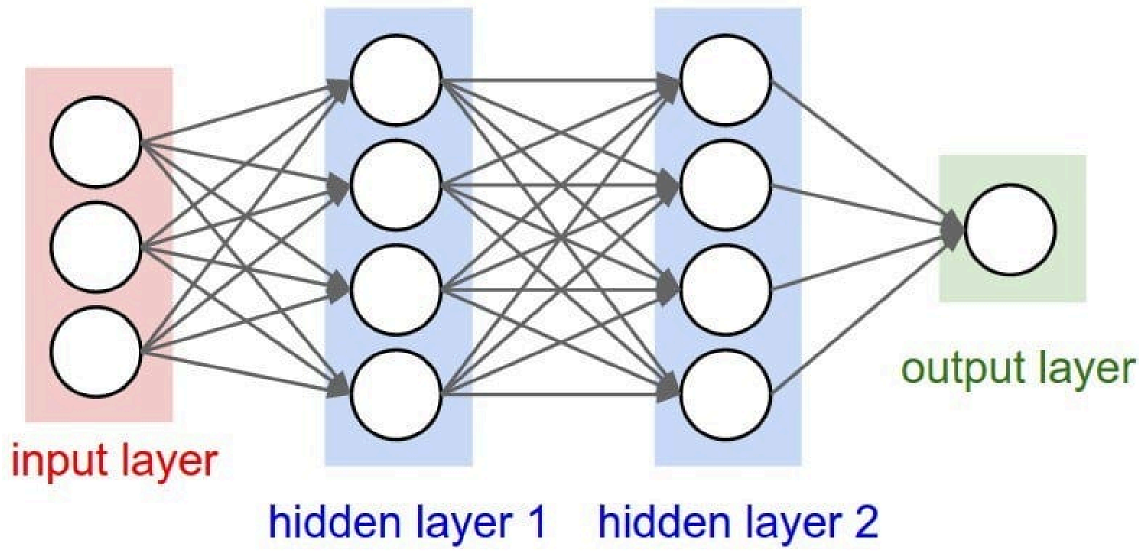
Rain Prediction Project: Artificial Neural Networks ANN

Deep Learning Based Project



What are ANNs?

Artificial neural networks are one of the main tools used in machine learning. As the “neural” part of their name suggests, they are brain-inspired systems which are intended to replicate the way that we humans learn. Neural networks consist of input and output layers, as well as (in most cases) a hidden layer consisting of units that transform the input into something that the output layer can use. ANNs have three layers that are interconnected. The first layer consists of input neurons. Those neurons send data on to the second layer, which in turn sends the output neurons to the third layer. ANNs are considered non-linear statistical data modeling tools where the complex relationships between inputs and outputs are modeled or patterns are found. Note that a neuron can also be referred to as a perceptron.

Artificial Neural Network (ANN):

ANN is a basic form of neural network where neurons are arranged in layers, typically including an input layer, one or more hidden layers, and an output layer. Each neuron in one layer is connected to every neuron in the next layer, and each connection has a weight associated with it. ANN is suitable for a wide range of tasks, including regression, classification, and pattern recognition. However, ANN may struggle with processing data like images where spatial relationships are important due to its fully connected nature.

Convolutional Neural Network (CNN):

CNN is a specialized type of neural network designed specifically for processing grid-like data, such as images. It utilizes convolutional layers to automatically and adaptively learn spatial hierarchies of features from the input data. CNNs are composed of multiple layers, including convolutional layers, pooling layers, and fully connected layers. CNNs excel at tasks involving image recognition, object detection, and image classification due to their ability to capture spatial patterns and relationships efficiently.

In summary, while both ANN and CNN are neural network architectures, CNNs are particularly well-suited for tasks involving image data due to their ability to extract and learn hierarchical features effectively, whereas ANNs are more general-purpose and can be

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In [49]:

```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import sklearn
from sklearn.metrics import classification_report
from sklearn import metrics
from sklearn import tree
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from keras.utils import to_categorical
from keras.models import Sequential
from keras.layers import Dense,BatchNormalization,Dropout,LSTM
from sklearn.metrics import confusion_matrix, accuracy_score,
classification_report, f1_score, precision_score, recall_score
from keras.optimizers import Adam

from keras.callbacks import EarlyStopping
from keras import callbacks
from keras.callbacks import ModelCheckpoint
from keras.models import load_model
import tensorflow as tf


import warnings
warnings.filterwarnings('ignore')
```

In [ ]:

```
# from google.colab import files
# files.upload()

#others
# from google.colab import drive
# drive.mount('')
```

In [2]:

```
data=pd.read_csv('weatherData.csv')
data.head()
```

Out[2]:

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	Wind
0	2008-12-01	Albury	13.4	22.9	0.6	NaN	NaN	W	
1	2008-12-02	Albury	7.4	25.1	0.0	NaN	NaN	WNW	
2	2008-12-03	Albury	12.9	25.7	0.0	NaN	NaN	WSW	
3	2008-12-04	Albury	9.2	28.0	0.0	NaN	NaN	NE	
4	2008-12-05	Albury	17.5	32.3	1.0	NaN	NaN	W	

