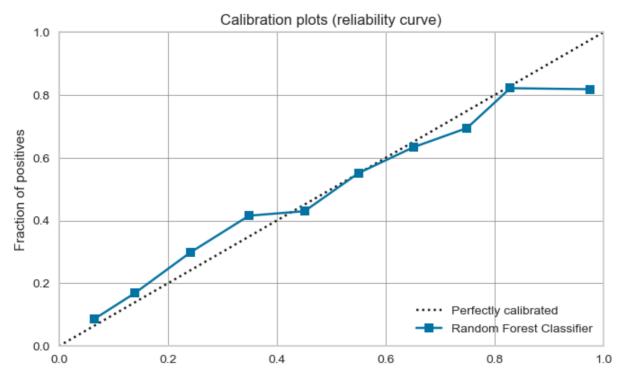
```
In [35]: plot_model(calibrated_rf, plot='calibration')
```



In [36]: calibrated\_rf\_isotonic = calibrate\_model(rf, method = 'isotonic')

	Accuracy	AUC	Recall	Prec.	F1	Kappa	мсс
0	0.8064	0.7634	0.3123	0.6124	0.4137	0.3120	0.3375
1	0.8308	0.7648	0.3983	0.6985	0.5073	0.4143	0.4381
2	0.8202	0.7686	0.3209	0.6914	0.4384	0.3480	0.3844
3	0.8221	0.7623	0.3696	0.6684	0.4760	0.3794	0.4035
4	0.8145	0.7704	0.3266	0.6514	0.4351	0.3385	0.3674
5	0.8289	0.7753	0.3840	0.6979	0.4954	0.4027	0.4288
6	0.8202	0.7688	0.3524	0.6685	0.4615	0.3658	0.3928
7	0.8246	0.7497	0.3496	0.6971	0.4656	0.3743	0.4062
8	0.8133	0.7532	0.3352	0.6393	0.4398	0.3407	0.3663
9	0.8169	0.7626	0.3649	0.6414	0.4652	0.3647	0.3858
Mean	0.8198	0.7639	0.3514	0.6666	0.4598	0.3640	0.3911
SD	0.0070	0.0073	0.0267	0.0285	0.0273	0.0292	0.0285

```
In [37]: plot_model(calibrated_rf_isotonic, plot='calibration')
```



In [ ]:

In [ ]: