Title - Rainfall Prediction and EDA on precipitation data and parameter analysis

Group No. - 10

Team Members -

Kulkarni Varun Venkatesh (22B2121)
Kukade Shreyas Pramod (22B2154)
Anuj Pratap Singh (22B0063)
Jaskaran Singh (22B2112)
Rohan Suresh Mekala (22B2106)
Patil Shahu Prashant (22B2146)

Link to video - https://drive.google.com/file/d/1NQ7AJHQH3IWx5v0jmhs09ZCZFE-9VPaM/view?usp=sharing

Link and information on the dataset used -

The dataset used for the purpose of our project is the precipitation dataset for the city of Los Angeles our the years 2016 to 2020. The dataset consists of various parameters like Average Wind Speed (AWND), Precipitation (PRCP), Max Temperature (TMAX), Min Temperature (TMIN), Fastest-2 minute wind speed (WSF2), Fastest-5 minute wind speed (WSF5), Direction of fastest 2-minute wind (WDF2), Direction of fastest 5-minute wind (WDF5).
Link to dataset - https://drive.google.com/file/d/1KgP4ctGWVXie09dyLuv1bDFgchlMB1Dz/view

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Contributions :-

1) Jaskaran Singh: Describing distribution of features of dataset

2) Anuj Pratap Singh: Describing correlation of features of dataset

3) Rohan Suresh Mekala: Hypothesis Testing (Using t-test)

4) Varun Kulkarni: Linear Regression (Point and Interval Estimates)

5) Shreyas Kukade: Hypothesis Testing to validate the regression model

6) Shahu Patil: Fitting, Classification and Hypothesis Testing of Neural Network

Firstly, we start by importing the necessary libraries.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import random
import seaborn as sns
```

Import the rainfall dataset in a dataframe named as ' df '.

```
df= pd.read_csv('dataset (1).csv')
df.head()
```

	STATION	NAME	DATE	AWND	PGTM	PRCP	TAVG	TMAX	TMIN	WDF2	WDF5
0	USW00093134	LOS ANGELES DOWNTOWN USC, CA US	2016-01-01	2.46	NaN	0.00	NaN	64	43	10.0	30.0
1	USW00093134	LOS ANGELES	2016-	2.01	NaN	0.00	NaN	65	47	270.0	30.0

But by the first observation of the dataset, it can be seen that the data consists of NaN values for several values. Some of the columns like 'WT01' and 'WT08' are replaced by the mode value for all the missing values. Also, some of the columns like 'PGTM', 'TAVG', 'WT02' are less relevant and can be removed.

```
df=df.dropna(axis=1,thresh=100)
df['WT01'].fillna(df['WT01'].mode()[0], inplace=True)
df['WT08'].fillna(df['WT08'].mode()[0], inplace=True)
df
```

```
<ipython-input-8-583817f94126>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
  df['WT01'].fillna(df['WT01'].mode()[0], inplace=True)
<ipython-input-8-583817f94126>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
  df['WT08'].fillna(df['WT08'].mode()[0], inplace=True)
```

	STATION	NAME	DATE	AWND	PRCP	TMAX	TMIN	WDF2	WDF5	WSF2	WSI
0	USW00093134	LOS ANGELES DOWNTOWN USC, CA US	2016-01-01	2.46	0.00	64	43	10.0	30.0	8.1	11
1	USW00093134	LOS ANGELES DOWNTOWN USC, CA US	2016-01-02	2.01	0.00	65	47	270.0	30.0	6.0	8
2	USW00093134	LOS ANGELES DOWNTOWN USC, CA US	2016-01-03	0.67	0.00	62	44	150.0	150.0	10.1	14
3	USW00093134	LOS ANGELES DOWNTOWN USC, CA US	2016-01-04	1.34	0.01	69	55	270.0	280.0	8.1	14

Moreover, for our analysis, we drop the columns 'WT01', 'WT08', 'STATION', 'NAME', 'DATE'.

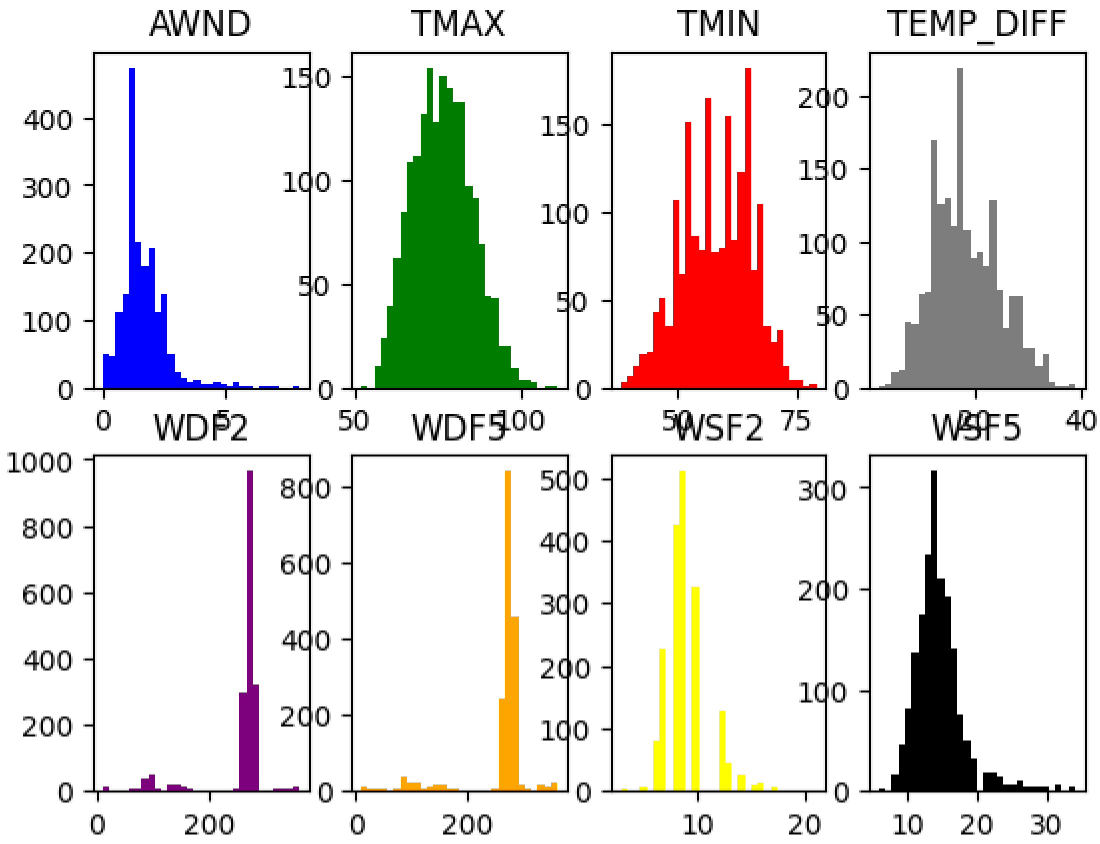
```
date= df['DATE']
df=df.drop(columns=['WT01','WT08','STATION','NAME','DATE'])
df
```

	AWND	PRCP	TMAX	TMIN	WDF2	WDF5	WSF2	WSF5
0	2.46	0.00	64	43	10.0	30.0	8.1	11.0
1	2.01	0.00	65	47	270.0	30.0	6.0	8.9
2	0.67	0.00	62	44	150.0	150.0	10.1	14.1
3	1.34	0.01	69	55	270.0	280.0	8.1	14.1
4	2.46	1.61	59	49	140.0	140.0	10.1	16.1
...	...	...	...	...	...	...	...	...
1822	1.12	0.01	66	55	270.0	260.0	8.9	18.1
1823	4.70	1.81	56	47	90.0	260.0	14.1	21.0
1824	1.57	0.00	65	42	340.0	360.0	10.1	18.1
1825	0.45	0.00	69	44	260.0	260.0	6.9	12.1
1826	1.57	0.00	70	43	350.0	350.0	12.1	19.9

1827 rows × 8 columns

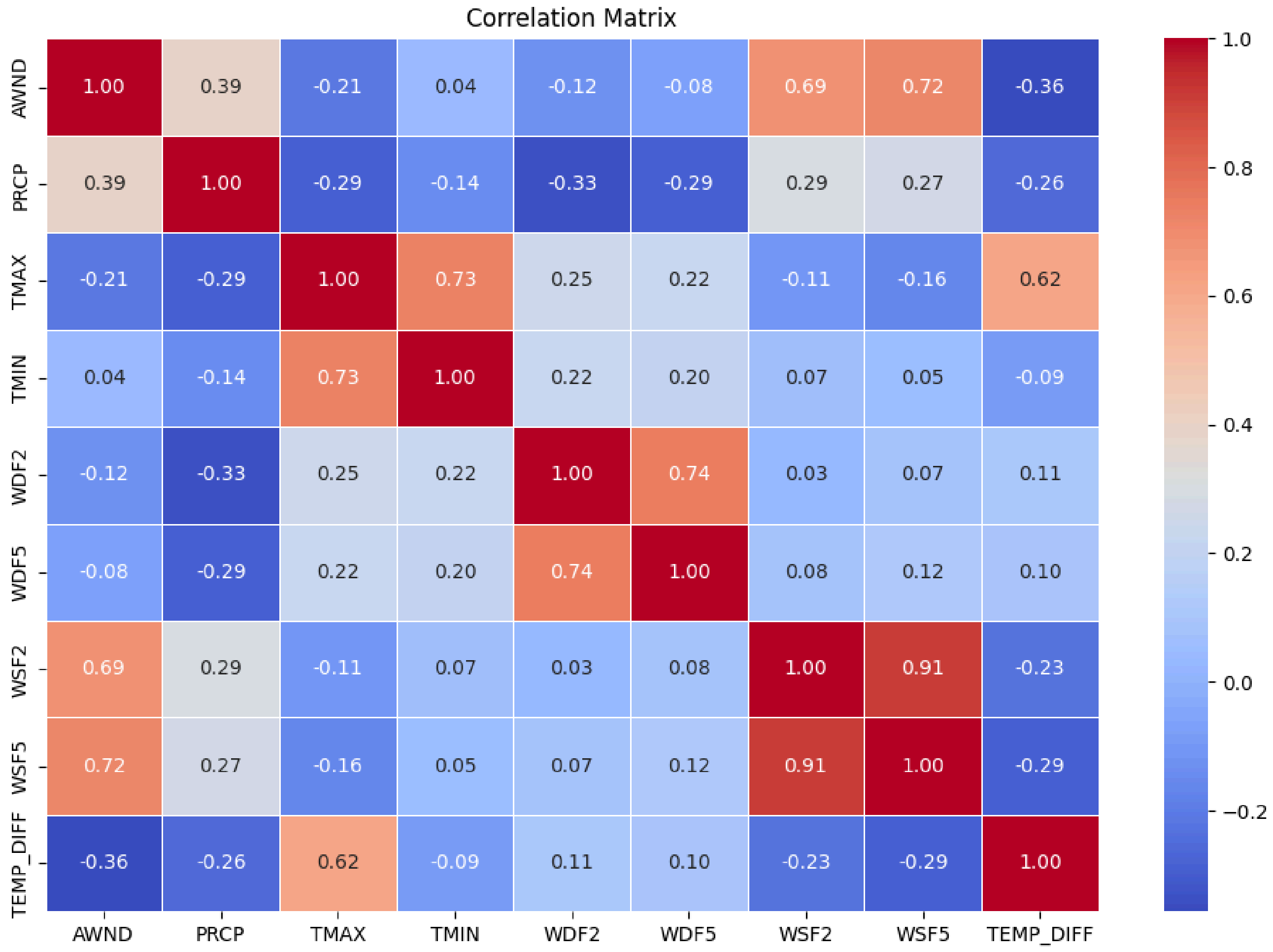
Now for all the remaining colummns, we plot the histograms of these variables in each column.