5 rows × 24 columns

In [3]:
```
data.info()
```

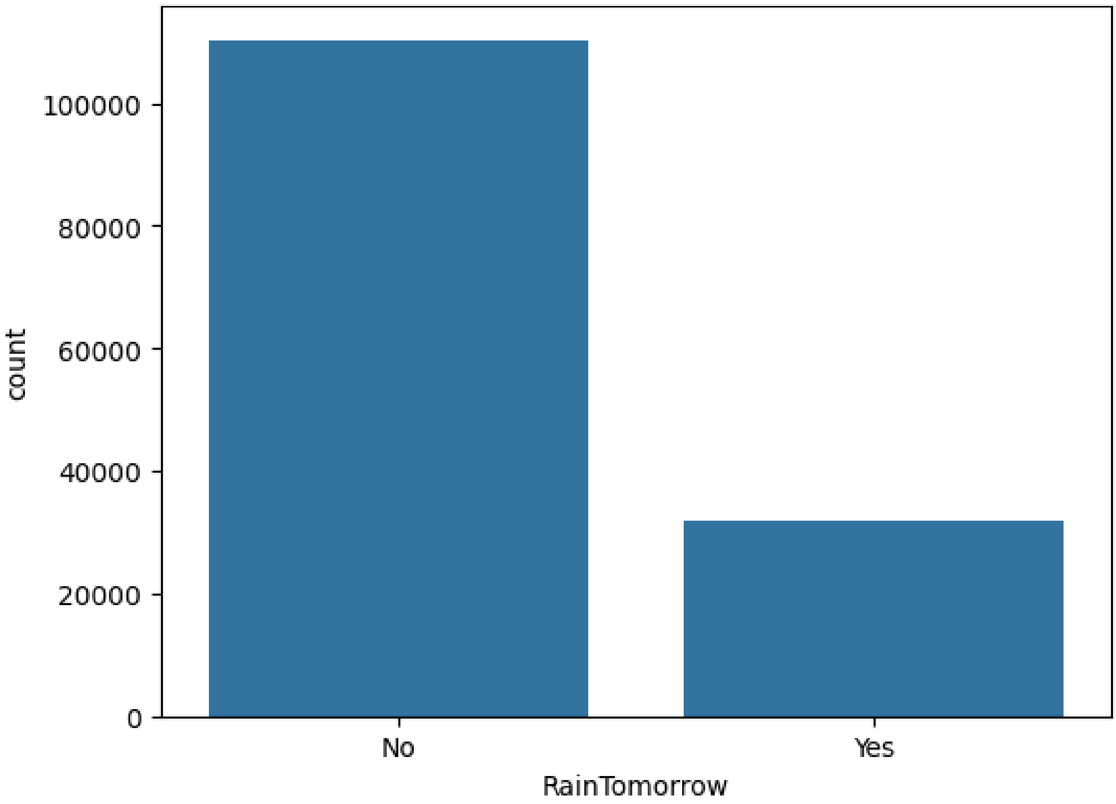
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 142193 entries, 0 to 142192
Data columns (total 24 columns):
 #   Column         Non-Null Count   Dtype  
---  ------         --------------   -----  
 0   Date           142193 non-null  object 
 1   Location       142193 non-null  object 
 2   MinTemp        141556 non-null  float64
 3   MaxTemp        141871 non-null  float64
 4   Rainfall       140787 non-null  float64
 5   Evaporation    81350 non-null   float64
 6   Sunshine       74377 non-null   float64
 7   WindGustDir    132863 non-null  object 
 8   WindGustSpeed  132923 non-null  float64
 9   WindDir9am     132180 non-null  object 
 10  WindDir3pm     138415 non-null  object 
 11  WindSpeed9am   140845 non-null  float64
 12  WindSpeed3pm   139563 non-null  float64
 13  Humidity9am    140419 non-null  float64
 14  Humidity3pm    138583 non-null  float64
 15  Pressure9am    128179 non-null  float64
 16  Pressure3pm    128212 non-null  float64
 17  Cloud9am       88536 non-null   float64
 18  Cloud3pm       85099 non-null   float64
 19  Temp9am        141289 non-null  float64
 20  Temp3pm        139467 non-null  float64
 21  RainToday      140787 non-null  object 
 22  RISK_MM        142193 non-null  float64
 23  RainTomorrow   142193 non-null  object 
dtypes: float64(17), object(7)
memory usage: 26.0+ MB
```

In [4]:
```
data.columns
```

Out[4]:
```
Index(['Date', 'Location', 'MinTemp', 'MaxTemp', 'Rainfall', 'Evaporatio
n',
       'Sunshine', 'WindGustDir', 'WindGustSpeed', 'WindDir9am', 'WindDir3
pm',
       'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am', 'Humidity3pm',
       'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm', 'Temp9am',
       'Temp3pm', 'RainToday', 'RISK_MM', 'RainTomorrow'],
      dtype='object')
```

In [5]:
```
sns.countplot(x=data['RainTomorrow'])
```

Out[5]: <Axes: xlabel='RainTomorrow', ylabel='count'>



In [6]:
```
float_columns=data.select_dtypes(include=['float64'])
print(float_columns.columns)
```

```
Index(['MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine',
       'WindGustSpeed', 'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am',
       'Humidity3pm', 'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3p
m',
       'Temp9am', 'Temp3pm', 'RISK_MM'],
      dtype='object')
```

In [7]:
```
data2=float_columns
data2.dtypes
```

Out[7]:

	0
MinTemp	float64
MaxTemp	float64
Rainfall	float64
Evaporation	float64
Sunshine	float64
WindGustSpeed	float64
WindSpeed9am	float64
WindSpeed3pm	float64
Humidity9am	float64
Humidity3pm	float64
Pressure9am	float64
Pressure3pm	float64
Cloud9am	float64
Cloud3pm	float64
Temp9am	float64
Temp3pm	float64
RISK_MM	float64

dtype: object

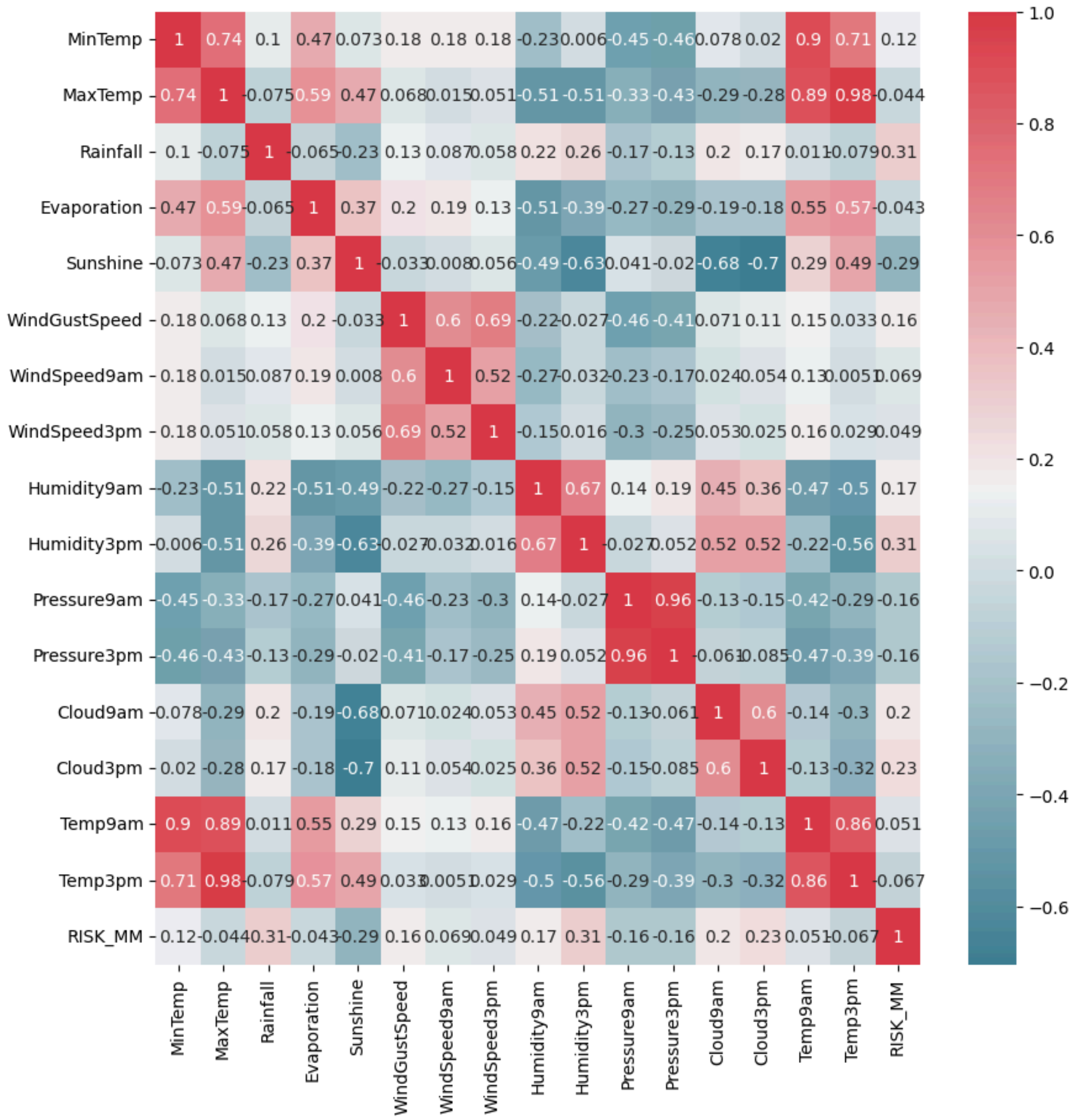
In [8]:
```
data2.head()
```

Out[8]:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9am	Wi
0	13.4	22.9	0.6	NaN	NaN	44.0	20.0	
1	7.4	25.1	0.0	NaN	NaN	44.0	4.0	
2	12.9	25.7	0.0	NaN	NaN	46.0	19.0	
3	9.2	28.0	0.0	NaN	NaN	24.0	11.0	
4	17.5	32.3	1.0	NaN	NaN	41.0	7.0	

In [9]:
```
#Correlation
corr=data2.corr()
cormp=sns.diverging_palette(220,10,as_cmap=True)
plt.figure(figsize=(10,10))
sns.heatmap(corr,cmap=cormp,annot=True)
```

Out[9]: <Axes: >



In [10]:

