aicte-internship-final-submission

July 31, 2025

[63]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import SelectKBest, f_classif,␣
 ↪mutual_info_classif
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import SelectKBest, f_classif,␣
 ↪mutual_info_classif
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import ␣
 ↪accuracy_score,classification_report,ConfusionMatrixDisplay
from sklearn.neighbors import KNeighborsClassifier
from xgboost import XGBClassifier
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
```

[64]:
```
df1 = pd.read_csv('modis_2021_India.csv')
df2 = pd.read_csv('modis_2022_India.csv')
df3 = pd.read_csv('modis_2023_India.csv')
```

[65]:
```
df1.head()
```

[65]:

	latitude	longitude	brightness	scan	track	acq_date	acq_time	\
0	28.0993	96.9983	303.0	1.1	1.1	2021-01-01	409	
1	30.0420	79.6492	301.8	1.4	1.2	2021-01-01	547	
2	30.0879	78.8579	300.2	1.3	1.1	2021-01-01	547	
3	30.0408	80.0501	302.0	1.5	1.2	2021-01-01	547	
4	30.6565	78.9668	300.9	1.3	1.1	2021-01-01	547	

	satellite	instrument	confidence	version	bright_t31	frp	daynight	type
0	Terra	MODIS	44	6.03	292.6	8.6	D	0
1	Terra	MODIS	37	6.03	287.4	9.0	D	0
2	Terra	MODIS	8	6.03	286.5	5.4	D	0
3	Terra	MODIS	46	6.03	287.7	10.7	D	0

```
4     Terra      MODIS          43     6.03       287.6   9.0         D     0
```

[66]:
```
df2.head()
```

[66]:
```
   latitude  longitude  brightness  scan  track    acq_date  acq_time  \
0   30.1138    80.0756       300.0   1.2    1.1  2022-01-01       511
1   23.7726    86.2078       306.1   1.6    1.2  2022-01-01       512
2   22.2080    84.8627       304.8   1.4    1.2  2022-01-01       512
3   23.7621    86.3946       306.9   1.6    1.2  2022-01-01       512
4   23.6787    86.0891       303.6   1.5    1.2  2022-01-01       512

  satellite instrument  confidence  version  bright_t31   frp daynight  type
0     Terra      MODIS           7     6.03       288.4   7.1         D     0
1     Terra      MODIS          62     6.03       293.5  10.4         D     2
2     Terra      MODIS          42     6.03       293.3   5.8         D     2
3     Terra      MODIS          38     6.03       295.2   9.3         D     2
4     Terra      MODIS          52     6.03       293.1   7.2         D     2
```

[67]:
```
df3.head()
```

[67]:
```
   latitude  longitude  brightness  scan  track    acq_date  acq_time  \
0    9.3280    77.6247       318.0   1.1    1.0  2023-01-01       821
1   10.4797    77.9378       313.8   1.0    1.0  2023-01-01       822
2   13.2478    77.2639       314.7   1.0    1.0  2023-01-01       822
3   12.2994    78.4085       314.3   1.0    1.0  2023-01-01       822
4   14.1723    75.5024       338.4   1.2    1.1  2023-01-01       823

  satellite instrument  confidence  version  bright_t31   frp daynight  type
0      Aqua      MODIS          62    61.03       305.0   7.6         D     0
1      Aqua      MODIS          58    61.03       299.4   4.3         D     0
2      Aqua      MODIS          55    61.03       302.4   4.9         D     0
3      Aqua      MODIS          58    61.03       301.9   4.8         D     0
4      Aqua      MODIS          88    61.03       305.3  41.5         D     0
```

[68]:
```
df = pd.concat([df1, df2, df3], ignore_index=True)
df.head()
```

[68]:
```
   latitude  longitude  brightness  scan  track    acq_date  acq_time  \
0   28.0993    96.9983       303.0   1.1    1.1  2021-01-01       409
1   30.0420    79.6492       301.8   1.4    1.2  2021-01-01       547
2   30.0879    78.8579       300.2   1.3    1.1  2021-01-01       547
3   30.0408    80.0501       302.0   1.5    1.2  2021-01-01       547
4   30.6565    78.9668       300.9   1.3    1.1  2021-01-01       547

  satellite instrument  confidence  version  bright_t31   frp daynight  type
0     Terra      MODIS          44     6.03       292.6   8.6         D     0
1     Terra      MODIS          37     6.03       287.4   9.0         D     0
```

```
2     Terra      MODIS          8     6.03       286.5   5.4        D     0
3     Terra      MODIS         46     6.03       287.7  10.7        D     0
4     Terra      MODIS         43     6.03       287.6   9.0        D     0
```

[69]:
```
df.shape
```

[69]:
```
(271217, 15)
```

[70]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 271217 entries, 0 to 271216
Data columns (total 15 columns):
 #   Column      Non-Null Count   Dtype  
---  ------      --------------   -----  
 0   latitude    271217 non-null  float64
 1   longitude   271217 non-null  float64
 2   brightness  271217 non-null  float64
 3   scan        271217 non-null  float64
 4   track       271217 non-null  float64
 5   acq_date    271217 non-null  object 
 6   acq_time    271217 non-null  int64  
 7   satellite   271217 non-null  object 
 8   instrument  271217 non-null  object 
 9   confidence  271217 non-null  int64  
 10  version     271217 non-null  float64
 11  bright_t31  271217 non-null  float64
 12  frp         271217 non-null  float64
 13  daynight    271217 non-null  object 
 14  type        271217 non-null  int64  
dtypes: float64(8), int64(3), object(4)
memory usage: 31.0+ MB
```

[71]:
```
df.isnull().sum()
```

[71]:
```
latitude      0
longitude     0
brightness    0
scan          0
track         0
acq_date      0
acq_time      0
satellite     0
instrument    0
confidence    0
version       0
bright_t31    0
```

```
frp           0
daynight      0
type          0
dtype: int64
```

[72]:
```
df.duplicated().sum()
```

[72]:
```
np.int64(0)
```

[73]:
```
df.columns
```

[73]:
```
Index(['latitude', 'longitude', 'brightness', 'scan', 'track', 'acq_date',
       'acq_time', 'satellite', 'instrument', 'confidence', 'version',
       'bright_t31', 'frp', 'daynight', 'type'],
      dtype='object')
```

[74]:
```
df.describe().T
```

[74]:

	count	mean	std	min	25%	50%	75%	max
latitude	271217.0	23.947505	4.919846	8.1362	20.9655	23.7888	27.7827	34.9734
longitude	271217.0	81.284024	6.559071	68.4526	75.8802	79.3209	84.7559	97.1044
brightness	271217.0	323.719192	14.147221	300.0000	314.5000	322.0000	330.7000	505.7000
scan	271217.0	1.421732	0.630742	1.0000	1.0000	1.2000	1.5000	4.8000
track	271217.0	1.152716	0.201943	1.0000	1.0000	1.1000	1.2000	2.0000
acq_time	271217.0	824.623755	353.966965	321.0000	648.0000	756.0000	825.0000	2202.0000
confidence	271217.0	64.065081	18.165329	0.0000	54.0000	66.0000	76.0000	100.0000
version	271217.0	21.933778	24.935515	6.0300	6.0300	6.0300	61.0300	61.0300
bright_t31	271217.0	303.499177	8.282440	267.2000	298.2000	302.5000	309.2000	400.1000
frp	271217.0	27.722058	81.017471	0.0000	8.7000	13.5000	24.5000	6961.8000
type	271217.0	0.100385	0.437215	0.0000	0.0000	0.0000	0.0000	3.0000

