```
import pandas as pd
In [1]:
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        %matplotlib inline
```

df = pd.read csv("weatherAUS.csv") In [2]:

df.head() In [3]:

Date Location MinTemp MaxTemp Rainfall Evaporation Sunshine WindGustDir WindGustSpeed WindDir Out[3]: 2008-Albury 13.4 22.9 0.6 NaN NaN W 44.0 12-01 2008-7.4 25.1 0.0 NaN WNW 44.0 Albury NaN 12-02 2008-12.9 25.7 0.0 NaN NaN WSW 46.0 Albury 12-03 2008-9.2 28.0 0.0 NaN NE 24.0 Albury NaN 12-04

1.0

NaN

NaN

W

41.0

5 rows × 23 columns

Albury

2008-

12-05

df.info() In [4]:

> <class 'pandas.core.frame.DataFrame'> RangeIndex: 145460 entries, 0 to 145459 Data columns (total 23 columns):

17.5

32.3

| #    | Column          | Non-Null Count  | Dtype   |
|------|-----------------|-----------------|---------|
|      |                 |                 |         |
| 0    | Date            | 145460 non-null | object  |
| 1    | Location        | 145460 non-null | object  |
| 2    | MinTemp         | 143975 non-null | float64 |
| 3    | MaxTemp         | 144199 non-null | float64 |
| 4    | Rainfall        | 142199 non-null | float64 |
| 5    | Evaporation     | 82670 non-null  | float64 |
| 6    | Sunshine        | 75625 non-null  | float64 |
| 7    | WindGustDir     | 135134 non-null | object  |
| 8    | WindGustSpeed   | 135197 non-null | float64 |
| 9    | WindDir9am      | 134894 non-null | object  |
| 10   | WindDir3pm      | 141232 non-null | object  |
| 11   | WindSpeed9am    | 143693 non-null | float64 |
| 12   | WindSpeed3pm    | 142398 non-null | float64 |
| 13   | Humidity9am     | 142806 non-null | float64 |
| 14   | Humidity3pm     | 140953 non-null | float64 |
| 15   | Pressure9am     | 130395 non-null | float64 |
| 16   | Pressure3pm     | 130432 non-null | float64 |
| 17   | Cloud9am        | 89572 non-null  | float64 |
| 18   | Cloud3pm        | 86102 non-null  | float64 |
| 19   | Temp9am         | 143693 non-null | float64 |
| 20   | Temp3pm         | 141851 non-null | float64 |
| 21   | RainToday       | 142199 non-null | object  |
| 22   | RainTomorrow    | 142193 non-null | object  |
| dtvp | es: float64(16) | , object(7)     |         |

dtypes: float64(16), object(7)

memory usage: 25.5+ MB

df.shape In [5]:

```
Out[5]: (145460, 23)
```

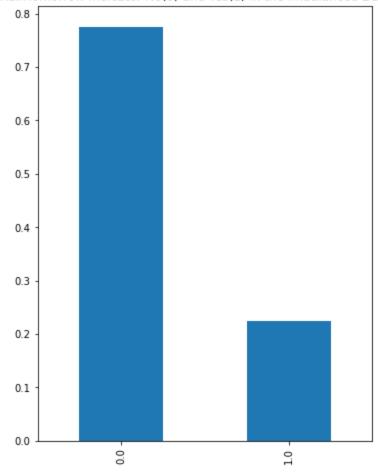
Both "RainToday" and "RainTomorrow" are object (Yes/No). We will convert them into binary (1/0) for our convenience.

```
In [6]: df['RainToday'].replace({'No':0,'Yes':1},inplace=True)
    df['RainTomorrow'].replace({'No':0,'Yes':1},inplace=True)
```

We will check if there is any imblance dataset. If dataset is imbalanced, we need to undersample majority and oversample minority.

```
In [7]: plt.figure(figsize=(6,8))
    df['RainTomorrow'].value_counts(normalize=True).plot(kind='bar')
    plt.title('RainTomorrow Indicator No(0) and Yes(1) in the Imbalanced Dataset')
    plt.show()
```

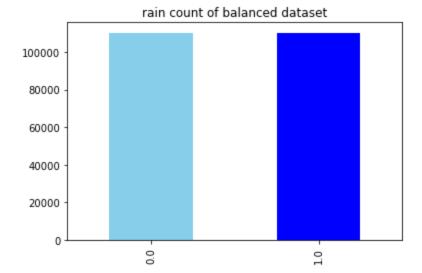
#### RainTomorrow Indicator No(0) and Yes(1) in the Imbalanced Dataset



since the class is imbalance, we need to balance the data by oversampling minority class since the dataset is quite small and undersampling doesn't make any sense here.

```
In [8]: from sklearn.utils import resample
  no = df[df.RainTomorrow==0]
  yes=df[df.RainTomorrow==1]
  yes_oversampled = resample(yes,replace=True,n_samples=len(no),random_state=123)
  oversampled = pd.concat([no,yes_oversampled])
```

```
In [9]: oversampled.RainTomorrow.value_counts().plot(kind='bar',color=['skyblue','blue'])
   plt.title('rain count of balanced dataset')
   plt.show()
```

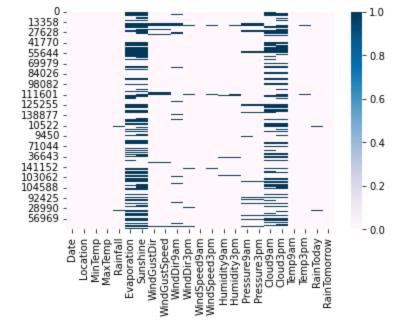


### Handling missing values

```
null values=oversampled.isnull().sum(axis=0)
In [10]:
        null values
        Date
                              0
Out[10]:
        Location
                              0
        MinTemp
                           1082
        MaxTemp
                            471
        Rainfall
                           3124
        Evaporation
                         95411
        Sunshine
                         104831
        WindGustDir
                         15491
        WindGustSpeed
                          15354
        WindDir9am
                         14728
        WindDir3pm
                           6440
        WindSpeed9am
                          2206
        WindSpeed3pm
                           4353
        Humidity9am
                           3171
        Humidity3pm
                           6031
        Pressure9am
                          21728
        Pressure3pm
                          21746
        Cloud9am
                          81339
        Cloud3pm
                          85614
        Temp9am
                          1653
        Temp3pm
                           4558
        RainToday
                           3124
                              0
        RainTomorrow
        dtype: int64
```

```
In [11]: sns.heatmap(oversampled.isnull(),cmap='PuBu')
```