```
colors = ['blue', 'green', 'red', 'grey', 'purple', 'orange', 'yellow', 'black']
df['TEMP_DIFF']=df['TMAX']-df['TMIN']
fig,axs= plt.subplots(2,4)
axs[0,0].hist(df['AWND'], bins = 30, color=colors[0])
axs[0,0].set_title('AWND')
axs[0,1].hist(df['TMAX'], bins = 30, color=colors[1])
axs[0,1].set_title('TMAX')
axs[0,2].hist(df['TMIN'], bins = 30, color=colors[2])
axs[0,2].set_title('TMIN')
axs[0,3].hist(df['TEMP_DIFF'], bins = 30, color=colors[3])
axs[0,3].set_title('TEMP_DIFF')
axs[1,0].hist(df['WDF2'], bins = 30,color=colors[4])
axs[1,0].set_title('WDF2')
axs[1,1].hist(df['WDF5'], bins = 30,color=colors[5])
axs[1,1].set_title('WDF5')
axs[1,2].hist(df['WSF2'], bins = 30, color=colors[6])
axs[1,2].set_title('WSF2')
axs[1,3].hist(df['WSF5'], bins = 30, color=colors[7])
axs[1,3].set_title('WSF5')
plt.show()
```



We are interested in knowing the correlation of the various variables which can be known using the correlation matrix.

```
correlation_matrix = df.corr()
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title('Correlation Matrix')
plt.show()
```



Now, we wish to know the data as per the year for further analysis.

```
for i in range(len(date)):
   date[i]= date[i][:4]
date= pd.DataFrame(date)
df['YEAR']= date
```

```
df
```

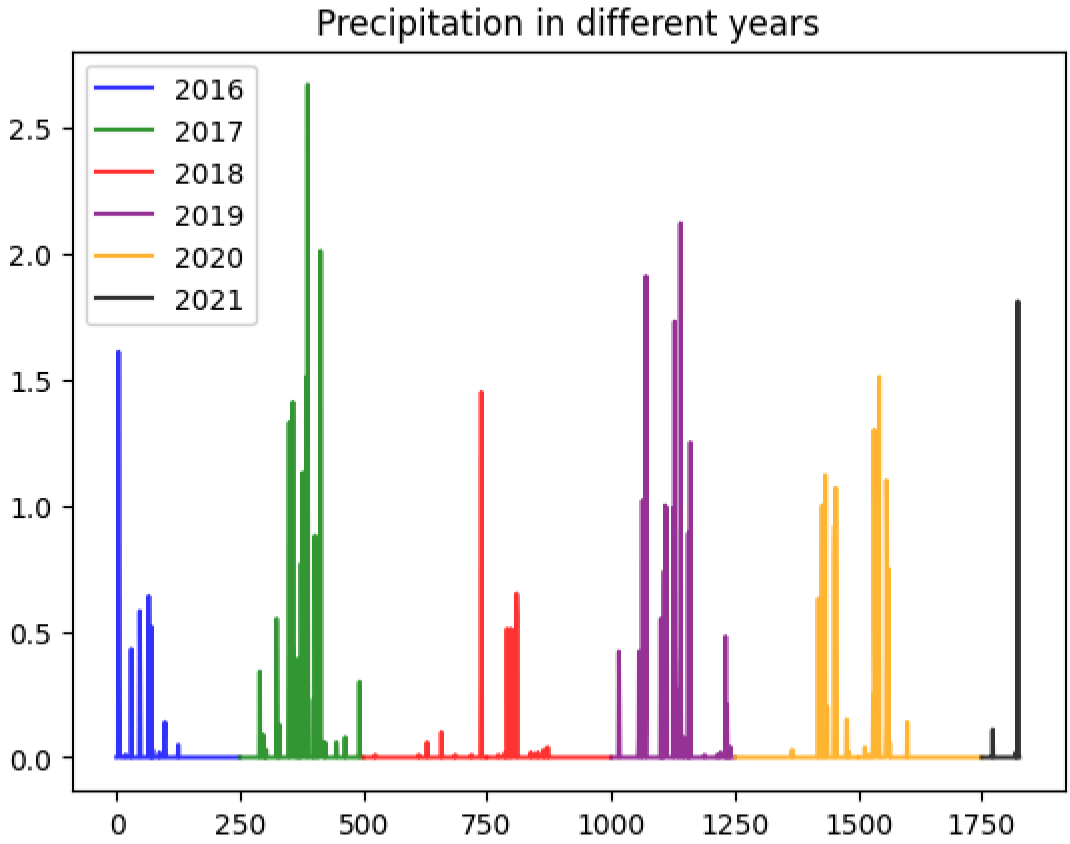
	AWND	PRCP	TMAX	TMIN	WDF2	WDF5	WSF2	WSF5	TEMP_DIFF	YEAR
0	2.46	0.00	64	43	10.0	30.0	8.1	11.0	21	2016
1	2.01	0.00	65	47	270.0	30.0	6.0	8.9	18	2016
2	0.67	0.00	62	44	150.0	150.0	10.1	14.1	18	2016
3	1.34	0.01	69	55	270.0	280.0	8.1	14.1	14	2016
4	2.46	1.61	59	49	140.0	140.0	10.1	16.1	10	2016
...	...	...	...	...	...	...	...	...	...	...
1822	1.12	0.01	66	55	270.0	260.0	8.9	18.1	11	2020
1823	4.70	1.81	56	47	90.0	260.0	14.1	21.0	9	2020
1824	1.57	0.00	65	42	340.0	360.0	10.1	18.1	23	2020
1825	0.45	0.00	69	44	260.0	260.0	6.9	12.1	25	2020
1826	1.57	0.00	70	43	350.0	350.0	12.1	19.9	27	2020

1827 rows × 10 columns

We can visualise the precipitation for every year separately in the plot below.