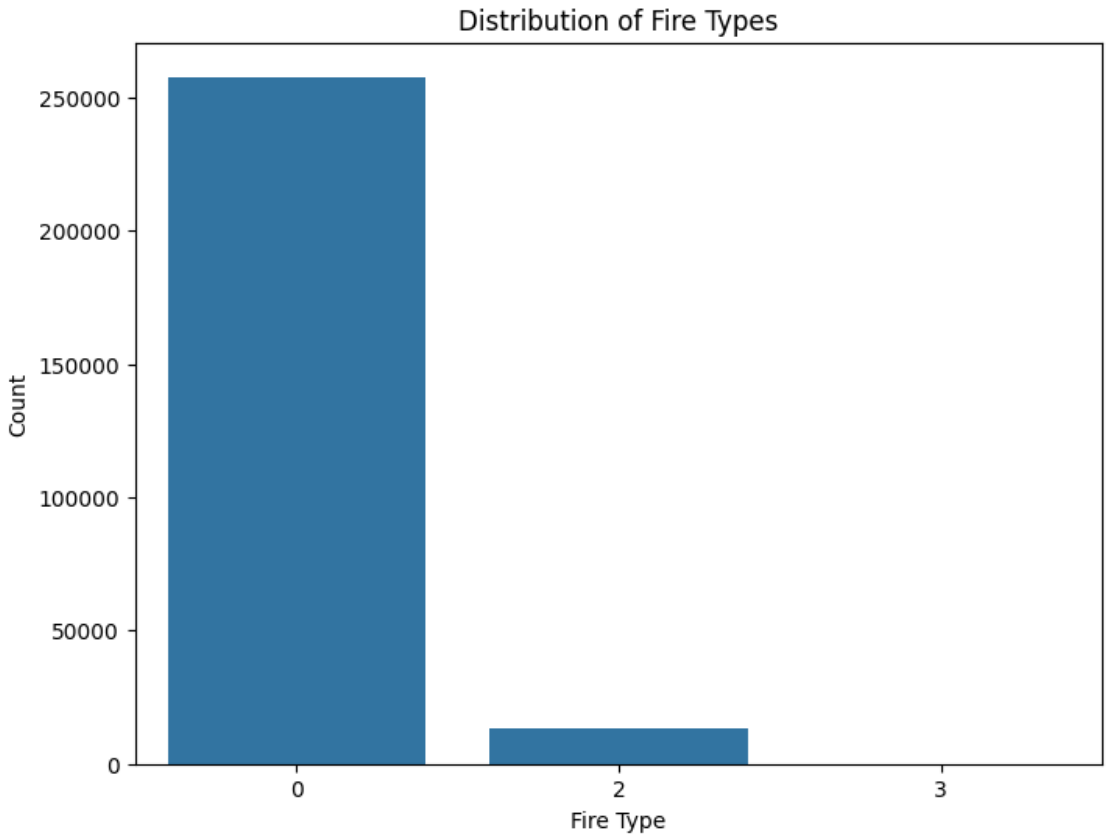
[75]:
```
df.type.value_counts()
```

[75]:
```
type
0    257625
2     13550
3        42
Name: count, dtype: int64
```

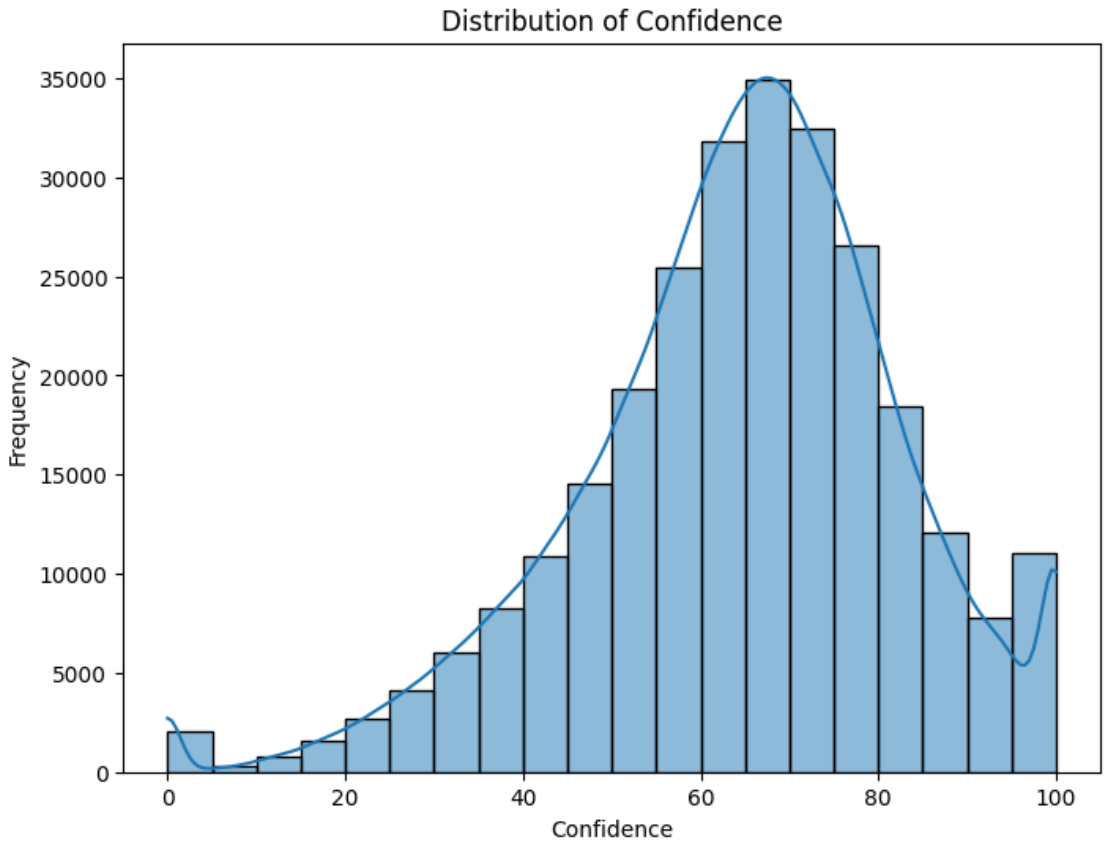
[76]:
```
for col in df.columns:
  if df[col].dtype == 'object':
    print(f"Column: {col}")
    print(f"Unique values: {df[col].unique()}")
    print(f"Number of unique values: {df[col].nunique()}")
    print("-" * 50)
```

```
Column: acq_date
Unique values: ['2021-01-01' '2021-01-02' '2021-01-03' … '2023-12-29'
'2023-12-30'
 '2023-12-31']
Number of unique values: 1088
--------------------------------------------------
Column: satellite
Unique values: ['Terra' 'Aqua']
Number of unique values: 2
--------------------------------------------------
Column: instrument
Unique values: ['MODIS']
Number of unique values: 1
--------------------------------------------------
Column: daynight
Unique values: ['D' 'N']
Number of unique values: 2
--------------------------------------------------
```