Out[11]: <AxesSubplot:>



from the above heatmap we can say that Evaporation, Sunshine, Cloud 9 am, Cloud 3 pm are having majority missing values

```
In [12]: total = oversampled.isnull().sum().sort_values(ascending=False)
    percent = (oversampled.isnull().sum()/oversampled.isnull().count()).sort_values(ascendin missing = pd.concat([total,percent],axis=1,keys=['Total','Percent'])
    missing.head()
```

| Out[12]: |             | Total  | Percent  |
|----------|-------------|--------|----------|
|          | Sunshine    | 104831 | 0.475140 |
|          | Evaporation | 95411  | 0.432444 |
|          | Cloud3pm    | 85614  | 0.388040 |
|          | Cloud9am    | 81339  | 0.368664 |
|          | Pressure3pm | 21746  | 0.098562 |

we observe that top 4 features are having >50% missing values. so, instead of discarding them we will consider then in our model with proper imputation

## Imputation and transformation

we will impute categorical values with the help of mode and then with the help of label encoder we will convert them into numerical values. Once the full dataframe's values are converted into numerical, we will handle the missing values with the help of MICE. Then we will detect the outliers with the help of IQR and remove them to get the final working dataset. Then we will check the correlation of features and if any of the 2 features are highly correlated, we will remove one of the features.

```
In [13]: oversampled.select_dtypes(include=['object']).columns
Out[13]: Index(['Date', 'Location', 'WindGustDir', 'WindDir9am', 'WindDir3pm'], dtype='object')
In [14]: oversampled['WindGustDir']=oversampled['WindGustDir'].fillna(oversampled['WindDir9am'].mod oversampled['WindDir3pm']=oversampled['WindDir3pm'].fillna(oversampled['WindDir3pm'].mod oversampled['WindDir3pm']=oversampled['WindDir3pm'].fillna(oversampled['WindDir3pm'].mod
```

```
In [15]: from sklearn.preprocessing import LabelEncoder
        lencoders = {}
        for col in oversampled.select dtypes(include=['object']).columns:
            lencoders[col] = LabelEncoder()
            oversampled[col] = lencoders[col].fit transform(oversampled[col])
        from sklearn.experimental import enable iterative imputer
In [16]:
        from sklearn.impute import IterativeImputer
        MiceImputed = oversampled.copy(deep=True)
        mice imputer = IterativeImputer()
        MiceImputed.iloc[:, :] = mice_imputer.fit transform(oversampled)
        C:\Users\LENOVO\anaconda3\lib\site-packages\sklearn\impute\ iterative.py:699: Convergenc
        eWarning: [IterativeImputer] Early stopping criterion not reached.
         warnings.warn(
In [20]: MiceImputed.isna().sum(axis=0)
                         0
        Date
Out[20]:
        Location
        MinTemp
                        Ω
        MaxTemp
        Rainfall
                       0
        Evaporation
        Sunshine
        WindGustDir 0
        WindGustSpeed 0
        WindDir9am
                       0
        WindDir3pm
        WindSpeed9am 0
        WindSpeed3pm
        Humidity9am
                         0
        Humidity3pm
        Pressure9am
        Pressure3pm
        Cloud9am
                       0
        Cloud3pm
                        0
                       0
        Temp9am
        Temp3pm
                       0
        RainToday
                        0
        RainTomorrow
        dtype: int64
In [21]: MiceImputed.shape
        (220632, 23)
Out[21]:
In [22]: Q1 = MiceImputed.quantile(0.25)
        Q3 = MiceImputed.quantile(0.75)
        IQR = Q3 - Q1
        print(IQR)
                       1535.000000
        Date
        Location
                       25.000000
        MinTemp
                          9.300000
        MaxTemp
Rainfall
Evaporation
                         10.200000
                          2.400000
                          4.120044
        Sunshine
                           5.979485
        WindGustDir 9.000000
WindGustSpeed 19.000000
        WindDir9am
                          8.000000
                           8.000000
        WindDir3pm
        WindSpeed9am 13.000000
```

```
Humidity3pm 30.0000000
Pressure9am 8.800000
Pressure3pm 8.800000
Cloud9am 4.000000
Cloud3pm 3.684676
Temp9am 9.300000
RainToday 1.000000
RainToday 1.000000
RainTomorrow 1.000000
dtype: float64

In [23]: MiceImputed = MiceImputed[~((MiceImputed < (Q1 - 1.5 * IQR)) | (MiceImputed > (Q3 + 1.5 * MiceImputed.shape)
```

The dataset is free of outliers now. We will check for the multicollinearity i.e., whether the features are correlated with each other

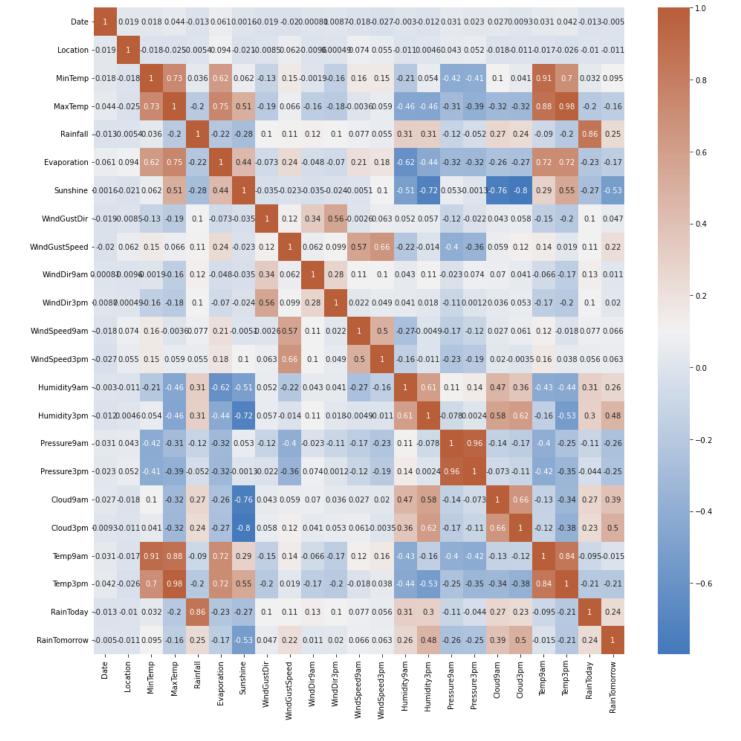
```
In [24]: plt.figure(figsize=(16,16))
    cmap = sns.diverging_palette(250, 25, as_cmap=True)
    sns.heatmap(MiceImputed.corr(),cmap= cmap,annot=True)
```

Out[24]: <AxesSubplot:>

WindSpeed3pm 11.000000

26.000000

Humidity9am



The following pairs of features are having high correlation between them: MaxTemp and MinTemp, Pressure9am and Pressure3pm, Temp9am and Temp3pm, Evaporation and MaxTemp MaxTemp and Temp3pm But in no case, the correlation value is equal to a perfect "1". So we are not discarding any feature.