```
data['Date']=pd.to_datetime(data['Date'])
data['Year']=data['Date'].dt.year
data['Month']=data['Date'].dt.month

#I will use neural network use months into cyclic continous
def encode(data,col,max_val):
  data[col+'_sin']=np.sin(2*np.pi*data[col]/max_val)
  data[col+'_cos']=np.cos(2*np.pi*data[col]/max_val)
  return data

data['Month']=data.Date.dt.month
data=encode(data,'Month',12)

data['Day']=data.Date.dt.day
day=encode(data,'Day',31)

data.head()
```

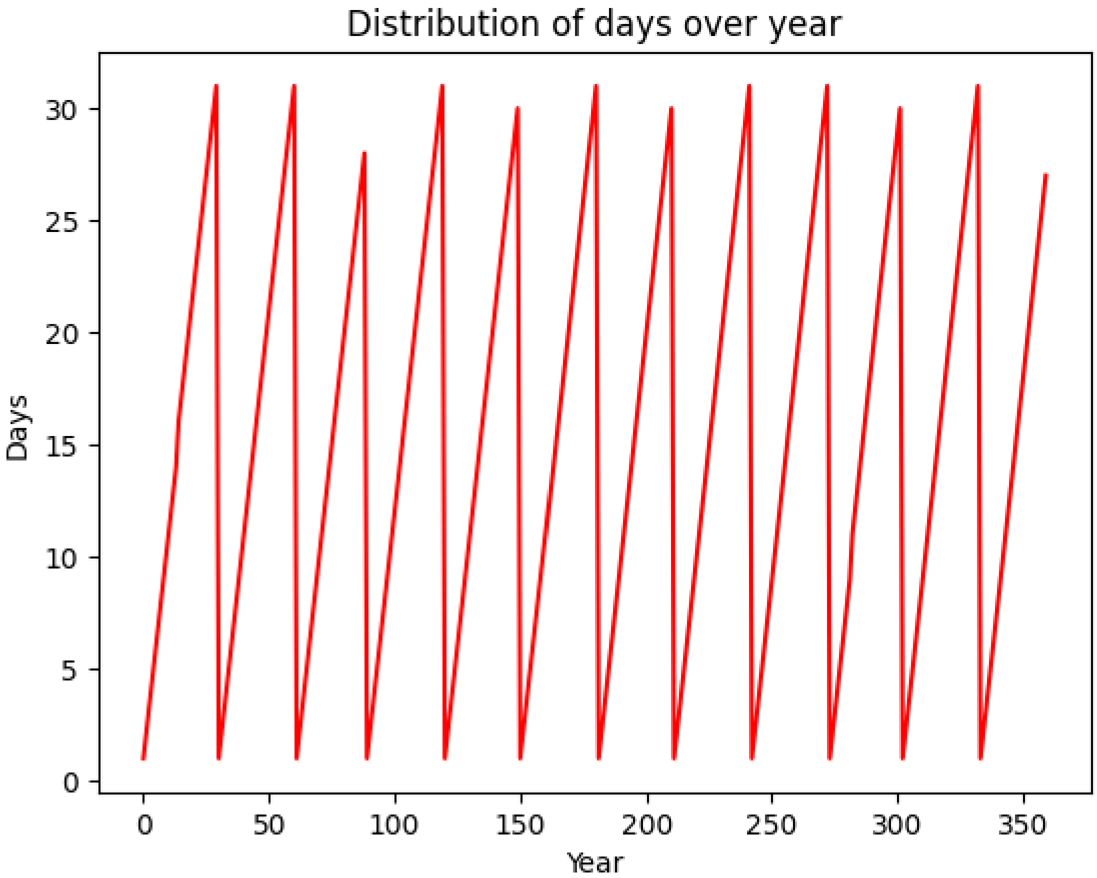
Out[10]:

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	Wind(
0	2008-12-01	Albury	13.4	22.9	0.6	NaN	NaN	W	
1	2008-12-02	Albury	7.4	25.1	0.0	NaN	NaN	WNW	
2	2008-12-03	Albury	12.9	25.7	0.0	NaN	NaN	WSW	
3	2008-12-04	Albury	9.2	28.0	0.0	NaN	NaN	NE	
4	2008-12-05	Albury	17.5	32.3	1.0	NaN	NaN	W	

5 rows × 31 columns

In [11]:
```
section=data[:360]
tm=section["Day"].plot(color='red')
tm.set_title("Distribution of days over year")
tm.set_xlabel("Year")
tm.set_ylabel("Days")
```

Out[11]:
```
Text(0, 0.5, 'Days')
```

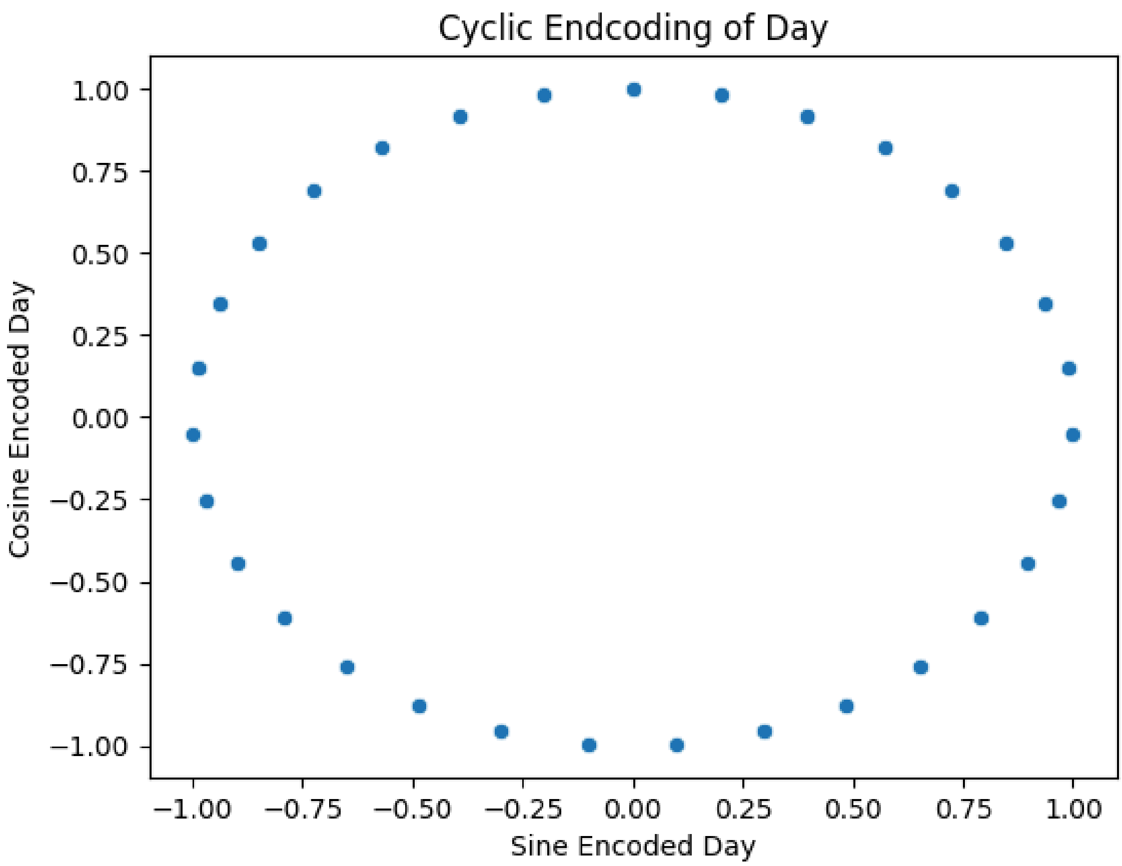


In [12]:
```
data.columns
#
```

Out[12]:
```
Index(['Date', 'Location', 'MinTemp', 'MaxTemp', 'Rainfall', 'Evaporatio
n',
       'Sunshine', 'WindGustDir', 'WindGustSpeed', 'WindDir9am', 'WindDir3
pm',
       'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am', 'Humidity3pm',
       'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm', 'Temp9am',
       'Temp3pm', 'RainToday', 'RISK_MM', 'RainTomorrow', 'Year', 'Month',
       'Month_sin', 'Month_cos', 'Day', 'Day_sin', 'Day_cos'],
      dtype='object')
```

In [13]:
```
c_month=sns.scatterplot(x='Day_sin',y='Day_cos',data=data)
c_month.set_title("Cyclic Endcoding of Day")
c_month.set_ylabel("Cosine Encoded Day")
c_month.set_xlabel("Sine Encoded Day")
```

Out[13]:
```
Text(0.5, 0, 'Sine Encoded Day')
```



In [14]:
```
#get Categorical Values
s=(data.dtypes=='object')
object_cols=list(s[s].index)