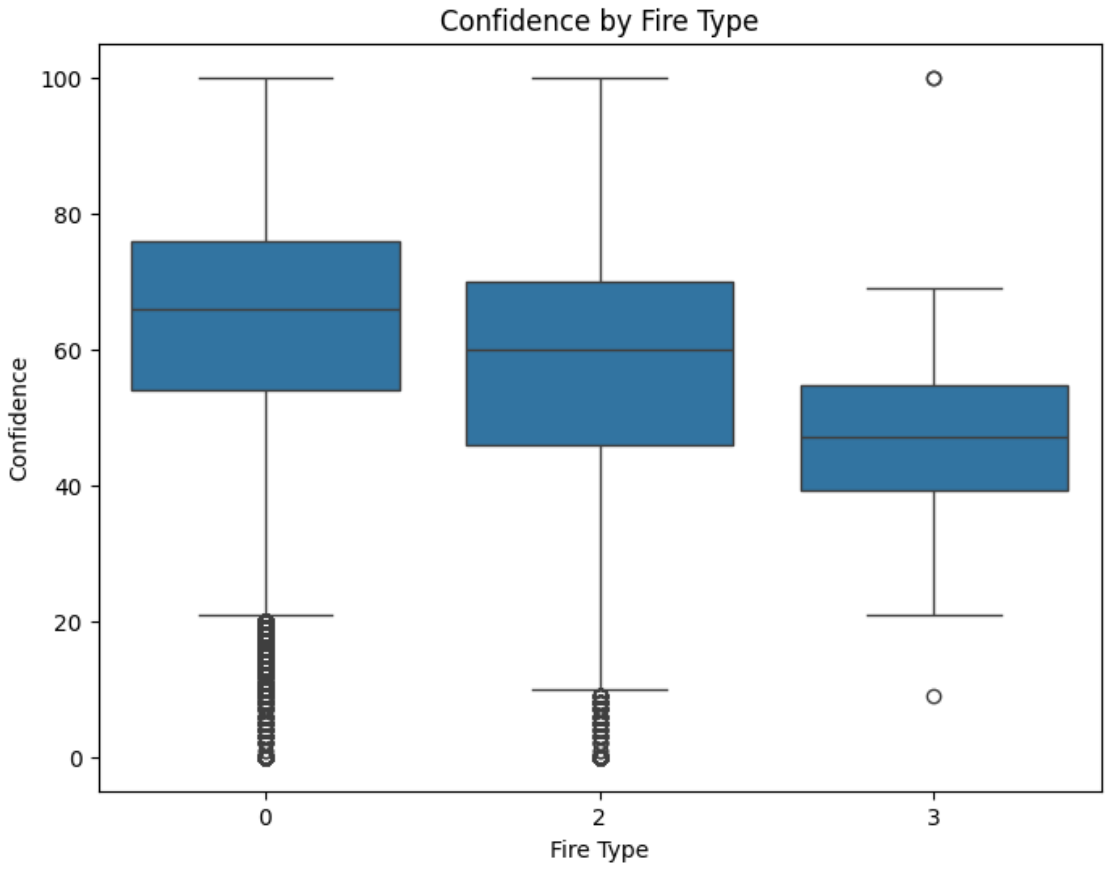
[77]:
```
plt.figure(figsize=(8, 6))
sns.countplot(x='type', data=df)
plt.title('Distribution of Fire Types')
plt.xlabel('Fire Type')
plt.ylabel('Count')
plt.show()
```



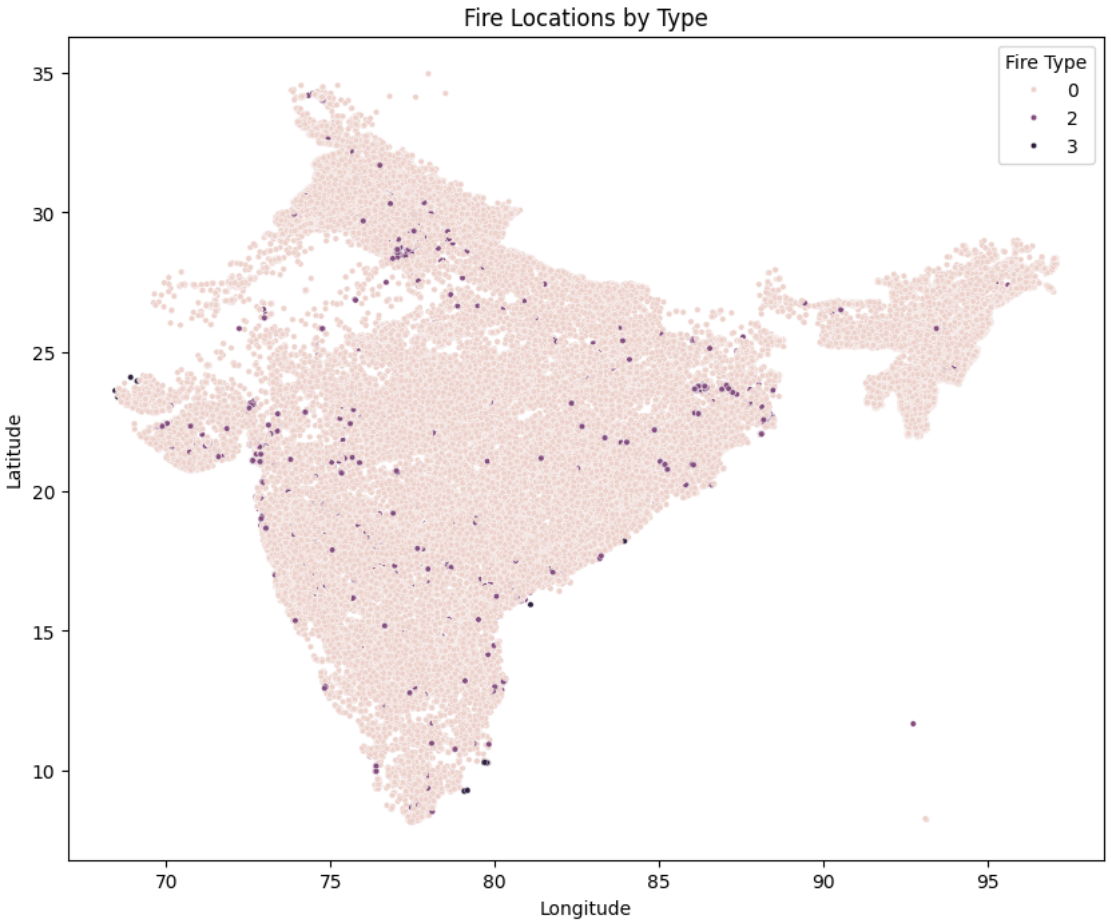
[78]:
```
plt.figure(figsize=(8, 6))
sns.histplot(df['confidence'], bins=20, kde=True)
plt.title('Distribution of Confidence')
plt.xlabel('Confidence')
plt.ylabel('Frequency')
plt.show()
```



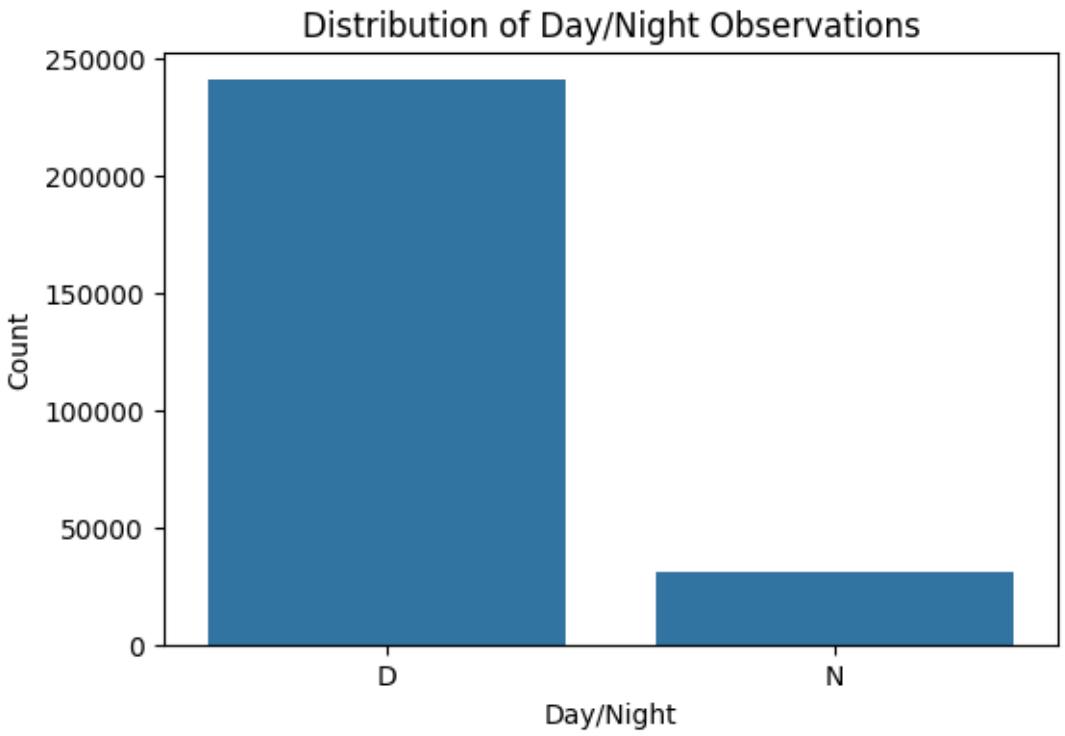
[79]:
```
plt.figure(figsize=(8, 6))
sns.boxplot(x='type', y='confidence', data=df)  # box plot
plt.title('Confidence by Fire Type')
plt.xlabel('Fire Type')
plt.ylabel('Confidence')
plt.show()
```