## **Feature Selection**

Feature selection by filter method (Chi-Square method): before doing feature selection we need to standardize our data. we are using MinMaxScaler instead of StandardScaler.

| Out[25]: |   | Date     | Location | MinTemp  | MaxTemp  | Rainfall | Evaporation | Sunshine | WindGustDir | WindGustSpeed | Win |
|----------|---|----------|----------|----------|----------|----------|-------------|----------|-------------|---------------|-----|
|          | 0 | 0.115284 | 0.041667 | 0.543417 | 0.514778 | 0.437385 | 0.569756    | 0.512042 | 0.866667    | 0.521127      |     |
|          | 1 | 0.115575 | 0.041667 | 0.375350 | 0.568966 | 0.374872 | 0.563868    | 0.745836 | 0.933333    | 0.521127      |     |
|          | 2 | 0.115866 | 0.041667 | 0.529412 | 0.583744 | 0.374872 | 0.695026    | 0.793365 | 1.000000    | 0.549296      |     |
|          | 3 | 0.116157 | 0.041667 | 0.425770 | 0.640394 | 0.374872 | 0.584743    | 0.762539 | 0.266667    | 0.239437      |     |
|          | 4 | 0.116448 | 0.041667 | 0.658263 | 0.746305 | 0.479060 | 0.638825    | 0.413485 | 0.866667    | 0.478873      |     |

5 rows × 23 columns

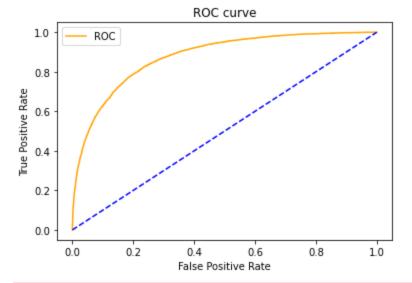
```
In [26]: from sklearn.feature selection import SelectKBest, chi2
         X = modified data.drop('RainTomorrow', axis=1)
         y = modified data['RainTomorrow']
         selector = SelectKBest(chi2, k=10)
         selector.fit(X,y)
         X new = selector.transform(X)
         print(X.columns[selector.get support(indices=True)])
         Index(['Rainfall', 'Sunshine', 'WindGustSpeed', 'Humidity9am', 'Humidity3pm',
                'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm', 'RainToday'],
              dtype='object')
        from sklearn.feature selection import SelectFromModel
In [27]:
         from sklearn.ensemble import RandomForestClassifier as rf
         X = modified data.drop('RainTomorrow', axis=1)
         y = modified data['RainTomorrow']
         selector = SelectFromModel(rf(n estimators=100, random state=0))
         selector.fit(X,y)
         support = selector.get support()
         features = X.loc[:,support].columns.tolist()
         print(features)
         print(rf(n estimators=100,random state=0).fit(X,y).feature importances )
         ['Sunshine', 'Humidity3pm', 'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm']
         [0.03251436 0.02889938 0.03316543 0.03250381 0.02138441 0.03312043
         0.13821858 0.02075391 0.04266396 0.02135522 0.02173827 0.02171846
         0.02339726 0.03437621 0.10775466 0.04842712 0.06112705 0.05757376
```

0.13952883 0.03151427 0.03611667 0.01214795]

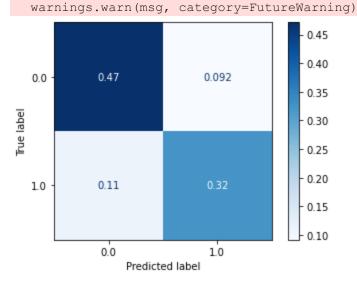
As explained by the dataset creator Joe Young, "RISKMM is the amount of rainfall in millimeters for the next day. It includes all forms of precipitation that reach the ground, such as rain, drizzle, hail and snow. And it was the column that was used to actually determine whether or not it rained to create the binary target. Since it contains information directly about the target variable, including it would leak the future information to our model" (Quoted from his comment). So "RISK\_MM" is excluded from the model. "Date" is also excluded from the model for the obvious reason since it is not adding any relevance in the current context.

```
In [29]: def plot roc curve(fper, tper):
            plt.plot(fper, tper, color='orange', label='ROC')
            plt.plot([0,1],[0,1],color='blue',linestyle='--')
            plt.xlabel('False Positive Rate')
            plt.ylabel('True Positive Rate')
            plt.title('ROC curve')
            plt.legend()
            plt.show()
In [31]: | import time
         from sklearn.metrics import accuracy score, roc auc score, cohen kappa score, plot confus
         def run model (model, X train, y train, X test, y test, verbose=True):
            t0=time.time()
            if verbose == False:
                model.fit(X train, y train, verbose = 0)
            else:
                model.fit(X train, y train)
            y pred = model.predict(X test)
            accuracy = accuracy score(y test, y pred)
            roc auc = roc auc score(y test, y pred)
            cohen kappa = cohen kappa score(y test, y pred)
            time taken = time.time()-t0
            print('Accuracy = {}'.format(accuracy))
            print('ROC area under curve = {}'.format(roc auc))
            print("Cohen's kappa = {}".format(cohen kappa))
            print('Time Taken = {}'.format(time taken))
            print(classification report(y test, y pred, digits=5))
            probs = model.predict proba(X test)
            probs = probs[:,1]
            fper, tper, thresholds = roc curve(y test, probs)
            plot roc curve(fper, tper)
            plot confusion matrix(model, X test,y test,cmap=plt.cm.Blues,normalize='all')
             return model, accuracy, roc auc, cohen kappa, time taken
In [32]: from sklearn.linear model import LogisticRegression
         params = {'penalty':'ll','solver':'liblinear'}
         model lr = LogisticRegression(**params)
        model lr,accuracy lr,roc auc lr,cohen lr,tt lr = run model (model lr, X train, y train, X t
        Accuracy = 0.7946704790475297
        ROC area under curve = 0.7885215334971366
        Cohen's kappa = 0.5803443732086091
        Time Taken = 3.77791166305542
                      precision recall f1-score support
                 0.0
                       0.80555 0.83738 0.82116
                                                        24019
                       0.77932 0.73966 0.75898
                 1.0
                                                        18649
                                            0.79467
                                                       42668
            accuracy
                       0.79244 0.78852 0.79007
                                                       42668
           macro avg
                       0.79409 0.79467 0.79398
                                                        42668
        weighted avg
```

X\_train = ss.fit\_transform(X\_train)
X test = ss.fit transform(X test)



C:\Users\LENOVO\anaconda3\lib\site-packages\sklearn\utils\deprecation.py:87: FutureWarning: Function plot\_confusion\_matrix is deprecated; Function `plot\_confusion\_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one of the class methods: ConfusionMatrixDisplay.from\_predictions or ConfusionMatrixDisplay.from\_estimator.