print("Categorical variables:")
print(object_cols)
```

```
Categorical variables:
['Location', 'WindGustDir', 'WindDir9am', 'WindDir3pm', 'RainToday', 'Rain
Tomorrow']
```

In [15]:
```
#Check Missing values
for a in object_cols:
  print(a,data[a].isnull().sum())
```

```
Location 0
WindGustDir 9330
WindDir9am 10013
WindDir3pm 3778
RainToday 1406
RainTomorrow 0
```

In [16]:
```
#fill the missing values
for a in object_cols:
  data[a].fillna(data[a].mode()[0],inplace=True)
```

In [17]:
```
#get the list of numeric values
s=(data.dtypes=='float64')
float_cols=list(s[s].index)

print("Numeric variables:")
print(float_cols)
#
```

```
Numeric variables:
['MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine', 'WindGustSpe
ed', 'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am', 'Humidity3pm', 'Pressu
re9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm', 'Temp9am', 'Temp3pm', 'RISK
_MM', 'Month_sin', 'Month_cos', 'Day_sin', 'Day_cos']
```

In [18]:
```
#missing numeric null values
for a in float_cols:
  print(a,data[a].isnull().sum())
```

```
MinTemp 637
MaxTemp 322
Rainfall 1406
Evaporation 60843
Sunshine 67816
WindGustSpeed 9270
WindSpeed9am 1348
WindSpeed3pm 2630
Humidity9am 1774
Humidity3pm 3610
Pressure9am 14014
Pressure3pm 13981
Cloud9am 53657
Cloud3pm 57094
Temp9am 904
Temp3pm 2726
RISK_MM 0
Month_sin 0
Month_cos 0
Day_sin 0
Day_cos 0
```

In [19]:
```python
#fill the missing values
for i in float_cols:
  data[i].fillna(data[i].median(),inplace=True)
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 142193 entries, 0 to 142192
Data columns (total 31 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   Date           142193 non-null  datetime64[ns]
 1   Location       142193 non-null  object
 2   MinTemp        142193 non-null  float64
 3   MaxTemp        142193 non-null  float64
 4   Rainfall       142193 non-null  float64
 5   Evaporation    142193 non-null  float64
 6   Sunshine       142193 non-null  float64
 7   WindGustDir    142193 non-null  object
 8   WindGustSpeed  142193 non-null  float64
 9   WindDir9am     142193 non-null  object
 10  WindDir3pm     142193 non-null  object
 11  WindSpeed9am   142193 non-null  float64
 12  WindSpeed3pm   142193 non-null  float64
 13  Humidity9am    142193 non-null  float64
 14  Humidity3pm    142193 non-null  float64
 15  Pressure9am    142193 non-null  float64
 16  Pressure3pm    142193 non-null  float64
 17  Cloud9am       142193 non-null  float64
 18  Cloud3pm       142193 non-null  float64
 19  Temp9am        142193 non-null  float64
 20  Temp3pm        142193 non-null  float64
 21  RainToday      142193 non-null  object
 22  RISK_MM        142193 non-null  float64
 23  RainTomorrow   142193 non-null  object
 24  Year           142193 non-null  int32
 25  Month          142193 non-null  int32
 26  Month_sin      142193 non-null  float64
 27  Month_cos      142193 non-null  float64
 28  Day            142193 non-null  int32
 29  Day_sin        142193 non-null  float64
 30  Day_cos        142193 non-null  float64
dtypes: datetime64[ns](1), float64(21), int32(3), object(6)
memory usage: 32.0+ MB
```

In [20]:

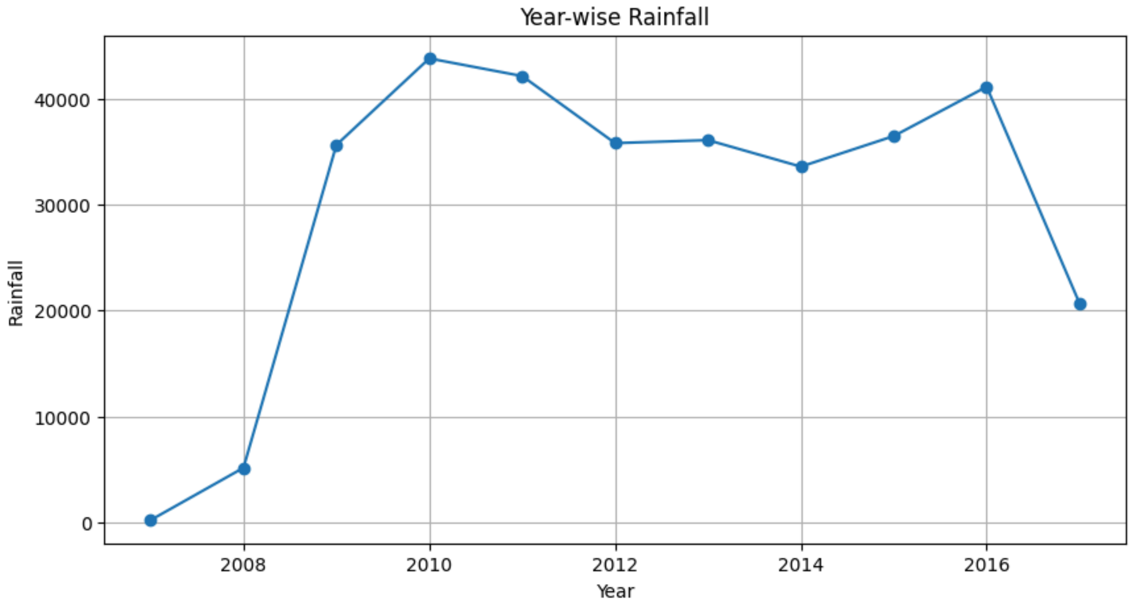
```python
data['year']=data['Year']
yearWise_Rainfall=data.groupby('year')['Rainfall'].sum().reset_index()
yearWise_Rainfall
```

Out[20]:

	year	Rainfall
0	2007	196.4