```
colors = ['blue', 'green', 'red', 'red', 'purple', 'orange', 'orange', 'black']
labels= ['2016', '2017', '2018', '', '2019', '', '2020', '2021']
for i in range(0, len(df), 250):
    plt.plot(df.index[i:i+250], df['PRCP'][i:i+250], color=colors[i//250 % len(colors)],

plt.legend()
plt.title('Precipitation in different years')
```

```
Text(0.5, 1.0, 'Precipitation in different years')
```



Step 3 -

We now wish to formulate the hypothesis that compares the average minimum temperatures at Los Angeles taking the level of significance to be 5%. We define the Null and Alternate hypothesis as follows:

Null Hypothesis (H0): The average minimum temperature at Los Angeles is the same in the years 2017 and 2018. (i.e mu_2017 = mu_2018)
Alternate Hypothesis (H1): The average minimum temperature at Los Angeles is not the same during 2017 and 2018.

For this we first calculate the sample means and variances for the variable 'TMIN' and perform the two sided hypothesis testing on the data.

```
df_TMIN_2017= df[df['YEAR']=='2017']['TMIN']
df_TMIN_2018= df[df['YEAR']=='2018']['TMIN']

sample_mean_17 = df_TMIN_2017.mean()
sample_mean_18 = df_TMIN_2018.mean()

std_17 = df_TMIN_2017.std(ddof=1)
std_18 = df_TMIN_2018.std(ddof=1)

sample_mean_17, sample_mean_18, std_17, std_18
```

```
(58.76164383561644, 58.07671232876712, 7.402899456787451, 7.696483436829546)
```

Now using the t-distribution, we can calculate the test statistic and consequently, the p-value for the test.

```
n_17, n_18= df_TMIN_2018.shape, df_TMIN_2017.shape
act_std = (std_17**2/n_17[0] + std_18**2/n_18[0])**0.5
z = (sample_mean_17 - sample_mean_18)/act_std
from scipy.stats import t

alpha = 0.05
p = 2*(1 - t.cdf(z, n_17[0] + n_18[0] - 2))
p
```

```
0.220832070781519
```

From the above analysis, it is found the the p-value for the above test comes out to be 0.22, which is much greater than the alpha value. Thus, we can say that we fail to reject the Null hypothesis.

So, from the hypothesis testing, we can conclude that the average minimum temperature during the years 2017 and 2018 can be said to be equal.

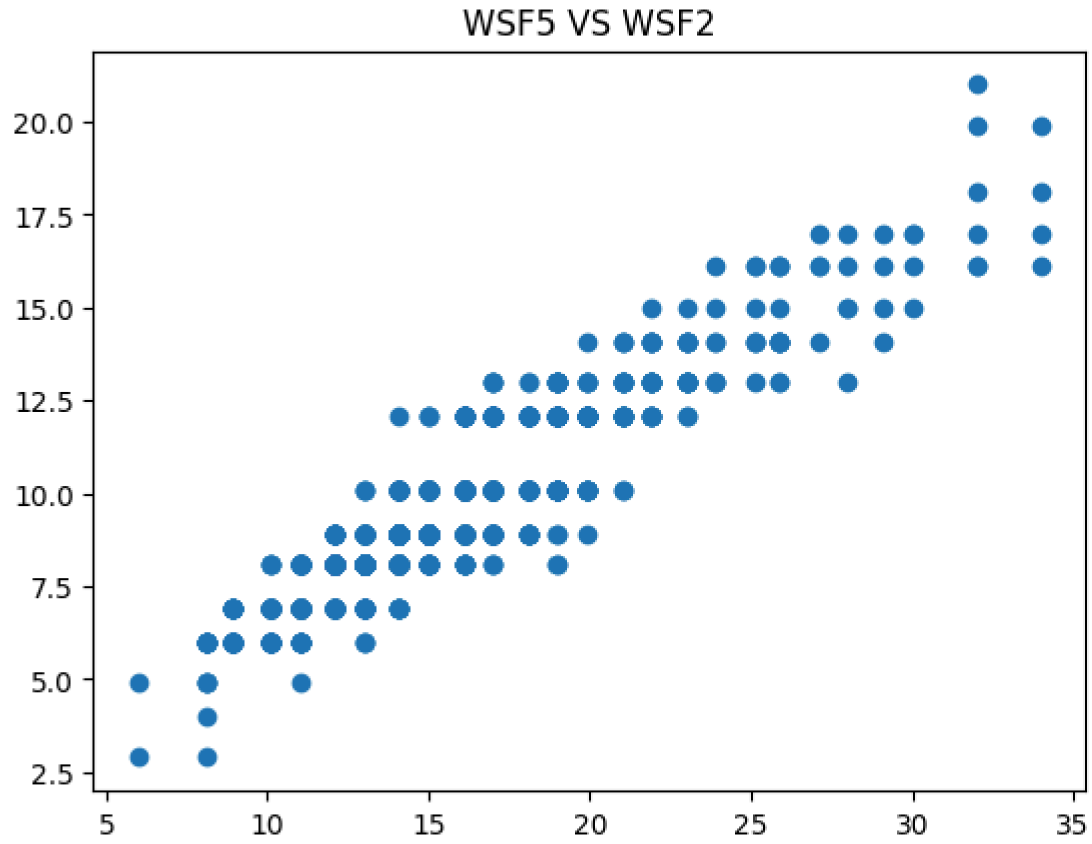
The result obtained tells us that there was no significant change in the min. temperatures in the subsequent year 2017 and 2018. This result justifies that a region has a specific climate conditions.

Step 4 -

Now we would focus on analysing the relationship between two chosen variables. For the analysis, we choose the variables 'WSF2' and 'WSF5'. From the correlation matrix, it can be seen that the correlation between these two variables is as high as 0.91. This can be visibly seen from the scatter plot between the two variables.

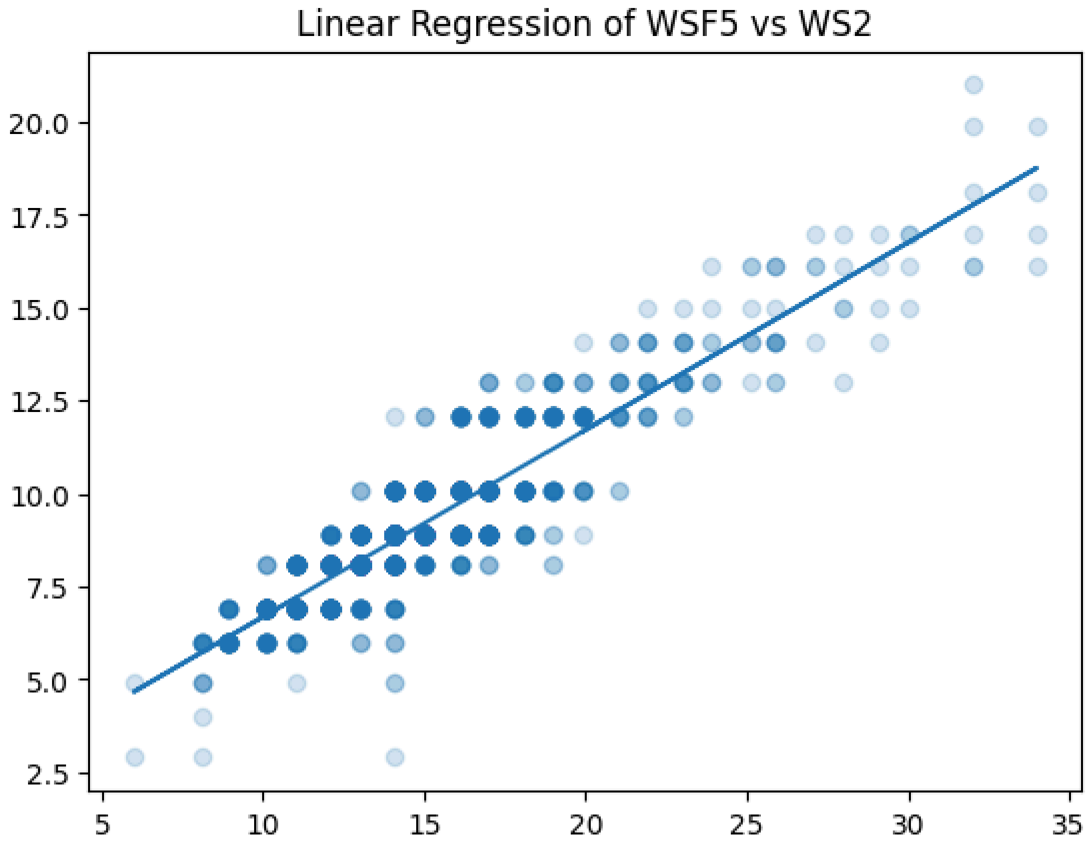
```
plt.scatter(df['WSF5'], df['WSF2'])
plt.title('WSF5 VS WSF2')
```