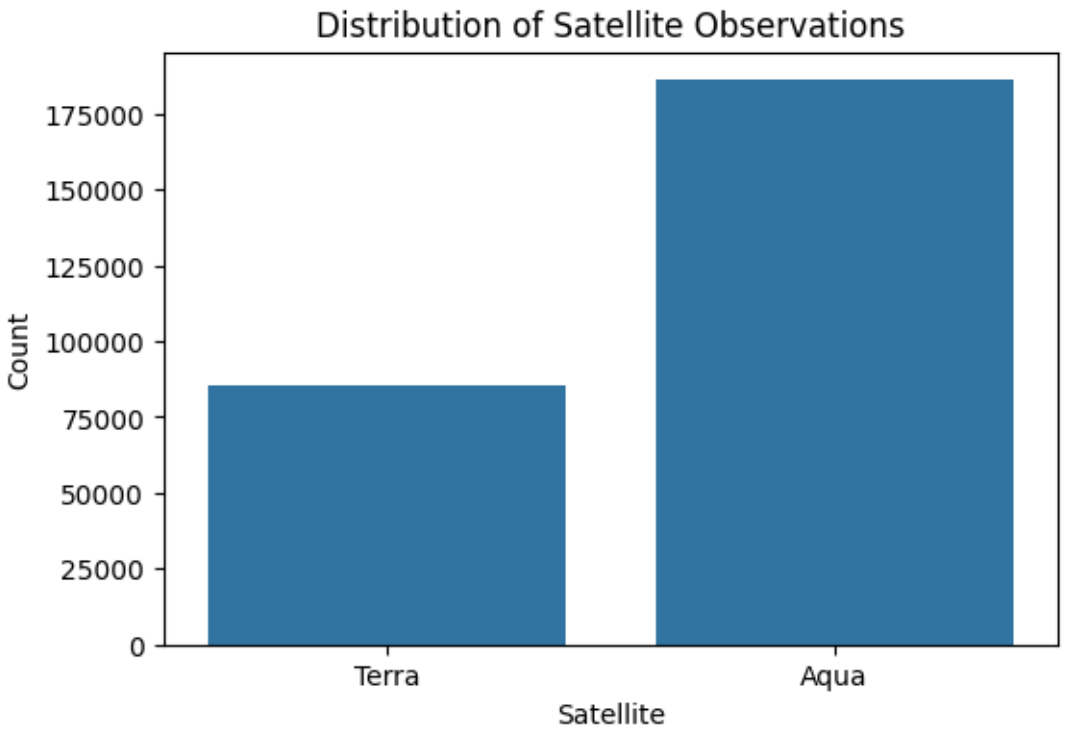
[80]:
```
plt.figure(figsize=(10, 8))
sns.scatterplot(x='longitude', y='latitude', data=df, hue='type', s=10)  #␣
 ↪scatterplot
plt.title('Fire Locations by Type')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.legend(title='Fire Type')
plt.show()
```



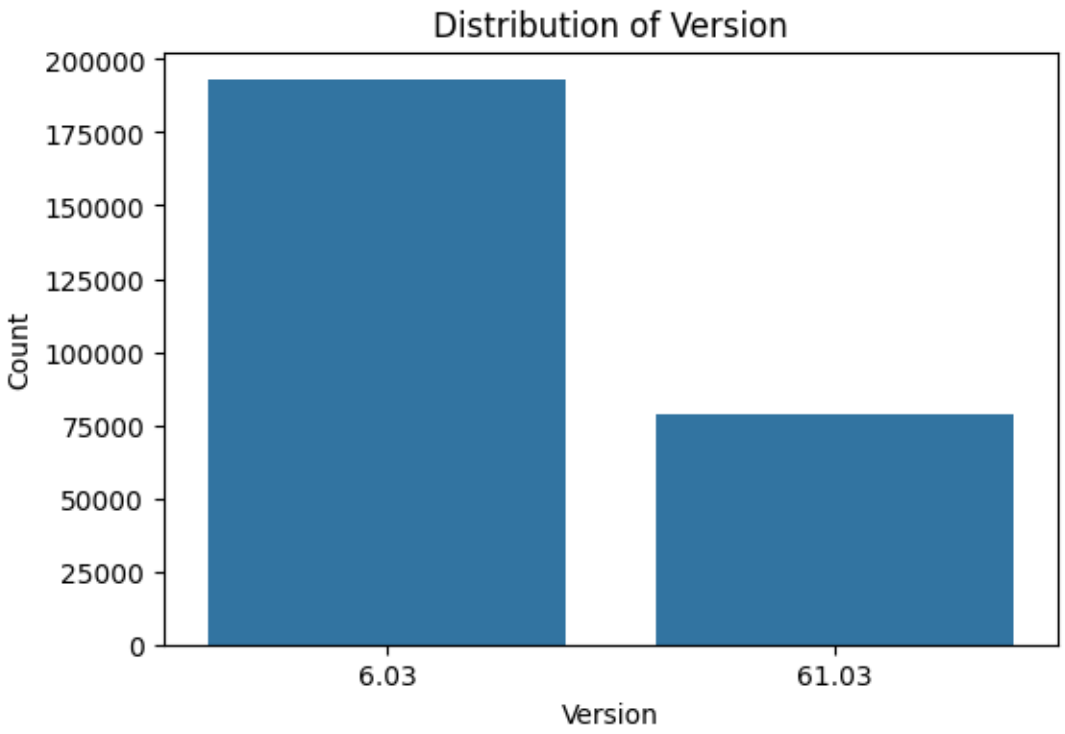
[81]:
```
plt.figure(figsize=(6, 4))
sns.countplot(x='daynight', data=df)  # count plot
plt.title('Distribution of Day/Night Observations')
plt.xlabel('Day/Night')
plt.ylabel('Count')
plt.show()
```