1	2008	5141.2
2	2009	35652.5
3	2010	43828.6
4	2011	42163.4
5	2012	35825.5
6	2013	36108.3
7	2014	33603.3
8	2015	36492.7
9	2016	41154.5
10	2017	20679.4

In [21]:

```python
plt.figure(figsize=(10,5))
plt.plot(yearWise_Rainfall['year'],yearWise_Rainfall['Rainfall'],marker='
o')
plt.xlabel('Year')
plt.ylabel('Rainfall')
plt.title('Year-wise Rainfall')
plt.grid(True)
plt.show()
```



In [24]:
```
#Apply label encoder to each column with Categroical Data
label_encoder=LabelEncoder()
for i in object_cols:
  data[i]=label_encoder.fit_transform(data[i])
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 142193 entries, 0 to 142192
Data columns (total 32 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   Date           142193 non-null  datetime64[ns]
 1   Location       142193 non-null  int64
 2   MinTemp        142193 non-null  float64
 3   MaxTemp        142193 non-null  float64
 4   Rainfall       142193 non-null  float64
 5   Evaporation    142193 non-null  float64
 6   Sunshine       142193 non-null  float64
 7   WindGustDir    142193 non-null  int64
 8   WindGustSpeed  142193 non-null  float64
 9   WindDir9am     142193 non-null  int64
 10  WindDir3pm     142193 non-null  int64
 11  WindSpeed9am   142193 non-null  float64
 12  WindSpeed3pm   142193 non-null  float64
 13  Humidity9am    142193 non-null  float64
 14  Humidity3pm    142193 non-null  float64
 15  Pressure9am    142193 non-null  float64
 16  Pressure3pm    142193 non-null  float64
 17  Cloud9am       142193 non-null  float64
 18  Cloud3pm       142193 non-null  float64
 19  Temp9am        142193 non-null  float64
 20  Temp3pm        142193 non-null  float64
 21  RainToday      142193 non-null  int64
 22  RISK_MM        142193 non-null  float64
 23  RainTomorrow   142193 non-null  int64
 24  Year           142193 non-null  int32
 25  Month          142193 non-null  int32
 26  Month_sin      142193 non-null  float64
 27  Month_cos      142193 non-null  float64
 28  Day            142193 non-null  int32
 29  Day_sin        142193 non-null  float64
 30  Day_cos        142193 non-null  float64
 31  year           142193 non-null  int32
dtypes: datetime64[ns](1), float64(21), int32(4), int64(6)
memory usage: 32.5 MB
```

In [25]:
```
data.head()
```

Out[25]:

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	Wind
0	2008-12-01	2	13.4	22.9	0.6	4.8	8.5	13	
1	2008-12-02	2	7.4	25.1	0.0	4.8	8.5	14	
2	2008-12-03	2	12.9	25.7	0.0	4.8	8.5	15	
3	2008-12-04	2	9.2	28.0	0.0	4.8	8.5	4	
4	2008-12-05	2	17.5	32.3	1.0	4.8	8.5	13	

5 rows × 32 columns

In [26]:
```
#Preparing attribute of scale the data
features=data.drop(['RainTomorrow','Date','Day','Month'],axis=1)
```

In [28]:
```
features.head()
```

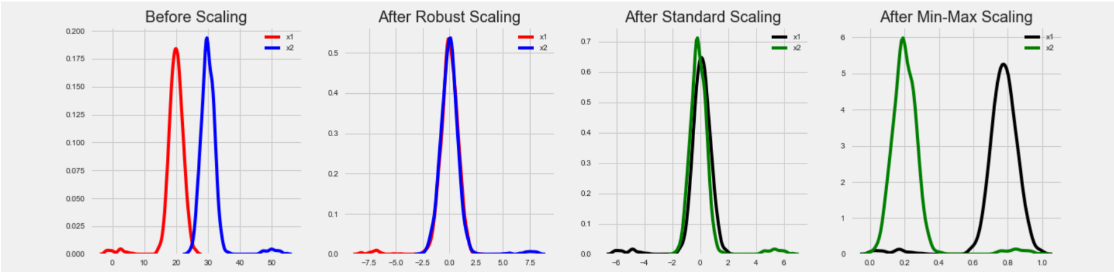
Out[28]:

	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustSp
0	2	13.4	22.9	0.6	4.8	8.5	13	4
1	2	7.4	25.1	0.0	4.8	8.5	14	4
2	2	12.9	25.7	0.0	4.8	8.5	15	4
3	2	9.2	28.0	0.0	4.8	8.5	4	2
4	2	17.5	32.3	1.0	4.8	8.5	13	4

5 rows × 28 columns

StandardScaler is a versatile and widely used preprocessing technique that contributes to the robustness, interpretability, and performance of machine learning models trained on diverse datasets.

Standardize features by removing the mean and scaling to unit variance



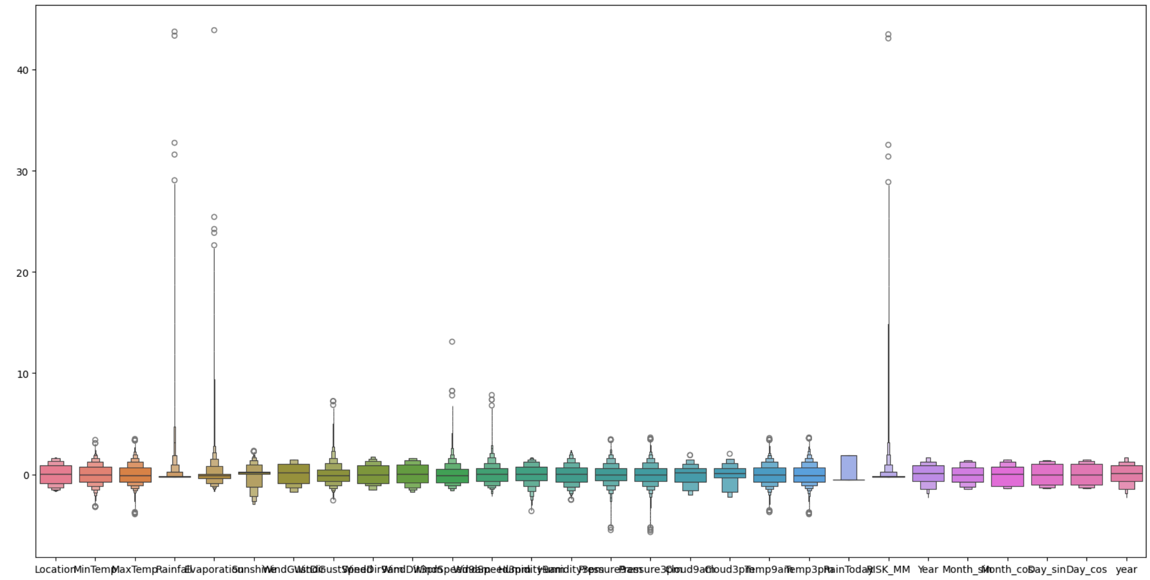
In [32]:
```python
target=data['RainTomorrow']