```
Text(0.5, 1.0, 'WSF5 VS WSF2')
```



For further analysis, we perforn regression on the dataset.(Note that the scatterplot, is made in the way that it can depict the density of points on the figure through the gradient in the colour). We get a curve fitting line that optimizes the l2 error function.

```
from sklearn.linear_model import LinearRegression

df['WSF2'].fillna(df['WSF2'].mode()[0], inplace=True)
df['WSF5'].fillna(df['WSF5'].mode()[0], inplace=True)

x,y= np.array(df['WSF5']), np.array(df['WSF2'])
slope, intercept = np.polyfit(x, y, 1)
y_pred= x*slope+intercept
plt.scatter(x,y, alpha=0.2)
plt.plot(x,y_pred)
plt.title('Linear Regression of WSF5 vs WS2')
plt.show()
```



Point Estimates for the regression curve.

```
print('Point Estimate for alpha is ', intercept)
print('Point Estimate of beta is ', slope)
```

```
Point Estimate for alpha is  1.6553877654860825
Point Estimate of beta is  0.5033013041497378
```

Defining the residual terms.

```
Sxy= np.sum(x*y)- x.size*np.mean(x)*np.mean(y)
Sxx= np.sum(x*x)- x.size*(np.mean(x))**2
Syy= np.sum(y*y)- x.size*(np.mean(y))**2
Ssr= (Sxx*Syy- (Sxy)**2)/Sxx
```

Confidence intervals for Alpha and Beta

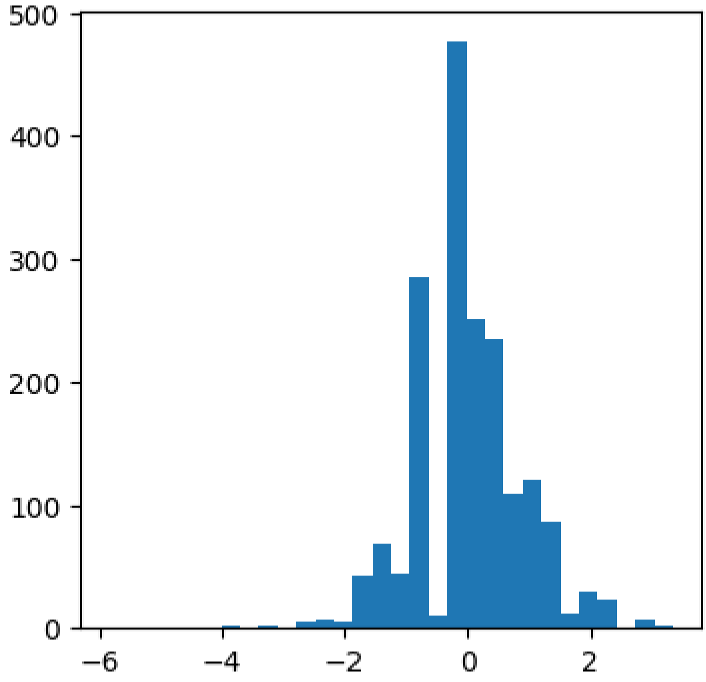
With the help of pre-known results for calculating the confidence interval, we obtain the confidence interval for alpha and beta. These are the interval estimates for alpha and beta.

```
import math
CI_B_lower= slope- math.sqrt(Ssr/((x.size-2)*Sxx))*t.cdf(0.025, x.size-2)
CI_B_higher= slope+ math.sqrt(Ssr/((x.size-2)*Sxx))*t.cdf(0.025, x.size-2)
CI_A_lower= intercept- t.cdf(0.025, x.size-2)*math.sqrt((Ssr*np.sum(x*x))/(x.size*(x.size
CI_A_higher= intercept+ t.cdf(0.025, x.size-2)*math.sqrt((Ssr*np.sum(x*x))/(x.size*(x.siz
print('Confidence intervals for Beta is (',CI_B_lower, ' ,',CI_B_higher, ')')
print('Confidence intervals for Alpha is (',CI_A_lower, ' ,',CI_A_higher, ')')
```