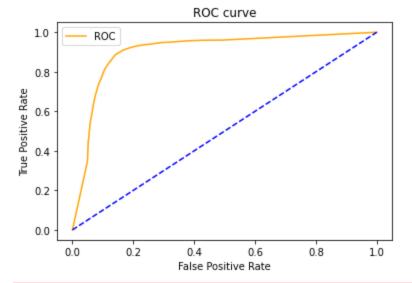
```
In [35]: from sklearn.tree import DecisionTreeClassifier
    params_dt = {'max_depth':16,'max_features':'sqrt'}
    model_dt = DecisionTreeClassifier(**params_dt)
    model_dt,accuracy_dt,roc_auc_dt,cohen_dt,tt_dt = run_model(model_dt,X_train,y_train,X_te)
```

Accuracy = 0.8703712383988 ROC area under curve = 0.8718125330521544

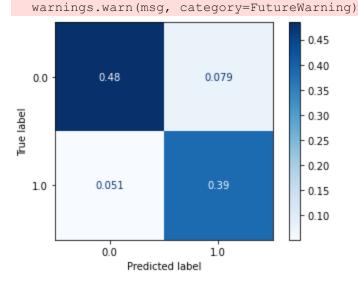
Cohen's kappa = 0.7384153864477985

Time Taken = 1.0401108264923096

|              | precision | recall             | f1-score           | support        |
|--------------|-----------|--------------------|--------------------|----------------|
| 0.0          | 0.90469   | 0.86036<br>0.88326 | 0.88197<br>0.85624 | 24019<br>18649 |
| accuracy     |           |                    | 0.87037            | 42668          |
| macro avg    | 0.86776   | 0.87181            | 0.86911            | 42668          |
| weighted avg | 0.87241   | 0.87037            | 0.87073            | 42668          |
|              |           |                    |                    |                |



C:\Users\LENOVO\anaconda3\lib\site-packages\sklearn\utils\deprecation.py:87: FutureWarning: Function plot\_confusion\_matrix is deprecated; Function `plot\_confusion\_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one of the class methods: ConfusionMatrixDisplay.from\_predictions or ConfusionMatrixDisplay.from\_estimator.



In [36]: from sklearn.neural\_network import MLPClassifier
 param\_nn = {'hidden\_layer\_sizes':(30,30,30),'activation':'logistic','solver':'lbfgs','ma
 model\_nn = MLPClassifier(\*\*param\_nn)
 model\_nn,accuracy\_nn, roc\_auc\_nn,cohen\_nn,tt\_nn = run\_model(model\_nn,X\_train,y\_train,X\_t

C:\Users\LENOVO\anaconda3\lib\site-packages\sklearn\neural\_network\\_multilayer\_perceptro
n.py:549: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max\_iter) or scale the data as shown in:
 https://scikit-learn.org/stable/modules/preprocessing.html
 self.n iter = check optimize result("lbfgs", opt res, self.max iter)

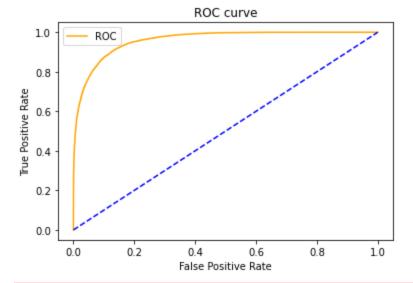
Accuracy = 0.8879253773319584

ROC area under curve = 0.8863973245875149

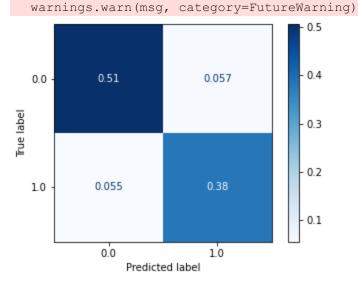
Cohen's kappa = 0.772368711242617

Time Taken = 427.7600727081299

| support                 | f1-score                      | recall             | precision          |                                       |
|-------------------------|-------------------------------|--------------------|--------------------|---------------------------------------|
| 24019<br>18649          | 0.90026<br>0.87210            | 0.89854<br>0.87426 | 0.90199<br>0.86996 | 0.0                                   |
| 42668<br>42668<br>42668 | 0.88793<br>0.88618<br>0.88796 | 0.88640<br>0.88793 | 0.88598<br>0.88799 | accuracy<br>macro avg<br>weighted avg |



C:\Users\LENOVO\anaconda3\lib\site-packages\sklearn\utils\deprecation.py:87: FutureWarning: Function plot\_confusion\_matrix is deprecated; Function `plot\_confusion\_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one of the class methods: ConfusionMatrixDisplay.from\_predictions or ConfusionMatrixDisplay.from\_estimator.



In [37]: from sklearn.ensemble import RandomForestClassifier
 params\_rf = { 'max\_depth':16, 'min\_samples\_leaf':1, 'min\_samples\_split':2, 'n\_estimators':1
 model\_rf = RandomForestClassifier(\*\*params\_rf)
 model\_rf,accuracy\_rf,roc\_auc\_rf,cohen\_rf,tt\_rf = run\_model(model\_rf,X\_train,y\_train,X\_te)

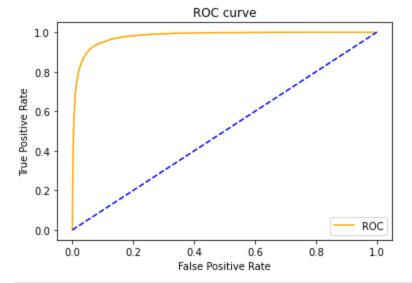
Accuracy = 0.9268069747820381

ROC area under curve = 0.9282394576222613

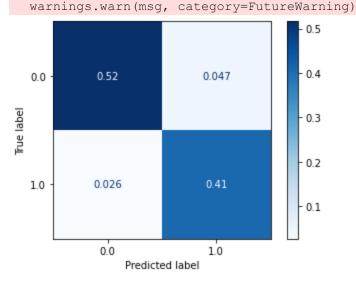
Cohen's kappa = 0.8520304817099031

Time Taken = 61.85880899429321

|                                       | precision          | recall             | f1-score                      | support                 |
|---------------------------------------|--------------------|--------------------|-------------------------------|-------------------------|
| 0.0                                   | 0.95136<br>0.89769 | 0.91686<br>0.93962 | 0.93379<br>0.91818            | 24019<br>18649          |
| accuracy<br>macro avg<br>weighted avg | 0.92453<br>0.92790 | 0.92824<br>0.92681 | 0.92681<br>0.92598<br>0.92697 | 42668<br>42668<br>42668 |



C:\Users\LENOVO\anaconda3\lib\site-packages\sklearn\utils\deprecation.py:87: FutureWarning: Function plot\_confusion\_matrix is deprecated; Function `plot\_confusion\_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one of the class methods: ConfusionMatrixDisplay.from\_predictions or ConfusionMatrixDisplay.from\_estimator.