#Standard Scaler for the features
col_names=list(features.columns)
std_scaler=preprocessing.StandardScaler()
features=std_scaler.fit_transform(features)

features=pd.DataFrame(features,columns=col_names)
features.head()
```

Out[32]:

	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGust
0	-1.527004	0.190085	-0.045764	-0.204920	-0.120303	0.16528	1.052556	0.3
1	-1.527004	-0.749042	0.263677	-0.276125	-0.120303	0.16528	1.265582	0.3
2	-1.527004	0.111824	0.348070	-0.276125	-0.120303	0.16528	1.478609	0.4
3	-1.527004	-0.467304	0.671577	-0.276125	-0.120303	0.16528	-0.864683	-1.2
4	-1.527004	0.831821	1.276393	-0.157450	-0.120303	0.16528	1.052556	0.0

5 rows × 28 columns

In [35]:
```
#Detect the outlier
#show scaled values
plt.figure(figsize=(20,10))
sns.boxenplot(data=features)
plt.show()
#
```



In [36]:
```
#Full Data
features['RainTomorrow']=target
features.head()
```

Out[36]:

	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGust
0	-1.527004	0.190085	-0.045764	-0.204920	-0.120303	0.16528	1.052556	0.3
1	-1.527004	-0.749042	0.263677	-0.276125	-0.120303	0.16528	1.265582	0.3
2	-1.527004	0.111824	0.348070	-0.276125	-0.120303	0.16528	1.478609	0.4
3	-1.527004	-0.467304	0.671577	-0.276125	-0.120303	0.16528	-0.864683	-1.2
4	-1.527004	0.831821	1.276393	-0.157450	-0.120303	0.16528	1.052556	0.0

5 rows × 29 columns

In [37]:
```
features.describe()
```

Out[37]:

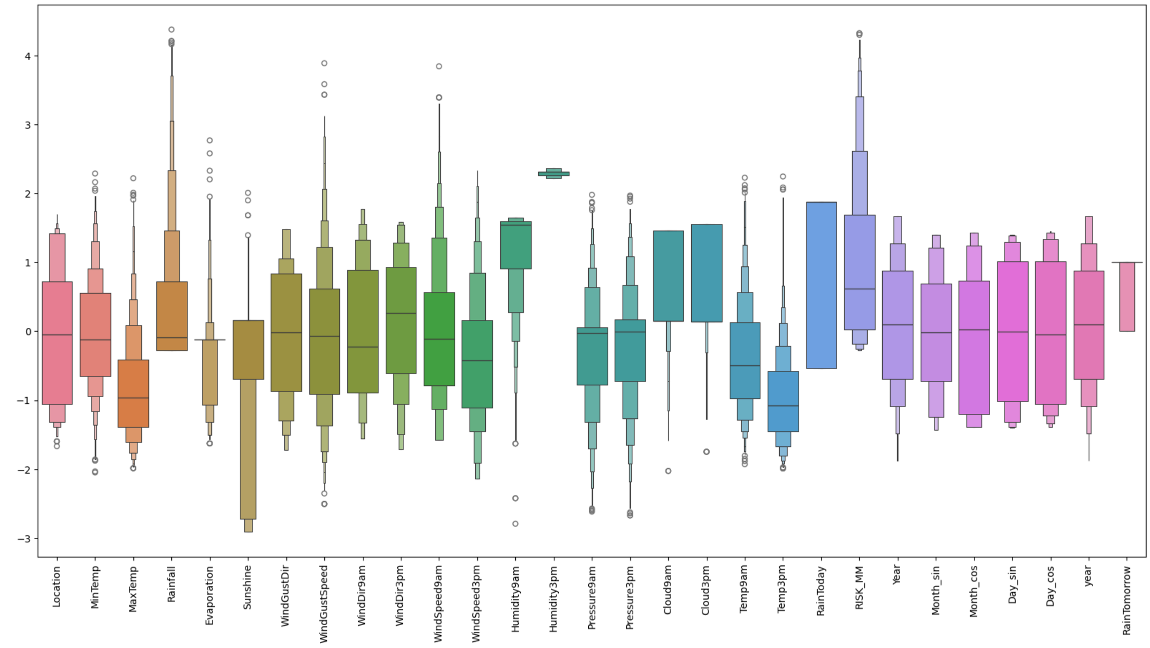
	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshi
count	1.421930e+05	1.421930e+05	1.421930e+05	1.421930e+05	1.421930e+05	1.421930e+
mean	2.398575e-17	3.166118e-16	3.421966e-16	8.594892e-17	-1.071363e-16	7.259686e-
std	1.000004e+00	1.000004e+00	1.000004e+00	1.000004e+00	1.000004e+00	1.000004e+
min	-1.667479e+00	-3.237728e+00	-3.941909e+00	-2.761249e-01	-1.627183e+00	-2.903725e+
25%	-8.948690e-01	-7.177378e-01	-7.490394e-01	-2.761249e-01	-3.714499e-01	5.696207e-