```
Confidence intervals for Beta is ( 0.500401340819497  , 0.5062012674799786 )
Confidence intervals for Alpha is ( 1.611452094050025  , 1.69932343692214 )
```

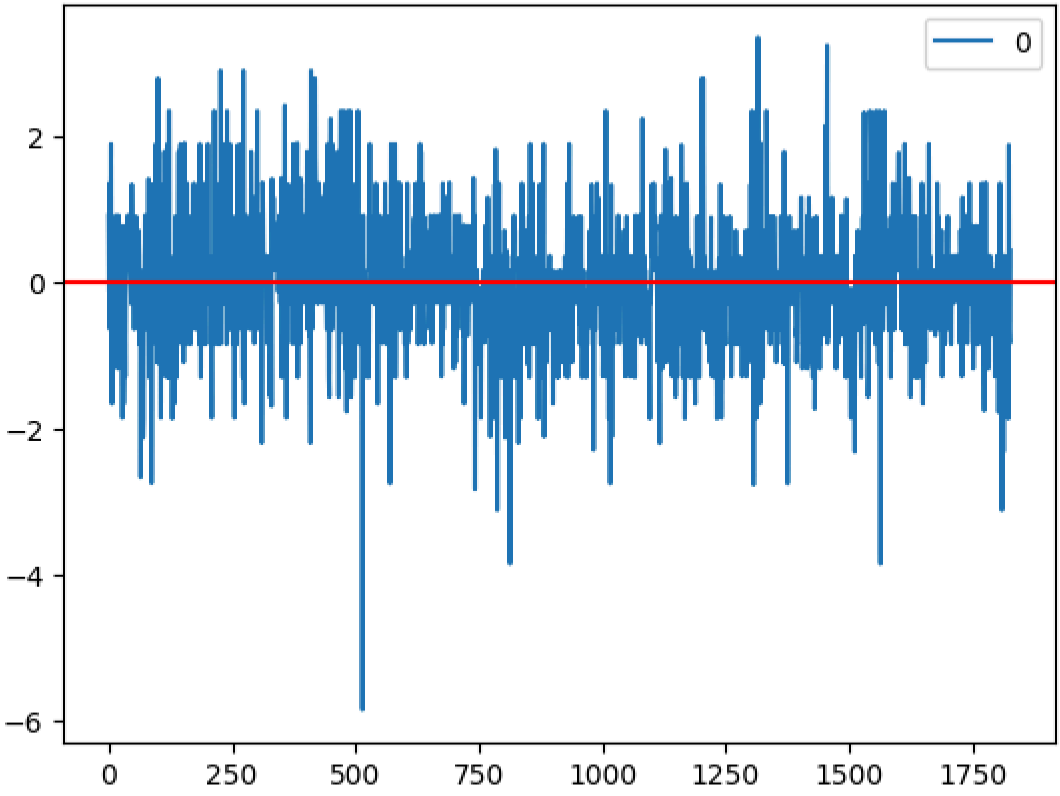
Now we will verify whether the regression model fitted on the data is relevant. For this, we will first visualise residuals errors between predicted value and actual value.

```
f = plt.figure()
f.set_figwidth(4)
f.set_figheight(4)
plt.hist(y-y_pred, bins=30)
plt.show()
```




```
f = plt.figure()
f.set_figwidth(3)
f.set_figheight(3)
pd.DataFrame(y-y_pred).plot()
plt.axhline(y=0, c='r')
plt.show()
```

```
<Figure size 300x300 with 0 Axes>
```



To verify the validity of the regression model, we will perform a two-sided hypothesis test with a level of significance of 1%.

Null Hypothesis (H0): Mean of residual = 0

Alternate Hypothesis (H1): Mean of residual is not 0

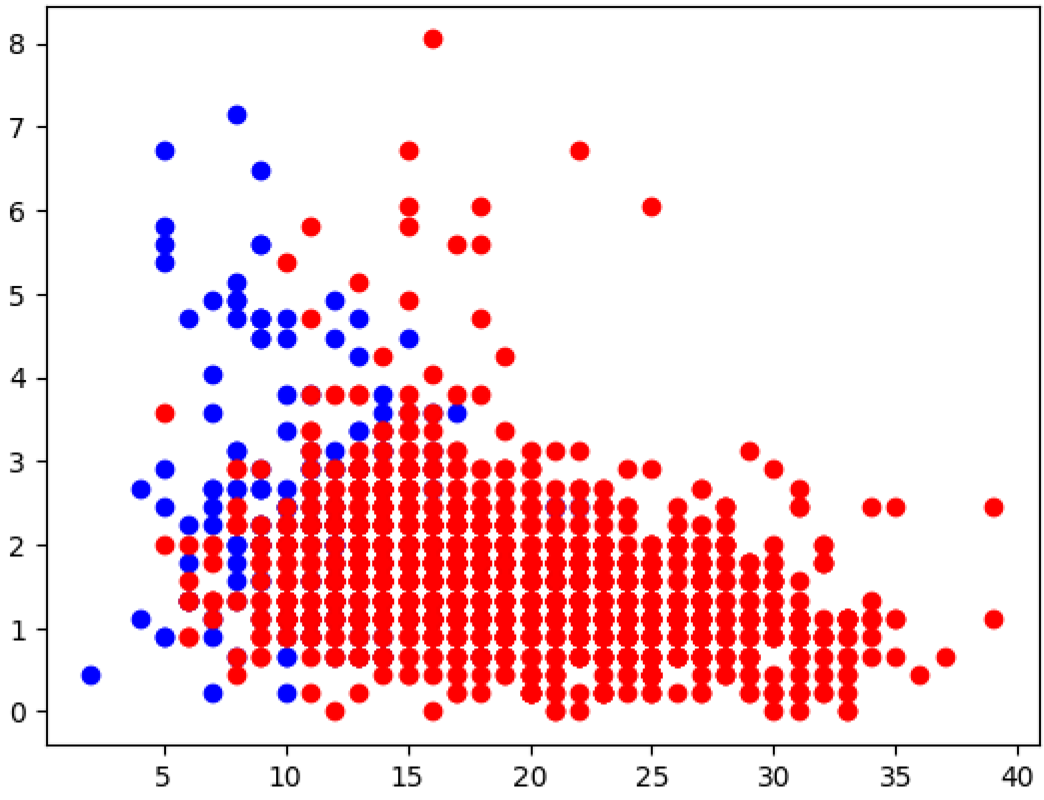
```
sample_mean= np.mean(y-y_pred)
sample_std= np.std(y-y_pred, ddof=1)
u=0
z= (sample_mean- u)/(sample_std/math.sqrt(x.size))
z_lower= u- t.cdf(0.005, x.size-2)
z_higher= u+ t.cdf(0.005, x.size-2)
print('Confidence intervals for Test statistics is (',z_lower, ' ,',z_higher, ')')
print('Value of Test Statistics is ',z)
```

```
Confidence intervals for Test statistics is ( -0.5019944298579171  , 0.50199442985791
Value of Test Statistics is  -5.140437822417571e-13
```

Since the test statistics lies in the acceptance region i.e the confidence interval for the test statistics, we fail to reject the Null Hypothesis. This implies that using Linear regression was a good choice for our analysis. We can say this with 99% confidence.

Fitting a Neural Network on the dataset for rainfall prediction.

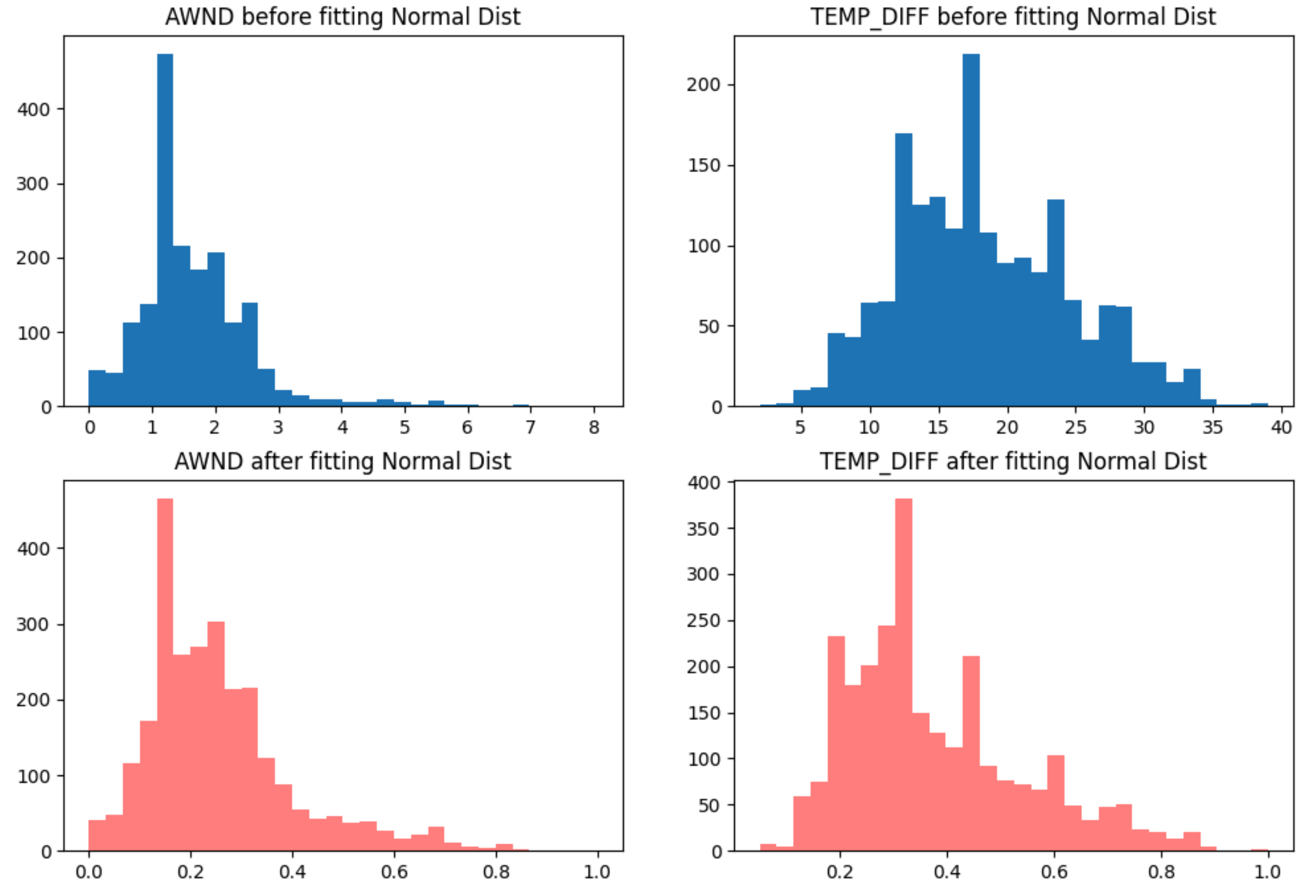
```
from sklearn.model_selection import train_test_split