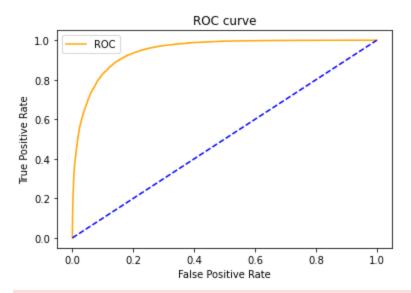
accuracy

```
In [44]:
         import lightgbm as lgb
         params lgb = { 'colsample bytree':0.95, 'max depth':16, 'min split gain':0.1, 'n estimators'
                       'reg alpha':1.2,'reg lambda':1.2,'subsample':0.95,'subsample freq':20}
         model lgb = lgb.LGBMClassifier(**params lgb)
        model lgb,accuracy lgb,roc auc lgb,cohen lgb,tt lgb = run model (model lgb,X train,y trai
         [LightGBM] [Info] Number of positive: 56370, number of negative: 71631
         [LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.
        029003 seconds.
        You can set `force col_wise=true` to remove the overhead.
         [LightGBM] [Info] Total Bins 4587
         [LightGBM] [Info] Number of data points in the train set: 128001, number of used feature
        s: 22
         [LightGBM] [Info] [binary:BoostFromScore]: pavg=0.440387 -> initscore=-0.239591
         [LightGBM] [Info] Start training from score -0.239591
        Accuracy = 0.8700665604199869
        ROC area under curve = 0.8675377644832898
        Cohen's kappa = 0.7357193999930121
        Time Taken = 8.545675039291382
                       precision
                                    recall f1-score
                                                        support
                  0.0
                         0.88227
                                   0.88763
                                             0.88494
                                                          24019
                  1.0
                         0.85413
                                   0.84744
                                             0.85078
                                                          18649
```

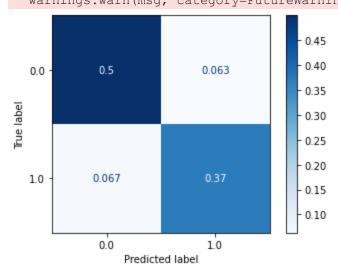
0.87007

42668

macro avg 0.86820 0.86754 0.86786 42668 weighted avg 0.86997 0.87007 0.87001 42668



C:\Users\LENOVO\anaconda3\lib\site-packages\sklearn\utils\deprecation.py:87: FutureWarni
ng: Function plot\_confusion\_matrix is deprecated; Function `plot\_confusion\_matrix` is de
precated in 1.0 and will be removed in 1.2. Use one of the class methods: ConfusionMatri
xDisplay.from\_predictions or ConfusionMatrixDisplay.from\_estimator.
 warnings.warn(msg, category=FutureWarning)



### In [48]: pip install --upgrade pip

Requirement already satisfied: pip in c:\users\lenovo\anaconda3\lib\site-packages (23.2. 1)

Note: you may need to restart the kernel to use updated packages.

### In [41]: pip install lightgbm

Collecting lightgbm

Obtaining dependency information for lightgbm from https://files.pythonhosted.org/packages/b3/f8/ee33e36194eb03a76eccf3adac3fba51f0e56fbd20609bb531659d48d3cb/lightgbm-4.1.0-py3-none-win amd64.whl.metadata

Downloading lightgbm-4.1.0-py3-none-win amd64.whl.metadata (19 kB)

Requirement already satisfied: numpy in c:\users\lenovo\anaconda3\lib\site-packages (fro m lightgbm) (1.21.5)

Requirement already satisfied: scipy in c:\users\lenovo\anaconda3\lib\site-packages (fro m lightgbm) (1.7.3)

Downloading lightgbm-4.1.0-py3-none-win amd64.whl (1.3 MB)