50%	1.821567e-02	-2.904480e-02	-8.796072e-02	-2.761249e-01	-1.203033e-01	1.652799e-
75%	8.610630e-01	7.222567e-01	6.997076e-01	-2.049201e-01	6.805667e-02	2.374917e-
max	1.703910e+00	3.398768e+00	3.498743e+00	4.375219e+01	4.389314e+01	2.331636e+

8 rows × 29 columns

In [45]:
```
#Drop the outlier
features=features[(features["MinTemp"]<3.39)&(features["MinTemp"]>-3.23)]
features=features[(features["MaxTemp"]<2.3)&(features["MaxTemp"]>-2)]
features=features[(features["Rainfall"]<4.5)]
features=features[(features["Evaporation"]<2.8)]
features=features[(features["Sunshine"]<4.5)]
features=features[(features["WindGustSpeed"]<4)&
(features["WindGustSpeed"]>-4)]
features=features[(features["WindSpeed9am"]<4)]
features=features[(features["WindSpeed3pm"]<2.5)]
features=features[(features["Humidity9am"]>-3)]
features=features[(features["Humidity3pm"]>2.2)]
features=features[(features["Pressure9am"]<2)&
(features["Pressure9am"]>-2.7)]
features=features[(features["Pressure3pm"]<2)&
(features["Pressure3pm"]>-2.7)]
features=features[(features["Cloud9am"]<1.8)]
features=features[(features["Cloud3pm"]<2)]
features=features[(features["Temp9am"]<2.3)&(features["Temp9am"]>-2)]
features=features[(features["Temp3pm"]<2.3)&(features["Temp3pm"]>-2)]
features=features[(features["RISK_MM"]<4.34)&(features["RISK_MM"]>-2.78)]
features.shape
```

Out[45]: (1092, 29)

In [46]:
```
#Show  scaled featrues without Outlier
plt.figure(figsize=(20,10))
sns.boxenplot(data=features)
plt.xticks(rotation=90)
plt.show()
```



Model Building

Spliting test and training sets

Initilising neural network

defining layers

compiling neural network

train the neural network

In [47]:
```
X=features.drop('RainTomorrow',axis=1)
y=features['RainTomorrow']
```

In [48]:
```
#Splitting
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_s
tate=42)
X.shape
```

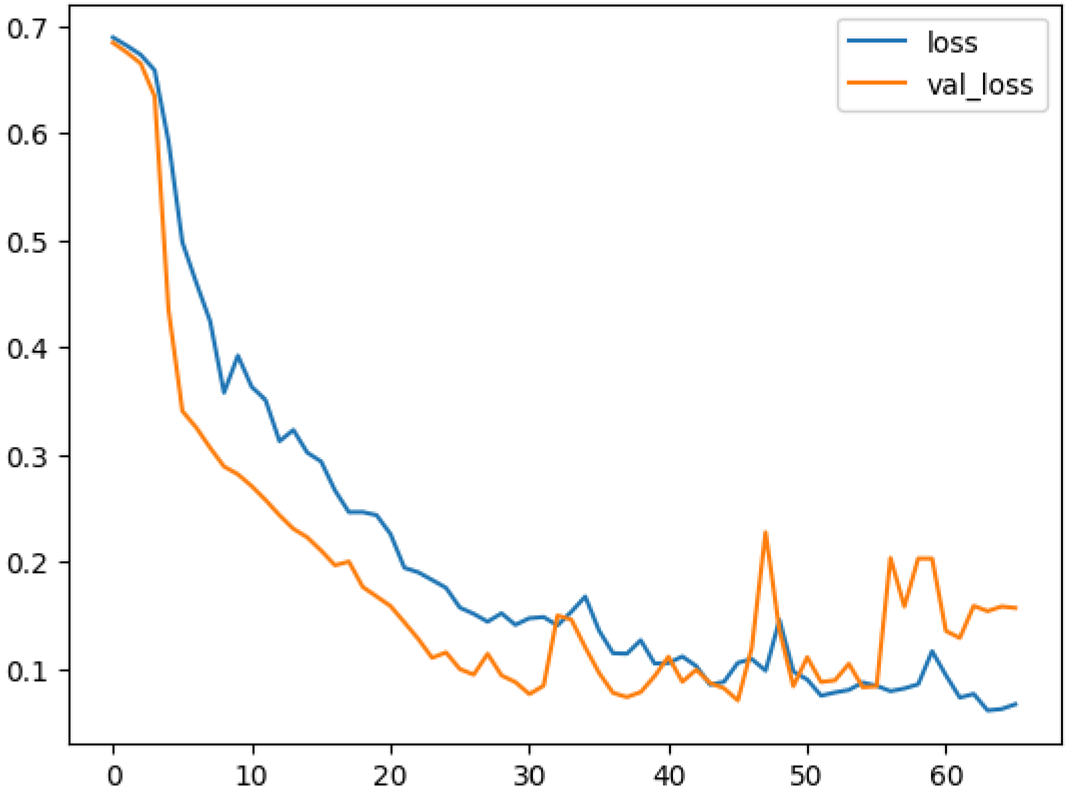
Out[48]: (1092, 28)

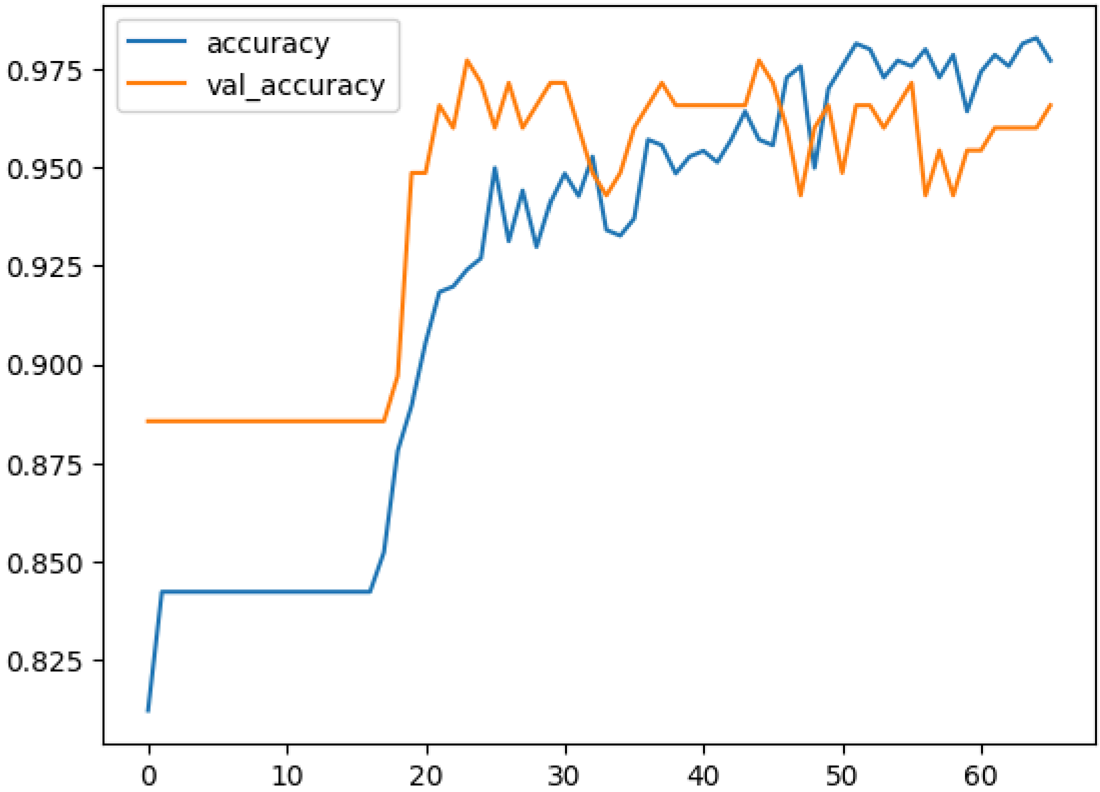
In [61]:
```
#Early Stopping