df.loc[df["PRCP"] > 0.0, "PRCP"] = 1.0
df_x= df.drop(columns= ['PRCP', 'YEAR'])
df_y= df['PRCP']
df_x = df_x.fillna(df_x.mode().iloc[0])
df_y = df_y.fillna(df_y.mode().iloc[0])
df_y= pd.DataFrame(df_y)
x_train, x_test, y_train, y_test = train_test_split(df_x, df_y, test_size=0.2, random_sta
plt.scatter(df.loc[df['PRCP'] == 1, 'TEMP_DIFF'],
            df.loc[df['PRCP'] == 1, 'AWND'],
            color='blue', label='Rain Occurred')

plt.scatter(df.loc[df['PRCP'] == 0, 'TEMP_DIFF'],
            df.loc[df['PRCP'] == 0, 'AWND'],
            color='red', label='No Rain')
plt.show()
```



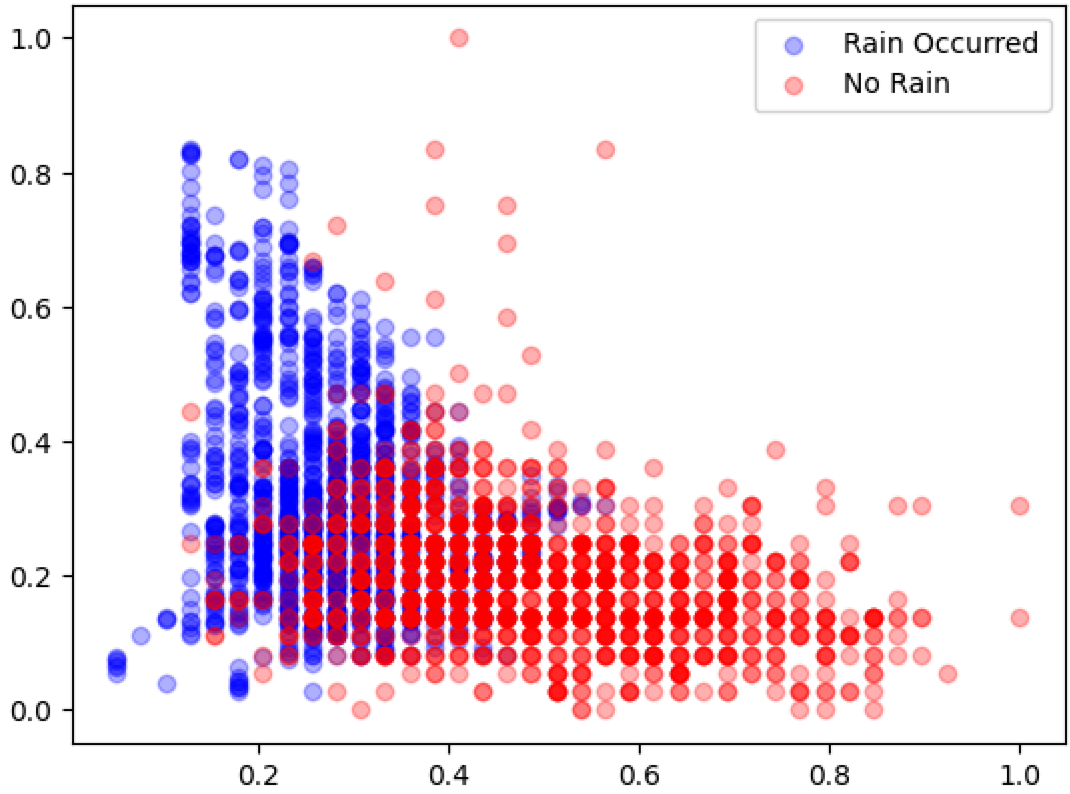
```
from sklearn.impute import SimpleImputer
from imblearn.over_sampling import SMOTE
df=df.dropna(axis=1,thresh=100)

imputer = SimpleImputer(strategy='mean')
df['AWND'] = imputer.fit_transform(df[['AWND']])
df['WDF2'] = imputer.fit_transform(df[['WDF2']])
df['WDF5'] = imputer.fit_transform(df[['WDF5']])
df['WSF2'] = imputer.fit_transform(df[['WSF2']])
df['WSF5'] = imputer.fit_transform(df[['WSF5']])
df['TMAX'] = imputer.fit_transform(df[['TMAX']])
df['TMIN'] = imputer.fit_transform(df[['TMIN']])
df['TEMP_DIFF'] = imputer.fit_transform(df[['TEMP_DIFF']])
smote = SMOTE(random_state=42)
x_resampled, y_resampled = smote.fit_resample(x_train, y_train)
new_df=pd.concat([x_resampled,y_resampled], axis=1)

dfnorm = new_df.copy()
for column in dfnorm.columns:
    dfnorm[column] = dfnorm[column]  / dfnorm[column].abs().max()
display(dfnorm)
```

	AWND	TMAX	TMIN	WDF2	WDF5	WSF2	WSF5	TEMP_DIFF	PI
0	0.332919	0.750000	0.759494	0.750000	0.750000	0.576190	0.500000	0.538462	
1	0.110559	0.814815	0.835443	0.722222	0.750000	0.385714	0.382353	0.564103	
2	0.110559	0.787037	0.797468	0.722222	0.722222	0.385714	0.382353	0.564103	
3	0.195031	0.796296	0.822785	0.750000	0.750000	0.423810	0.414706	0.538462	
4	0.305590	0.740741	0.835443	0.722222	0.722222	0.385714	0.414706	0.358974	
...	...	...	...	...	...	...	...	...	
2655	0.131647	0.638889	0.721519	0.750000	0.722222	0.413831	0.390827	0.282051	
2656	0.380945	0.564815	0.708861	0.305556	0.283161	0.507716	0.554013	0.128205	
2657	0.269526	0.601852	0.670886	0.750000	0.722222	0.510717	0.505242	0.307692	
2658	0.311781	0.564815	0.658228	0.235890	0.097443	0.480952	0.449393	0.230769	
2659	0.313359	0.592593	0.670886	0.750000	0.750000	0.485249	0.619477	0.256410	