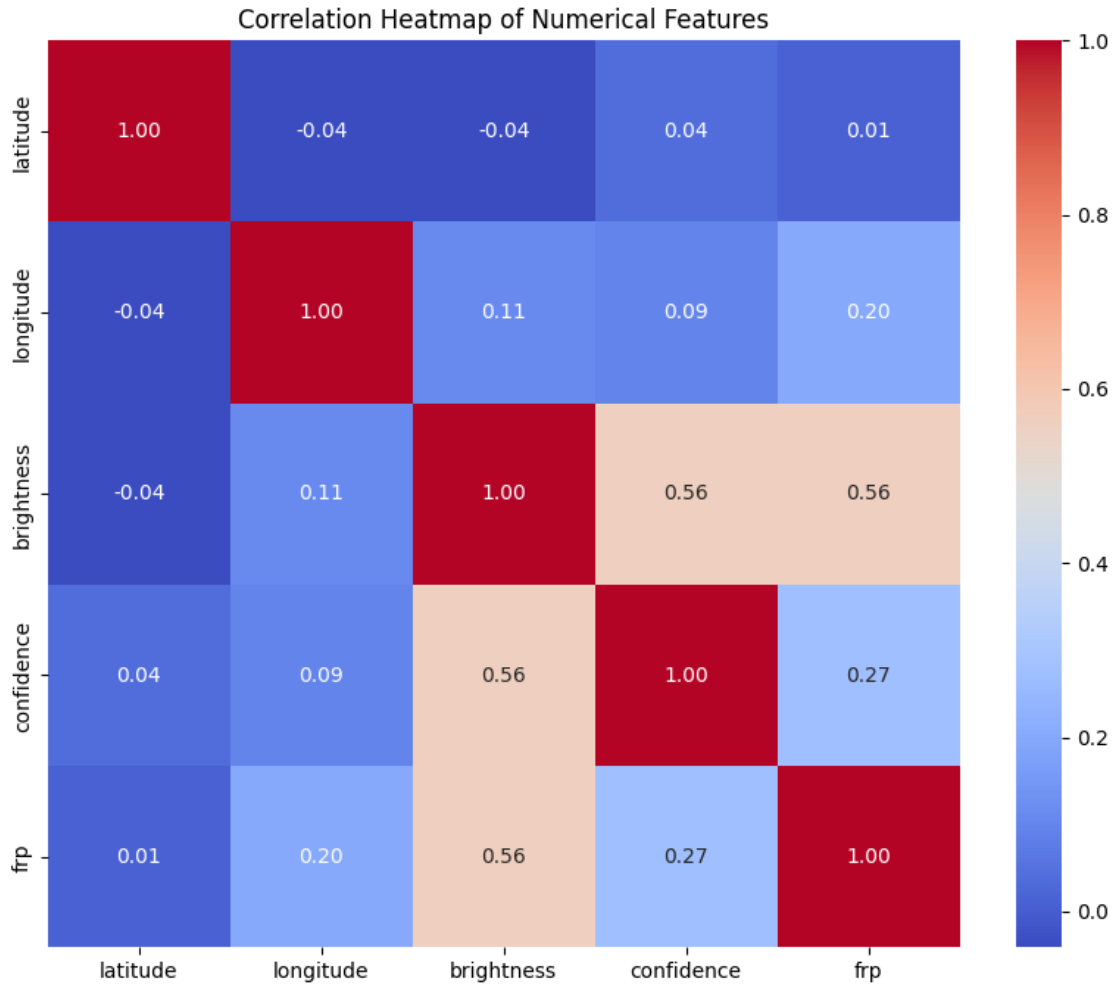
[82]:
```
plt.figure(figsize=(6, 4))
sns.countplot(x='satellite', data=df)  # satellite count plot
plt.title('Distribution of Satellite Observations')
plt.xlabel('Satellite')
plt.ylabel('Count')
plt.show()
```



[83]:
```
plt.figure(figsize=(6, 4))
sns.countplot(x='version', data=df)
plt.title('Distribution of Version')
plt.xlabel('Version')
plt.ylabel('Count')
plt.show()
```



[84]:
```
plt.figure(figsize=(10, 8))
correlation_matrix = df[['latitude', 'longitude', 'brightness', 'confidence',␣
 ↪'frp']].corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")  #␣
 ↪heatmap
plt.title('Correlation Heatmap of Numerical Features')
plt.show()
```

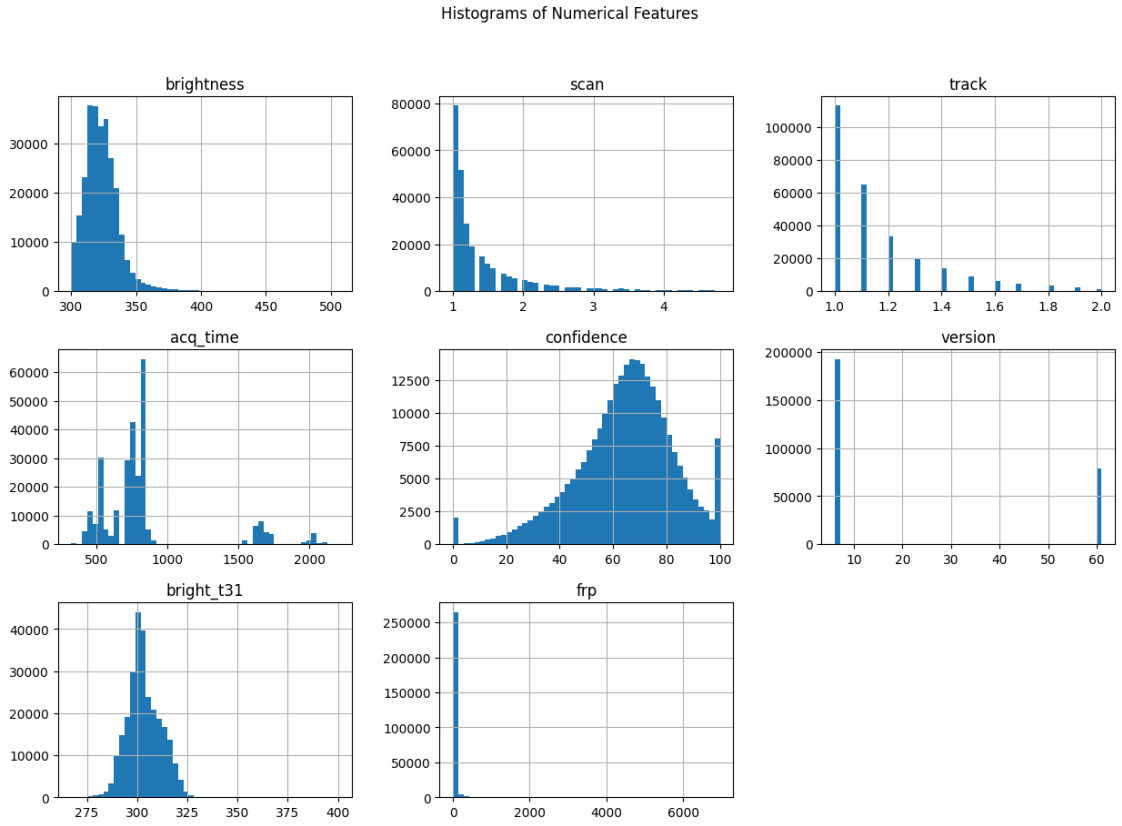


[85]:
```
numerical_cols = df.select_dtypes(include=np.number).columns
```

[86]:
```
numerical_cols
```

[86]:
```
Index(['latitude', 'longitude', 'brightness', 'scan', 'track', 'acq_time',
       'confidence', 'version', 'bright_t31', 'frp', 'type'],
      dtype='object')
```

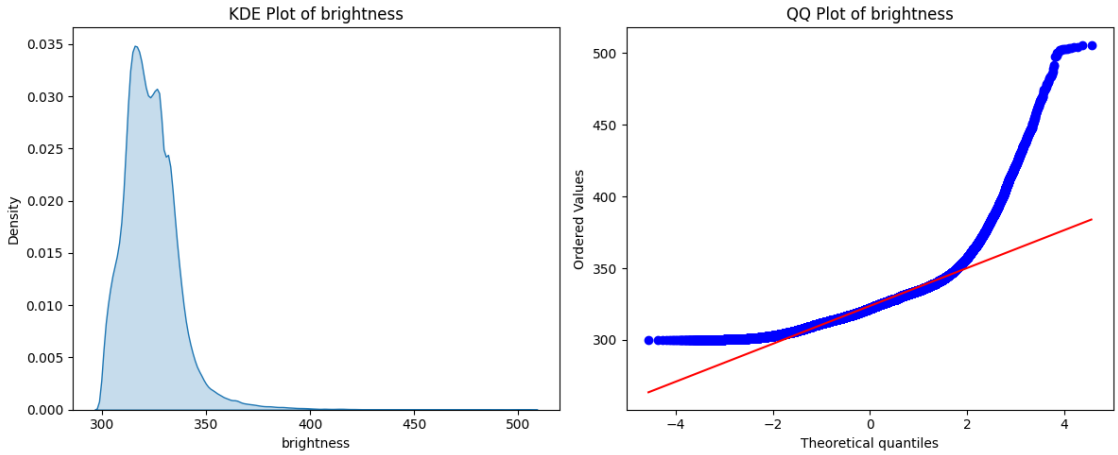
[87]:
```
numerical_cols = ['brightness', 'scan', 'track', 'acq_time','confidence',␣
 ↪'version', 'bright_t31', 'frp']
df[numerical_cols].hist(bins=50, figsize=(15, 10))
plt.suptitle('Histograms of Numerical Features')
plt.show()
```