early_Stopping=callbacks.EarlyStopping(min_delta=0.001,patience=20,restor
e_best_weights=True)

#Initilizing
model=Sequential()

#Layers


model.add(Dense(units=32,kernel_initializer='normal',activation='relu',in
put_dim=28))

model.add(Dense(units=32,kernel_initializer='uniform',activation='relu'))
model.add(Dense(units=16,kernel_initializer='uniform',activation='relu'))
model.add(Dense(units=8,kernel_initializer='uniform',activation='relu'))

model.add(Dropout(0.25))
model.add(Dense(units=8,kernel_initializer='uniform',activation='relu'))

model.add(Dropout(0.5))
model.add(Dense(units=1,kernel_initializer='uniform',activation='sigmoid'
))

#Compiling
# opt=Adam(learning_rate=0.00009)
model.compile(optimizer='adam',loss='binary_crossentropy',metrics=
['accuracy'])


#Train the ANN
history=model.fit(X_train,y_train,batch_size=32,epochs=150,callbacks=
[early_Stopping],validation_split=0.2)
```

```
Epoch 1/150
22/22 ━━━━━━━━━━━━━━━━━━━━ 3s 32ms/step - accuracy: 0.7404 - loss: 0.69
13 - val_accuracy: 0.8857 - val_loss: 0.6847
Epoch 2/150
22/22 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.8508 - loss: 0.683
5 - val_accuracy: 0.8857 - val_loss: 0.6756
Epoch 3/150
22/22 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.8581 - loss: 0.674
8 - val_accuracy: 0.8857 - val_loss: 0.6652
Epoch 4/150
22/22 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8315 - loss: 0.665
5 - val_accuracy: 0.8857 - val_loss: 0.6346
Epoch 5/150
22/22 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.8502 - loss: 0.615
9 - val_accuracy: 0.8857 - val_loss: 0.4352
Epoch 6/150
22/22 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8397 - loss: 0.510
0 - val_accuracy: 0.8857 - val_loss: 0.3409
Epoch 7/150
```

In [62]:
```
history_df=pd.DataFrame(history.history)
history_df.loc[:,['loss','val_loss']].plot()
history_df.loc[:,['accuracy','val_accuracy']].plot()
#
```

Out[62]: <Axes: >





Conclusion

In [63]:
```
#predicting the result
y_pred=model.predict(X_test)
y_pred=(y_pred>0.5)
```

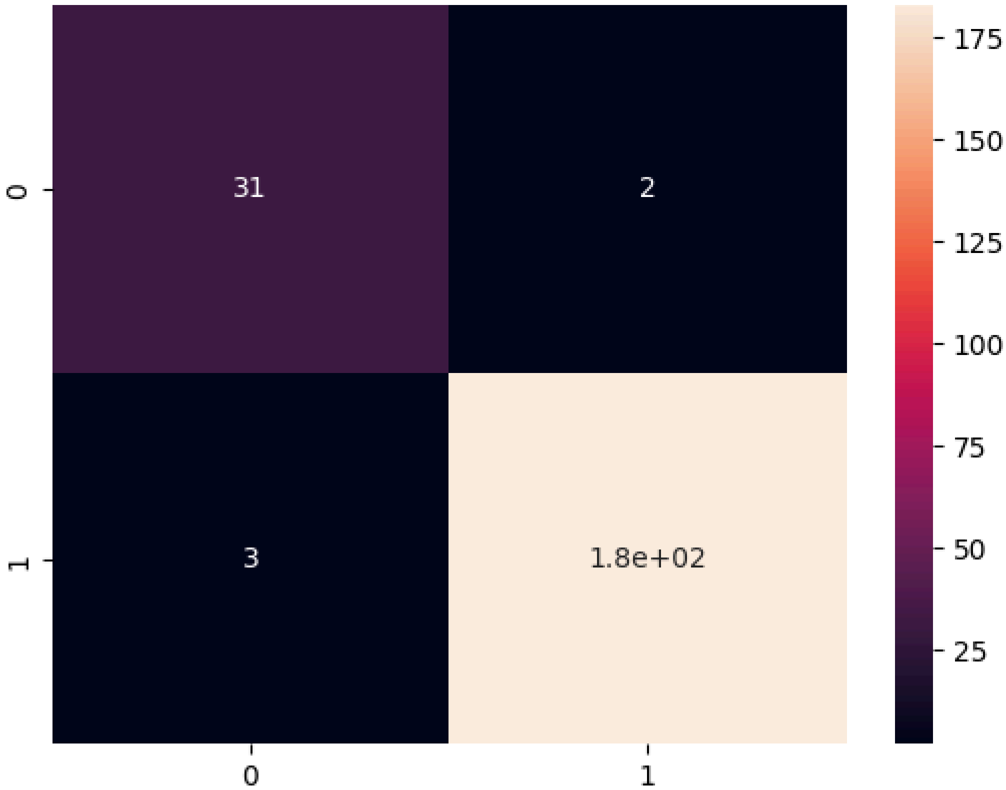
```
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
```

In [64]:
```
#Confusion Matrix
cm=confusion_matrix(y_test,y_pred)
cm
```

Out[64]:
```
array([[ 31,   2],
       [  3, 183]])
```

In [65]:
```
sns.heatmap(cm,annot=True)
```

Out[65]:
```
<Axes: >
```



In [68]:
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.91      0.94      0.93        33
           1       0.99      0.98      0.99       186

    accuracy                           0.98       219
   macro avg       0.95      0.96      0.96       219
weighted avg       0.98      0.98      0.98       219
```