```
fig, axs= plt.subplots(2,2, figsize=(12, 8))

axs[0,0].hist(df['AWND'], bins=30)
axs[0,0].set_title('AWND before fitting Normal Dist')
axs[0,1].hist(df['TEMP_DIFF'], bins=30)
axs[0,1].set_title('TEMP_DIFF before fitting Normal Dist')
axs[1,0].hist(dfnorm['AWND'],bins=30, color='r', alpha=0.5)
axs[1,0].set_title('AWND after fitting Normal Dist')
axs[1,1].hist(dfnorm['TEMP_DIFF'], bins=30, color='r', alpha=0.5)
axs[1,1].set_title('TEMP_DIFF after fitting Normal Dist')

plt.show()
```



```
plt.scatter(dfnorm.loc[dfnorm['PRCP'] == 1, 'TEMP_DIFF'],
            dfnorm.loc[dfnorm['PRCP'] == 1, 'AWND'],
            color='blue', label='Rain Occurred',alpha=0.3)

plt.legend()
plt.scatter(dfnorm.loc[dfnorm['PRCP'] == 0, 'TEMP_DIFF'],
            dfnorm.loc[dfnorm['PRCP'] == 0, 'AWND'],
            color='red', label='No Rain', alpha=0.3)
plt.legend()
plt.show()
```



Classification using Neural Networks

```
from tensorflow import keras
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_

x= dfnorm.drop(['PRCP'],axis=1)
y= dfnorm['PRCP']
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)

nnmodel = keras.Sequential([
    keras.layers.Dense(32, activation='relu', input_shape=(x_train.shape[1],)),
    keras.layers.Dense(32, activation='relu', input_shape=(x_train.shape[1],)),
    keras.layers.Dense(1, activation='sigmoid')
])
nnmodel.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
history = nnmodel.fit(x_train, y_train, epochs=50, batch_size=32, validation_split=0.2)

y_pred1 = nnmodel.predict(x_test)
y_pred1 = (y_pred1 > 0.5).astype(int)
acc3= accuracy_score(y_test,y_pred1)
roc3= roc_auc_score(y_test,y_pred1)
report= classification_report(y_test,y_pred1,output_dict=True)
report_df3 = pd.DataFrame(report).transpose()
report_df3
```

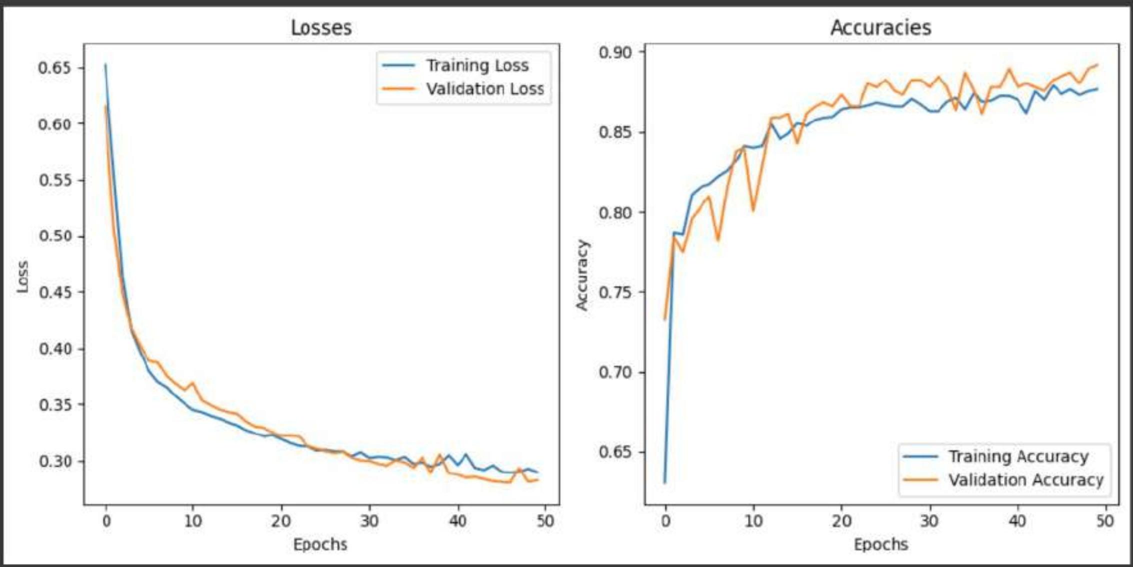
```
Epoch 1/50
54/54 [==============================] - 1s 7ms/step - loss: 0.6519 - accuracy: 0.630
Epoch 2/50
54/54 [==============================] - 0s 3ms/step - loss: 0.5549 - accuracy: 0.787
Epoch 3/50
54/54 [==============================] - 0s 4ms/step - loss: 0.4629 - accuracy: 0.786
Epoch 4/50
54/54 [==============================] - 0s 3ms/step - loss: 0.4149 - accuracy: 0.810
Epoch 5/50
54/54 [==============================] - 0s 4ms/step - loss: 0.3958 - accuracy: 0.815
Epoch 6/50
54/54 [==============================] - 0s 3ms/step - loss: 0.3796 - accuracy: 0.817
Epoch 7/50
54/54 [==============================] - 0s 3ms/step - loss: 0.3701 - accuracy: 0.822
Epoch 8/50
54/54 [==============================] - 0s 3ms/step - loss: 0.3654 - accuracy: 0.825
Epoch 9/50
54/54 [==============================] - 0s 4ms/step - loss: 0.3571 - accuracy: 0.832
Epoch 10/50
54/54 [==============================] - 0s 3ms/step - loss: 0.3505 - accuracy: 0.841
Epoch 11/50
54/54 [==============================] - 0s 3ms/step - loss: 0.3450 - accuracy: 0.840
Epoch 12/50
54/54 [==============================] - 0s 3ms/step - loss: 0.3429 - accuracy: 0.841
Epoch 13/50
54/54 [==============================] - 0s 3ms/step - loss: 0.3398 - accuracy: 0.854
Epoch 14/50
54/54 [==============================] - 0s 4ms/step - loss: 0.3372 - accuracy: 0.845
Epoch 15/50
54/54 [==============================] - 0s 3ms/step - loss: 0.3342 - accuracy: 0.849
Epoch 16/50
54/54 [==============================] - 0s 3ms/step - loss: 0.3314 - accuracy: 0.855
Epoch 17/50
54/54 [==============================] - 0s 4ms/step - loss: 0.3272 - accuracy: 0.853
Epoch 18/50
54/54 [==============================] - 0s 4ms/step - loss: 0.3244 - accuracy: 0.857
Epoch 19/50
54/54 [==============================] - 0s 5ms/step - loss: 0.3214 - accuracy: 0.859
Epoch 20/50
54/54 [==============================] - 0s 4ms/step - loss: 0.3227 - accuracy: 0.859
Epoch 21/50
54/54 [==============================] - 0s 4ms/step - loss: 0.3192 - accuracy: 0.864
Epoch 22/50
54/54 [==============================] - 0s 4ms/step - loss: 0.3157 - accuracy: 0.865
Epoch 23/50
54/54 [==============================] - 0s 5ms/step - loss: 0.3131 - accuracy: 0.865
Epoch 24/50
54/54 [==============================] - 0s 6ms/step - loss: 0.3127 - accuracy: 0.866
Epoch 25/50
54/54 [==============================] - 0s 5ms/step - loss: 0.3089 - accuracy: 0.868
Epoch 26/50
54/54 [==============================] - 0s 6ms/step - loss: 0.3095 - accuracy: 0.867
Epoch 27/50
54/54 [==============================] - 0s 6ms/step - loss: 0.3082 - accuracy: 0.866
Epoch 28/50
54/54 [==============================] - 0s 3ms/step - loss: 0.3082 - accuracy: 0.866
Epoch 29/50
54/54 [==============================] - 0s 3ms/step - loss: 0.3040 - accuracy: 0.870
Epoch 30/50
54/54 [==============================] - 0s 3ms/step - loss: 0.3074 - accuracy: 0.867
```