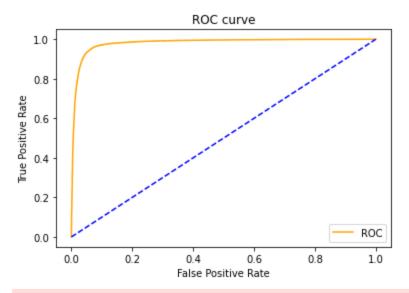
----- 1.3/1.3 MB 6.9 MB/s eta 0:00:00

Installing collected packages: lightgbm Successfully installed lightgbm-4.1.0

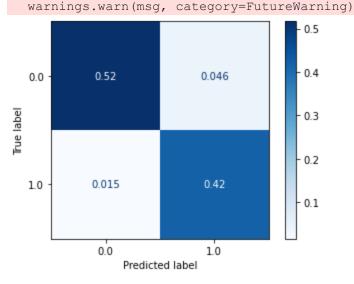
Note: you may need to restart the kernel to use updated packages.

```
import catboost as cb
In [50]:
        params cb = {'iterations':50,'max depth':16}
        model cb = cb.CatBoostClassifier(**params cb)
        model cb,accuracy cb,roc auc cb,cohen cb,tt cb = run model (model cb, X train, y train, X te
        Learning rate set to 0.5
           learn: 0.4472116
                                     total: 15.6s
                                                     remaining: 12m 44s
        1:
               learn: 0.3574969
                                     total: 31s
                                                    remaining: 12m 24s
               learn: 0.3141450
                                    total: 47.4s
                                                   remaining: 12m 23s
                                    total: 1m 4s remaining: 12m 16s
        3:
              learn: 0.2722785
               learn: 0.2531531
                                    total: 1m 19s remaining: 11m 53s
                                    total: 1m 34s remaining: 11m 34s
        5:
              learn: 0.2268741
              learn: 0.2144528
                                    total: 1m 50s remaining: 11m 19s
        7:
                                     total: 2m 6s
              learn: 0.1976329
                                                    remaining: 11m 1s
               learn: 0.1841044
                                    total: 2m 23s remaining: 10m 51s
        9:
              learn: 0.1698949
                                    total: 2m 40s remaining: 10m 42s
        10:
              learn: 0.1601591
                                    total: 2m 56s remaining: 10m 24s
                                    total: 3m 11s remaining: 10m 6s
        11:
              learn: 0.1465690
              learn: 0.1306025
                                    total: 3m 26s remaining: 9m 48s
        12:
        13:
              learn: 0.1222357
                                    total: 3m 42s remaining: 9m 31s
                                    total: 3m 57s remaining: 9m 14s
        14:
              learn: 0.1142074
                                    total: 4m 12s
        15:
               learn: 0.1064090
                                                   remaining: 8m 56s
        16:
              learn: 0.0999262
                                    total: 4m 28s remaining: 8m 40s
                                    total: 4m 43s remaining: 8m 24s
        17:
              learn: 0.0936589
              learn: 0.0889488
                                    total: 5m
                                                    remaining: 8m 10s
        18:
        19:
               learn: 0.0853652
                                    total: 5m 17s
                                                   remaining: 7m 56s
              learn: 0.0795958
                                    total: 5m 33s remaining: 7m 41s
        20:
        21:
              learn: 0.0750938
                                    total: 5m 49s remaining: 7m 25s
              learn: 0.0698156
                                    total: 6m 6s
        22:
                                                    remaining: 7m 9s
              learn: 0.0648131
                                    total: 6m 22s remaining: 6m 53s
        23:
        24:
              learn: 0.0612370
                                    total: 6m 37s remaining: 6m 37s
                                    total: 6m 53s remaining: 6m 21s
        25:
              learn: 0.0578781
                                    total: 7m 9s
        26:
               learn: 0.0542923
                                                    remaining: 6m 5s
        27:
              learn: 0.0521816
                                    total: 7m 25s remaining: 5m 49s
              learn: 0.0494492
                                    total: 7m 41s remaining: 5m 34s
        28:
              learn: 0.0480432
                                    total: 7m 57s remaining: 5m 18s
        29:
        30:
               learn: 0.0451091
                                    total: 8m 13s remaining: 5m 2s
        31:
              learn: 0.0422153
                                    total: 8m 28s remaining: 4m 46s
        32:
              learn: 0.0403113
                                    total: 8m 45s remaining: 4m 30s
                                    total: 9m 3s
              learn: 0.0374490
        33:
                                                    remaining: 4m 15s
              learn: 0.0361466
                                    total: 9m 19s remaining: 3m 59s
        34:
        35:
              learn: 0.0349447
                                    total: 9m 35s remaining: 3m 43s
                                    total: 9m 52s remaining: 3m 28s
        36:
              learn: 0.0332030
        37:
               learn: 0.0318026
                                    total: 10m 8s
                                                   remaining: 3m 12s
                                   total: 10m 24s remaining: 2m 56s
        38:
              learn: 0.0302421
                                    total: 10m 40s remaining: 2m 40s
        39:
              learn: 0.0287733
                                    total: 10m 56s remaining: 2m 24s total: 11m 13s remaining: 2m 8s
              learn: 0.0277999
        40:
        41:
               learn: 0.0271262
                                    total: 11m 29s remaining: 1m 52s
        42:
              learn: 0.0261170
        43:
              learn: 0.0250922
                                    total: 11m 45s remaining: 1m 36s
        44:
              learn: 0.0241705
                                    total: 12m 3s remaining: 1m 20s
              learn: 0.0235713
                                    total: 12m 23s remaining: 1m 4s
        45:
              learn: 0.0227772
                                    total: 12m 39s remaining: 48.5s
        47:
              learn: 0.0221359
                                     total: 12m 56s remaining: 32.4s
               learn: 0.0211556
                                     total: 13m 13s remaining: 16.2s
                                    total: 13m 30s remaining: 0us
        49:
               learn: 0.0204431
        Accuracy = 0.9384784850473423
        ROC area under curve = 0.9414235413765718
        Cohen's kappa = 0.8759529549980067
        Time Taken = 796.8755328655243
                     precision recall f1-score
                                                  support
                0.0
                       0.97111 0.91802 0.94382
                                                     24019
                       0.90136 0.96482 0.93201
                                                    18649
            accuracy
                                          0.93848
                                                    42668
```

macro avg 0.93624 0.94142 0.93792 42668 weighted avg 0.94062 0.93848 0.93866 42668



C:\Users\LENOVO\anaconda3\lib\site-packages\sklearn\utils\deprecation.py:87: FutureWarning: Function plot\_confusion\_matrix is deprecated; Function `plot\_confusion\_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one of the class methods: ConfusionMatrixDisplay.from\_predictions or ConfusionMatrixDisplay.from\_estimator.



In [49]: !pip install catboost

Collecting catboost

Obtaining dependency information for catboost from https://files.pythonhosted.org/packages/0c/cd/a05bbb220e9b45b4cadcb22d5e801aeece7b301f5775d78e13972d0f60cf/catboost-1.2.2-cp39-cp39-win amd64.whl.metadata

Using cached catboost-1.2.2-cp39-cp39-win amd64.whl.metadata (1.2 kB)

Requirement already satisfied: graphviz in c:\users\lenovo\anaconda3\lib\site-packages (from catboost) (0.20.1)

Requirement already satisfied: matplotlib in c:\users\lenovo\anaconda3\lib\site-packages (from catboost) (3.5.1)

Requirement already satisfied: numpy>=1.16.0 in c:\users\lenovo\anaconda3\lib\site-packa ges (from catboost) (1.21.5)

Requirement already satisfied: pandas>=0.24 in c:\users\lenovo\anaconda3\lib\site-packag es (from catboost) (1.4.2)

Requirement already satisfied: scipy in c:\users\lenovo\anaconda3\lib\site-packages (fro m catboost) (1.7.3)

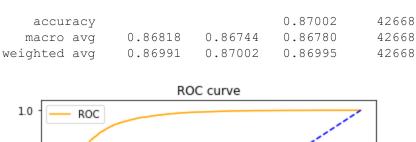
Requirement already satisfied: plotly in c:\users\lenovo\anaconda3\lib\site-packages (from catboost) (5.6.0)

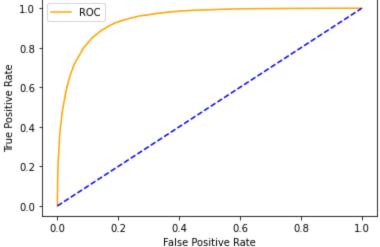
Requirement already satisfied: six in c:\users\lenovo\anaconda3\lib\site-packages (from catboost) (1.16.0)

Requirement already satisfied: python-dateutil>=2.8.1 in c:\users\lenovo\anaconda3\lib\s

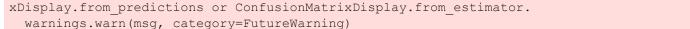
```
Requirement already satisfied: pytz>=2020.1 in c:\users\lenovo\anaconda3\lib\site-packag
        es (from pandas>=0.24->catboost) (2021.3)
        Requirement already satisfied: cycler>=0.10 in c:\users\lenovo\anaconda3\lib\site-packag
        es (from matplotlib->catboost) (0.11.0)
        Requirement already satisfied: fonttools>=4.22.0 in c:\users\lenovo\anaconda3\lib\site-p
        ackages (from matplotlib->catboost) (4.25.0)
        Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\lenovo\anaconda3\lib\site-p
        ackages (from matplotlib->catboost) (1.3.2)
        Requirement already satisfied: packaging>=20.0 in c:\users\lenovo\anaconda3\lib\site-pac
        kages (from matplotlib->catboost) (21.3)
        Requirement already satisfied: pillow>=6.2.0 in c:\users\lenovo\anaconda3\lib\site-packa
        ges (from matplotlib->catboost) (9.0.1)
        Requirement already satisfied: pyparsing>=2.2.1 in c:\users\lenovo\anaconda3\lib\site-pa
        ckages (from matplotlib->catboost) (3.0.4)
        Requirement already satisfied: tenacity>=6.2.0 in c:\users\lenovo\anaconda3\lib\site-pac
        kages (from plotly->catboost) (8.0.1)
        Downloading catboost-1.2.2-cp39-cp39-win amd64.whl (101.0 MB)
           ----- 101.0/101.0 MB 6.0 MB/s eta 0:00:00
        Installing collected packages: catboost
        Successfully installed catboost-1.2.2
In [51]:
        import xgboost as xgb
        params xgb = {'n estimators':500,'mx depth':16}
        model xgb = xgb.XGBClassifier(**params)
        model xgb,accuracy xgb,roc auc xgb,cohen xgb,tt xgb = run model (model xgb,X train,y trai
        [23:37:32] WARNING: C:\Users\dev-admin\croot2\xgboost-split 1675461376218\work\src\learn
        er.cc:767:
        Parameters: { "penalty", "solver" } are not used.
        Accuracy = 0.8700196868847848
```