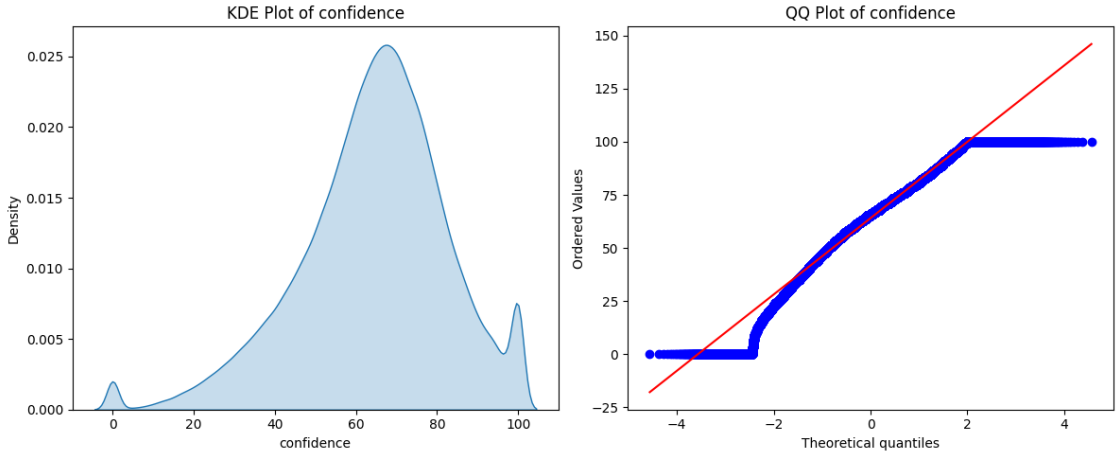
[88]:
```
import statsmodels.api as sm
import scipy.stats as stats

numerical_features = ['brightness', 'confidence', 'frp', 'bright_t31', 'scan',␣
 ↪'track']
for feature in numerical_features:
    print(f"Analyzing distribution for: {feature}")
    plt.figure(figsize=(12, 5)) # kde plot

    plt.subplot(1, 2, 1)
    sns.kdeplot(df[feature], fill=True)
    plt.title(f'KDE Plot of {feature}')
    plt.xlabel(feature)
    plt.ylabel('Density')

    plt.subplot(1, 2, 2)
    stats.probplot(df[feature], dist="norm", plot=plt)
    plt.title(f'QQ Plot of {feature}')    # QQ plot

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

```
    print("-" * 50)
```

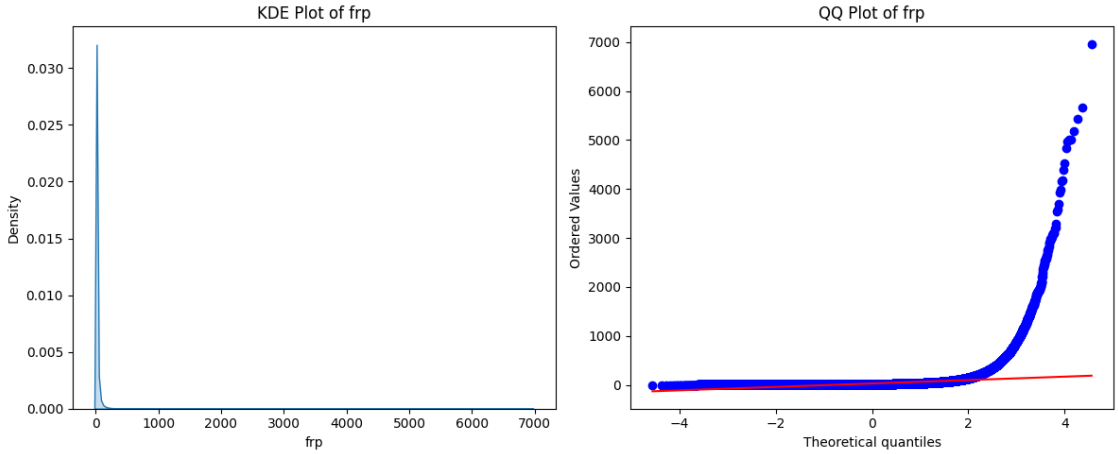
```
Analyzing distribution for: brightness
```



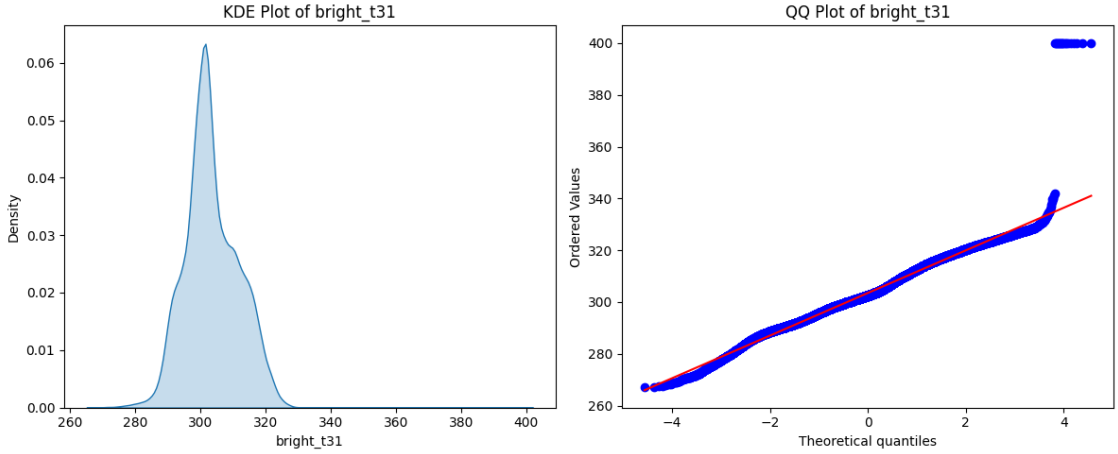

```
--------------------------------------------------
Analyzing distribution for: confidence
```



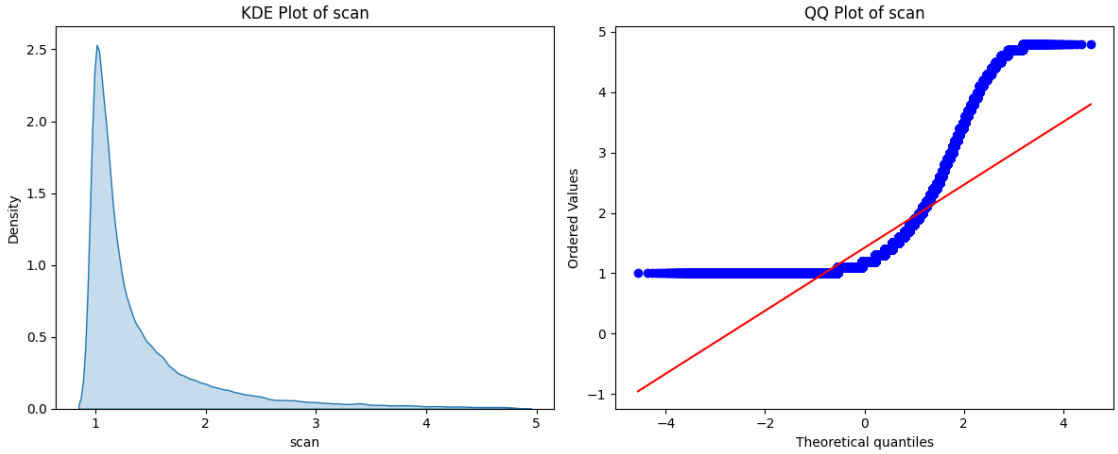