```
Epoch 31/50
```

```
54/54 [==============================] - 0s 3ms/step - loss: 0.3048 - accuracy: 0.8707 - val_loss: 0.3030 - val_accuracy: 0.8826
Epoch 30/50
54/54 [==============================] - 0s 3ms/step - loss: 0.3074 - accuracy: 0.8672 - val_loss: 0.3003 - val_accuracy: 0.8826
Epoch 31/50
54/54 [==============================] - 0s 4ms/step - loss: 0.3025 - accuracy: 0.8631 - val_loss: 0.2998 - val_accuracy: 0.8779
Epoch 32/50
54/54 [==============================] - 0s 3ms/step - loss: 0.3036 - accuracy: 0.8631 - val_loss: 0.2972 - val_accuracy: 0.8850
Epoch 33/50
54/54 [==============================] - 0s 3ms/step - loss: 0.3031 - accuracy: 0.8690 - val_loss: 0.2957 - val_accuracy: 0.8779
Epoch 34/50
54/54 [==============================] - 0s 3ms/step - loss: 0.3007 - accuracy: 0.8713 - val_loss: 0.3005 - val_accuracy: 0.8638
Epoch 35/50
54/54 [==============================] - 0s 3ms/step - loss: 0.3033 - accuracy: 0.8643 - val_loss: 0.2986 - val_accuracy: 0.8873
Epoch 36/50
54/54 [==============================] - 0s 3ms/step - loss: 0.2972 - accuracy: 0.8743 - val_loss: 0.2939 - val_accuracy: 0.8756
Epoch 37/50
54/54 [==============================] - 0s 3ms/step - loss: 0.2985 - accuracy: 0.8690 - val_loss: 0.3029 - val_accuracy: 0.8615
Epoch 38/50
54/54 [==============================] - 0s 4ms/step - loss: 0.2948 - accuracy: 0.8696 - val_loss: 0.2893 - val_accuracy: 0.8779
Epoch 39/50
54/54 [==============================] - 0s 3ms/step - loss: 0.2973 - accuracy: 0.8725 - val_loss: 0.3056 - val_accuracy: 0.8779
Epoch 40/50
54/54 [==============================] - 0s 3ms/step - loss: 0.3048 - accuracy: 0.8725 - val_loss: 0.2888 - val_accuracy: 0.8897
Epoch 41/50
54/54 [==============================] - 0s 3ms/step - loss: 0.2962 - accuracy: 0.8702 - val_loss: 0.2874 - val_accuracy: 0.8779
Epoch 42/50
54/54 [==============================] - 0s 3ms/step - loss: 0.3057 - accuracy: 0.8619 - val_loss: 0.2849 - val_accuracy: 0.8803
Epoch 43/50
54/54 [==============================] - 0s 3ms/step - loss: 0.2938 - accuracy: 0.8754 - val_loss: 0.2855 - val_accuracy: 0.8779
Epoch 44/50
54/54 [==============================] - 0s 3ms/step - loss: 0.2918 - accuracy: 0.8702 - val_loss: 0.2836 - val_accuracy: 0.8756
Epoch 45/50
54/54 [==============================] - 0s 3ms/step - loss: 0.2958 - accuracy: 0.8790 - val_loss: 0.2818 - val_accuracy: 0.8826
Epoch 46/50
54/54 [==============================] - 0s 3ms/step - loss: 0.2901 - accuracy: 0.8737 - val_loss: 0.2810 - val_accuracy: 0.8850
Epoch 47/50
54/54 [==============================] - 0s 3ms/step - loss: 0.2897 - accuracy: 0.8766 - val_loss: 0.2803 - val_accuracy: 0.8873
Epoch 48/50
54/54 [==============================] - 0s 3ms/step - loss: 0.2901 - accuracy: 0.8731 - val_loss: 0.2934 - val_accuracy: 0.8803
Epoch 49/50
54/54 [==============================] - 0s 3ms/step - loss: 0.2929 - accuracy: 0.8754 - val_loss: 0.2812 - val_accuracy: 0.8897
Epoch 50/50
54/54 [==============================] - 0s 3ms/step - loss: 0.2900 - accuracy: 0.8766 - val_loss: 0.2836 - val_accuracy: 0.8920
17/17 [==============================] - 0s 2ms/step
```

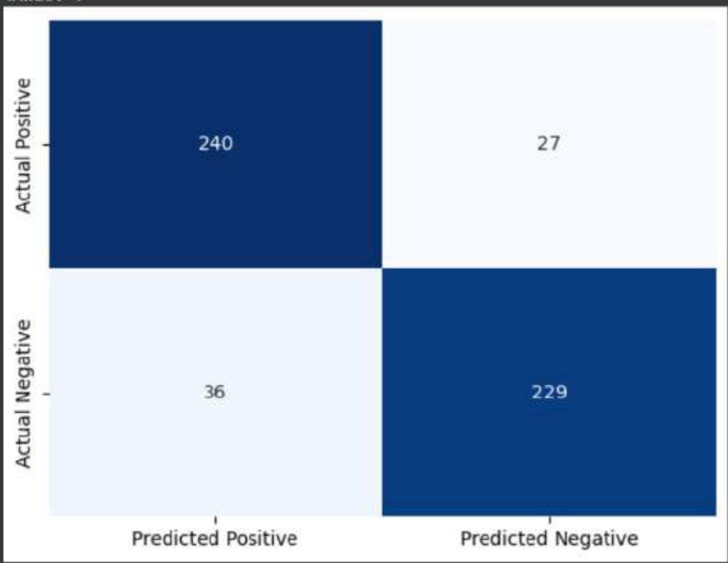
	precision	recall	f1-score	support
0.0	0.869565	0.898876	0.883978	267.000000
1.0	0.894531	0.864151	0.879079	265.000000
accuracy	0.881579	0.881579	0.881579	0.881579
macro avg	0.882048	0.881514	0.881528	532.000000
weighted avg	0.882001	0.881579	0.881538	532.000000

```python
train_loss = history.history['loss']
val_loss = history.history['val_loss']
train_accuracy = history.history['accuracy']
val_accuracy = history.history['val_accuracy']

plt.figure(figsize=(10, 5))
plt.subplot(1, 2, 1)
plt.plot(train_loss, label='Training Loss')
plt.plot(val_loss, label='Validation Loss')
plt.title('Losses')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(train_accuracy, label='Training Accuracy')
plt.plot(val_accuracy, label='Validation Accuracy')
plt.title('Accuracies')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```



```
[ ] cm= confusion_matrix(y_test,y_pred1)
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", cbar=False,
                xticklabels=['Predicted Positive', 'Predicted Negative'],
                yticklabels=['Actual Positive', 'Actual Negative'])
```

```
<Axes: >
```



Null Hypothesis Ho => Mean of residual =0, H1 => Mean of residual is not 0

```
sample_mean= np.mean(y_test.values-y_pred1)
sample_std= np.std(y_test.values-y_pred1, ddof=1)
u=0
z= (sample_mean- u)/(sample_std/math.sqrt(x.size))
z_lower= u- t.cdf(0.05, x.size-2)
z_higher= u+ t.cdf(0.05, x.size-2)
print('Confidence intervals for Test statistics is (',z_lower, ' ,',z_higher, ')')
print('Value of Test Statistics is ',z)
```

```
Confidence intervals for Test statistics is ( -0.5199385711842266  , 0.5199385711842266 )
Value of Test Statistics is  3.4912902637457854
```

Neural Networks used to classify whether rain occued on a particular day was succesfull on test data at an accuracy of 88%. But we will have to reject the above hypothesis since value of test statistics is not in the confidence interval for our Test statistics.