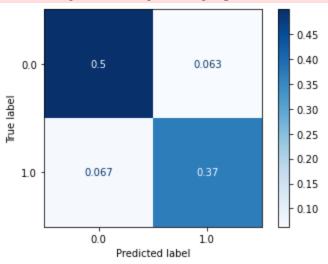
ite-packages (from pandas>=0.24->catboost) (2.8.2)





C:\Users\LENOVO\anaconda3\lib\site-packages\sklearn\utils\deprecation.py:87: FutureWarning: Function plot\_confusion\_matrix is deprecated; Function `plot\_confusion\_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one of the class methods: ConfusionMatri

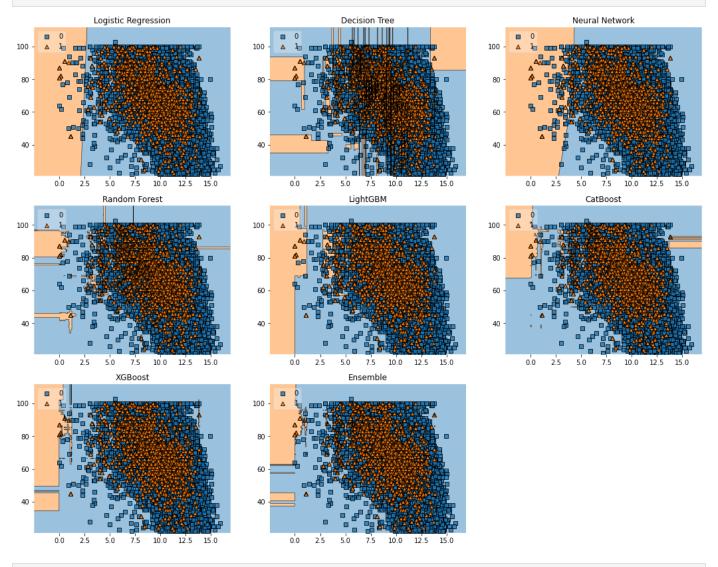




# Plotting Decision Tree for all models

```
import matplotlib.gridspec as gridspec
In [61]:
         import itertools
         from mlxtend.classifier import EnsembleVoteClassifier
         from mlxtend.plotting import plot decision regions
         value = 1.80
         width = 0.90
         clf1 = LogisticRegression(random state=12345)
         clf2 = DecisionTreeClassifier(random state=12345)
         clf3 = MLPClassifier(random state=12345, verbose=0)
         clf4 = RandomForestClassifier(random state=12345)
         clf5 = lgb.LGBMClassifier(random state=12345, verbose=0)
         clf6 = cb.CatBoostClassifier(random state=12345, verbose=0)
         clf7 = xgb.XGBClassifier(random state=12345)
         eclf = EnsembleVoteClassifier(clfs=[clf4,clf5,clf6,clf7],weights=[1,1,1,1],voting='soft'
        X list = MiceImputed[["Sunshine", "Humidity9am", "Cloud3pm"]]
         X = np.asarray(X list, dtype=np.float32)
         y list = MiceImputed["RainTomorrow"]
         y = np.asarray(y list, dtype=np.int32)
         # Plotting Decision Regions
         gs = gridspec.GridSpec(3,3)
         fig = plt.figure(figsize=(18, 14))
         labels = ['Logistic Regression',
                   'Decision Tree',
                   'Neural Network',
                   'Random Forest',
                   'LightGBM',
                   'CatBoost',
                   'XGBoost',
                   'Ensemble']
         for clf, lab, grd in zip([clf1, clf2, clf3, clf4, clf5, clf6, clf7, eclf],
                                   labels,
                                  itertools.product([0, 1, 2],
                                  repeat=2)):
             clf.fit(X, y)
             ax = plt.subplot(gs[grd[0], grd[1]])
             fig = plot decision regions (X=X, y=y, clf=clf,
                                          filler feature values={2: value},
```

plt.title(lab)



In [54]: !pip install mlxtend

Collecting mlxtend

Obtaining dependency information for mlxtend from https://files.pythonhosted.org/packages/73/da/d5d77a9a7a135c948dbf8d3b873655b105a152d69e590150c83d23c3d070/mlxtend-0.23.0-py3-none-any.whl.metadata

Downloading mlxtend-0.23.0-py3-none-any.whl.metadata (7.3 kB)

Requirement already satisfied: scipy>=1.2.1 in c:\users\lenovo\anaconda3\lib\site-packag es (from mlxtend) (1.7.3)

Requirement already satisfied: numpy>=1.16.2 in c:\users\lenovo\anaconda3\lib\site-packa ges (from mlxtend) (1.21.5)

Requirement already satisfied: pandas>=0.24.2 in c:\users\lenovo\anaconda3\lib\site-pack ages (from mlxtend) (1.4.2)

Requirement already satisfied: scikit-learn>=1.0.2 in c:\users\lenovo\anaconda3\lib\site -packages (from mlxtend) (1.0.2)

Requirement already satisfied: matplotlib>=3.0.0 in c:\users\lenovo\anaconda3\lib\site-p ackages (from mlxtend) (3.5.1)

Requirement already satisfied: joblib>=0.13.2 in c:\users\lenovo\anaconda3\lib\site-pack ages (from mlxtend) (1.2.0)

Requirement already satisfied: cycler>=0.10 in c:\users\lenovo\anaconda3\lib\site-packag es (from matplotlib>=3.0.0->mlxtend) (0.11.0)