```
--------------------------------------------------
Analyzing distribution for: frp
```



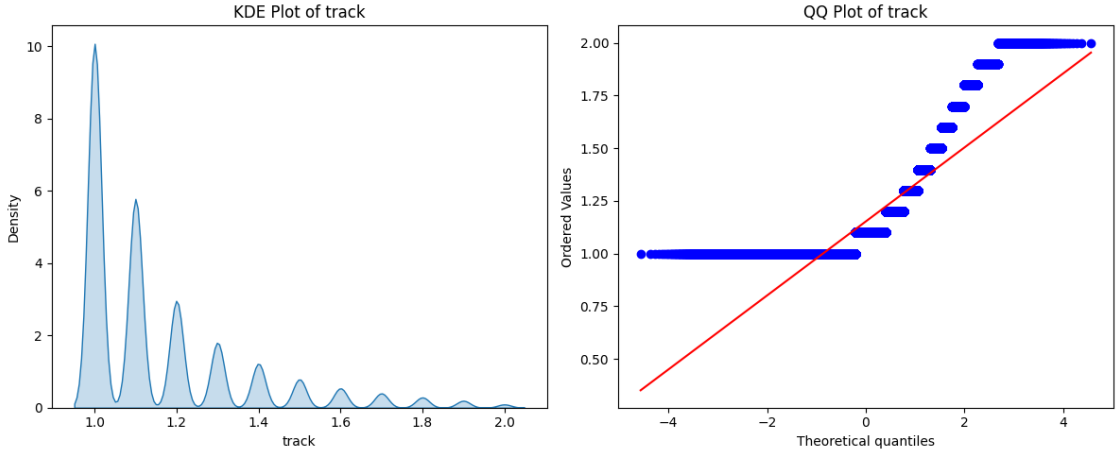
Analyzing distribution for: bright_t31



Analyzing distribution for: scan



Analyzing distribution for: track



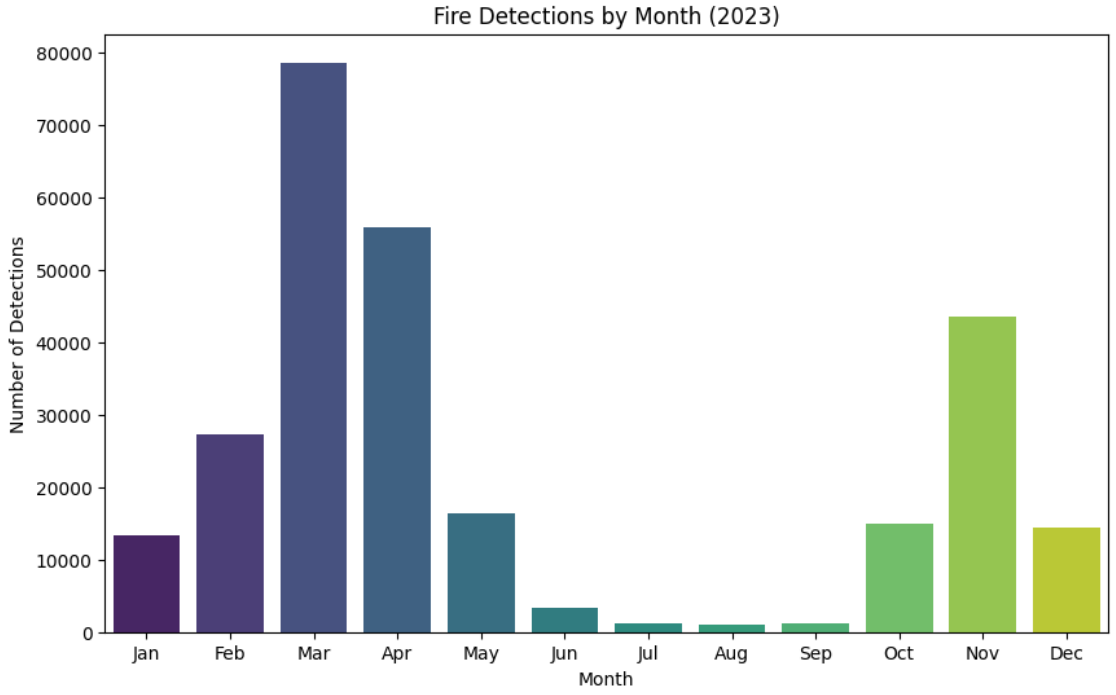
---

[89]:
```
df['acq_date'] = pd.to_datetime(df['acq_date'])

df['year'] = df['acq_date'].dt.year
df['month'] = df['acq_date'].dt.month
df['day_of_week'] = df['acq_date'].dt.dayofweek
df['day_of_year'] = df['acq_date'].dt.dayofyear
df['hour'] = df['acq_time'].astype(str).str[:2].astype(int)
```

[90]:
```
plt.figure(figsize=(10, 6))
sns.countplot(data=df, x='month', palette='viridis')
plt.title('Fire Detections by Month (2023)')
```