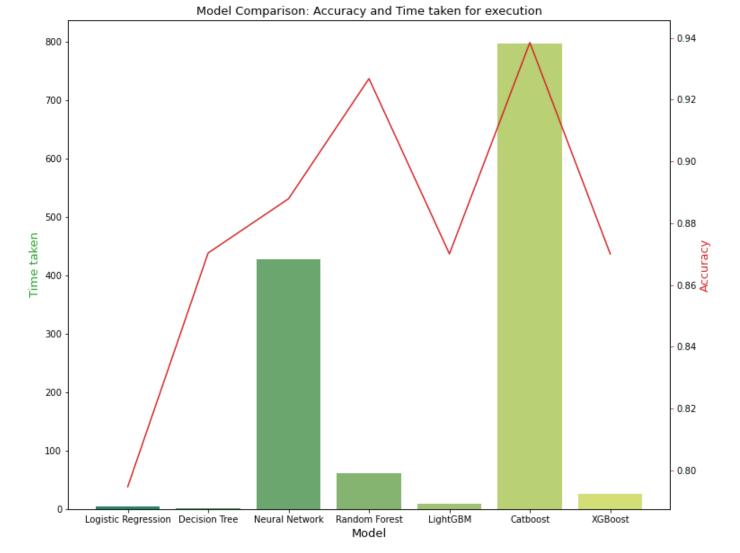
Requirement already satisfied: fonttools>=4.22.0 in c:\users\lenovo\anaconda3\lib\site-p ackages (from matplotlib>=3.0.0->mlxtend) (4.25.0)

Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\lenovo\anaconda3\lib\site-p ackages (from matplotlib>=3.0.0->mlxtend) (1.3.2)

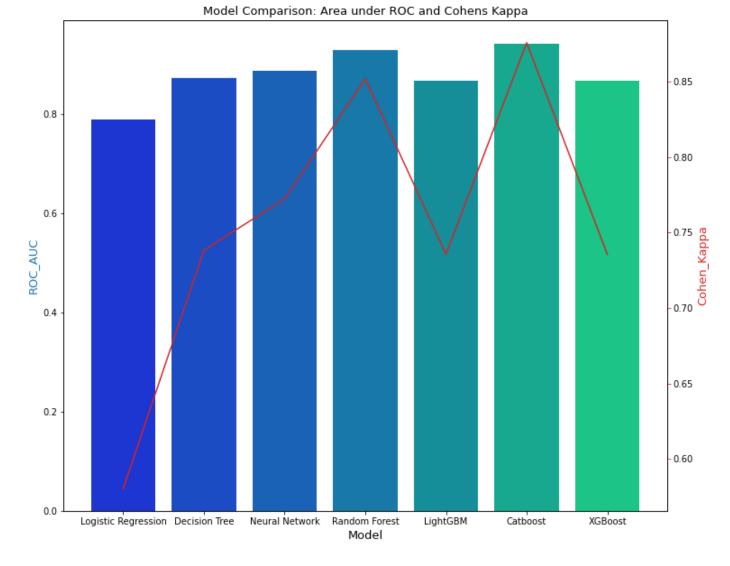
Requirement already satisfied: packaging>=20.0 in c:\users\lenovo\anaconda3\lib\site-pac

```
kages (from matplotlib>=3.0.0->mlxtend) (21.3)
Requirement already satisfied: pillow>=6.2.0 in c:\users\lenovo\anaconda3\lib\site-packa
ges (from matplotlib>=3.0.0->mlxtend) (9.0.1)
Requirement already satisfied: pyparsing>=2.2.1 in c:\users\lenovo\anaconda3\lib\site-pa
ckages (from matplotlib>=3.0.0->mlxtend) (3.0.4)
Requirement already satisfied: python-dateutil>=2.7 in c:\users\lenovo\anaconda3\lib\sit
e-packages (from matplotlib>=3.0.0->mlxtend) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in c:\users\lenovo\anaconda3\lib\site-packag
es (from pandas\geq=0.24.2\rightarrowmlxtend) (2021.3)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\lenovo\anaconda3\lib\sit
e-packages (from scikit-learn>=1.0.2->mlxtend) (2.2.0)
Requirement already satisfied: six>=1.5 in c:\users\lenovo\anaconda3\lib\site-packages
(from python-dateutil>=2.7->matplotlib>=3.0.0->mlxtend) (1.16.0)
Downloading mlxtend-0.23.0-py3-none-any.whl (1.4 MB)
  ------ 1.4/1.4 MB 8.4 MB/s eta 0:00:00
Installing collected packages: mlxtend
Successfully installed mlxtend-0.23.0
```

```
In [63]: accuracy scores = [accuracy lr, accuracy dt, accuracy nn, accuracy rf, accuracy lgb, acc
         roc auc scores = [roc auc lr, roc auc dt, roc auc nn, roc auc rf, roc auc lgb, roc auc c
         coh kap scores = [cohen lr, cohen dt, cohen nn, cohen rf, cohen lgb, cohen cb, cohen xgb
         tt = [tt lr, tt dt, tt nn, tt rf, tt lgb, tt cb, tt xgb]
         model data = {'Model': ['Logistic Regression','Decision Tree','Neural Network','Random F
                       'Accuracy': accuracy scores,
                       'ROC AUC': roc auc scores,
                       'Cohen Kappa': coh kap scores,
                       'Time taken': tt}
         data = pd.DataFrame(model data)
         fig, ax1 = plt.subplots(figsize=(12,10))
         ax1.set title('Model Comparison: Accuracy and Time taken for execution', fontsize=13)
         color = 'tab:green'
         ax1.set xlabel('Model', fontsize=13)
         ax1.set ylabel('Time taken', fontsize=13, color=color)
         ax2 = sns.barplot(x='Model', y='Time taken', data = data, palette='summer')
         ax1.tick params(axis='y')
         ax2 = ax1.twinx()
         color = 'tab:red'
         ax2.set ylabel('Accuracy', fontsize=13, color=color)
         ax2 = sns.lineplot(x='Model', y='Accuracy', data = data, sort=False, color=color)
         ax2.tick params(axis='y', color=color)
```



```
In [64]:
    fig, ax3 = plt.subplots(figsize=(12,10))
        ax3.set_title('Model Comparison: Area under ROC and Cohens Kappa', fontsize=13)
        color = 'tab:blue'
        ax3.set_xlabel('Model', fontsize=13)
        ax3.set_ylabel('ROC_AUC', fontsize=13, color=color)
        ax4 = sns.barplot(x='Model', y='ROC_AUC', data = data, palette='winter')
        ax3.tick_params(axis='y')
        ax4 = ax3.twinx()
        color = 'tab:red'
        ax4.set_ylabel('Cohen_Kappa', fontsize=13, color=color)
        ax4 = sns.lineplot(x='Model', y='Cohen_Kappa', data = data, sort=False, color=color)
        ax4.tick_params(axis='y', color=color)
        plt.show()
```



We can observe that XGBoost, CatBoost and Random Forest have performed better compared to other models. However, if speed is an important thing to consider, we can stick to Random Forest instead of XGBoost or CatBoost.