```
plt.xlabel('Month')
plt.ylabel('Number of Detections')
plt.xticks(ticks=range(12), labels=['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun',␣
  ↪'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'])
plt.show()
```

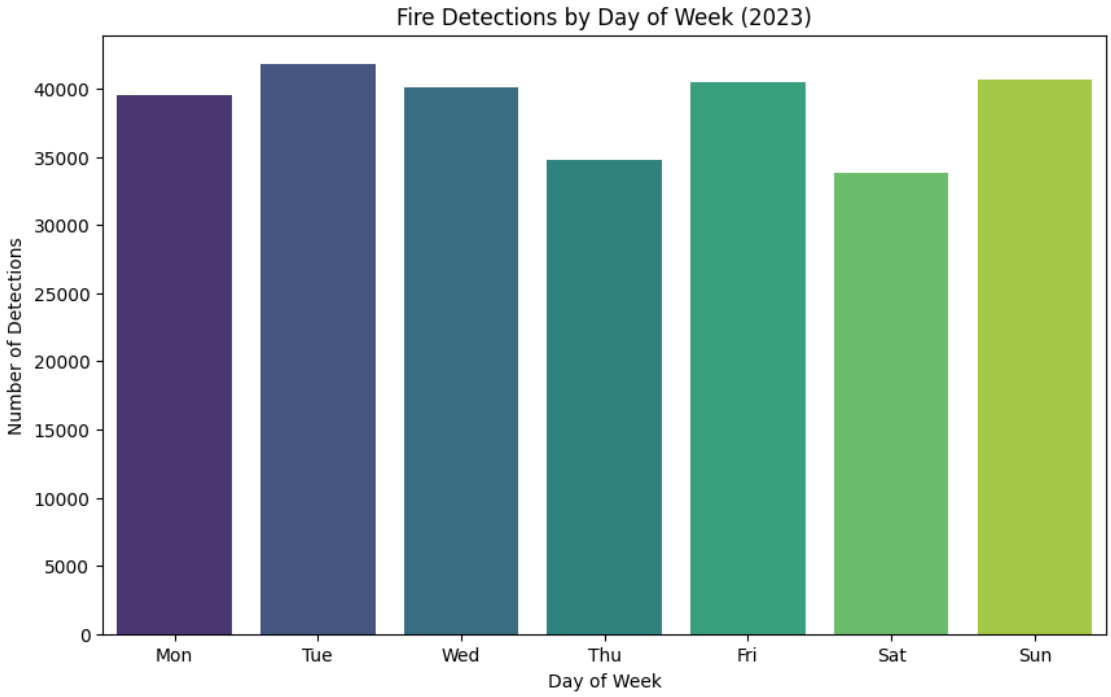
```
/tmp/ipython-input-2672674236.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(data=df, x='month', palette='viridis')
```



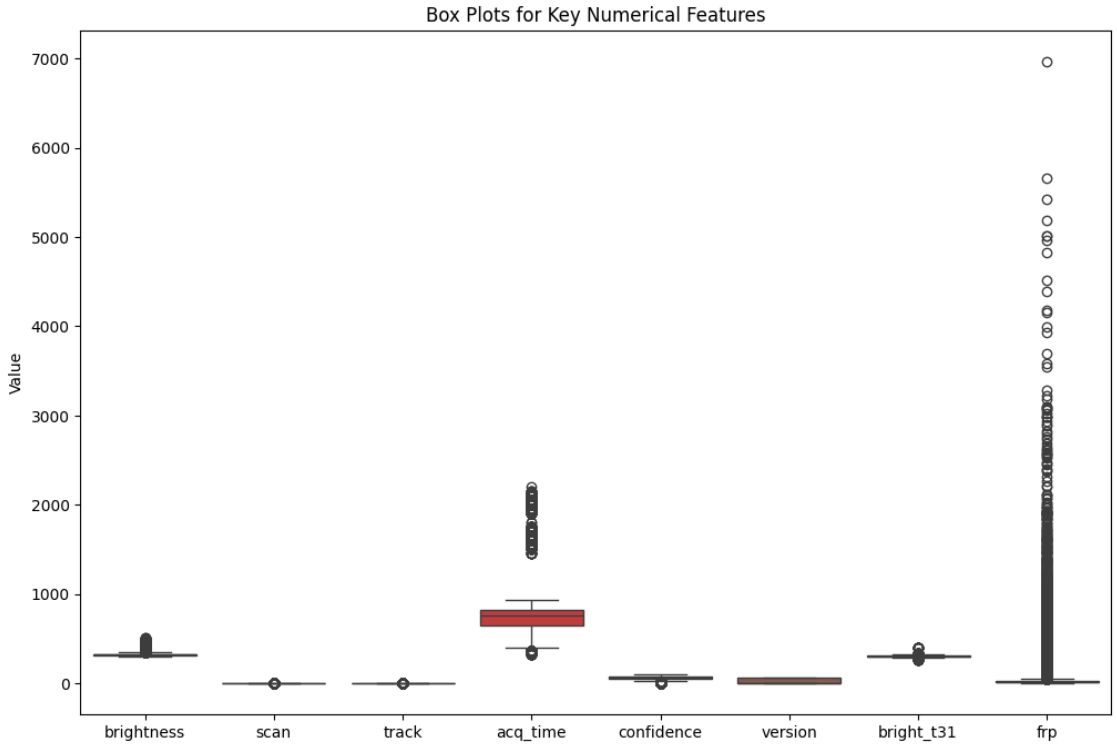
[91]:
```
plt.figure(figsize=(10, 6))
sns.countplot(data=df, x='day_of_week', palette='viridis')
plt.title('Fire Detections by Day of Week (2023)')
plt.xlabel('Day of Week')
plt.ylabel('Number of Detections')
plt.xticks(ticks=range(7), labels=['Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat',␣
  ↪'Sun'])
plt.show()
```

```
/tmp/ipython-input-1413927136.py:2: FutureWarning:
```

```
Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(data=df, x='day_of_week', palette='viridis')
```



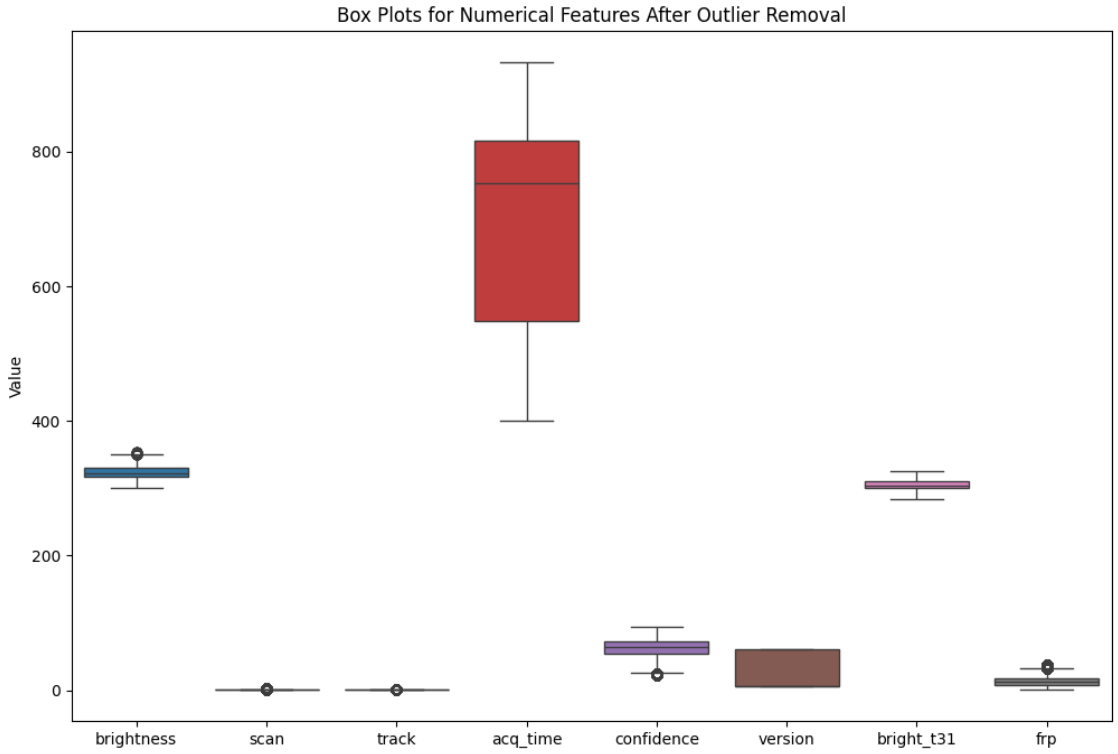
[92]:
```
plt.figure(figsize=(12, 8))
sns.boxplot(data=df[numerical_cols])  # box plot for outliers
plt.title('Box Plots for Key Numerical Features')
plt.ylabel('Value')
plt.show()
```



[93]:
```
def remove_outliers_iqr(df, column):
  Q1 = df[column].quantile(0.25)
  Q3 = df[column].quantile(0.75)
  IQR = Q3 - Q1
  lower_bound = Q1 - 1.5 * IQR
  upper_bound = Q3 + 1.5 * IQR
  df_cleaned = df[(df[column] >= lower_bound) & (df[column] <= upper_bound)].
 ↪copy()
  return df_cleaned

for col in numerical_cols:
  df = remove_outliers_iqr(df, col)

print("Shape after removing outliers:", df.shape)
```

```
Shape after removing outliers: (189370, 20)
```

[94]:
```
#box plots after outlier removal
plt.figure(figsize=(12, 8))
sns.boxplot(data=df[numerical_cols])
plt.title('Box Plots for Numerical Features After Outlier Removal')
plt.ylabel('Value')
plt.show()
```



[95]:
```
df.head()
```

[95]:

	latitude	longitude	brightness	scan	track	acq_date	acq_time	satellite	instrument	confidence	version	bright_t31	frp	daynight	type	year	month	day_of_week	day_of_year	hour
0	28.0993	96.9983	303.0	1.1	1.1	2021-01-01	409	Terra	MODIS	44	6.03	292.6	8.6	D	0	2021	1	4	1	40
1	30.0420	79.6492	301.8	1.4	1.2	2021-01-01	547	Terra	MODIS	37	6.03	287.4	9.0	D	0	2021	1	4	1	54
3	30.0408	80.0501	302.0	1.5	1.2	2021-01-01	547	Terra	MODIS	46	6.03	287.7	10.7	D	0	2021	1	4	1	54
4	30.6565	78.9668	300.9	1.3	1.1	2021-01-01	547	Terra	MODIS	43	6.03	287.6	9.0	D	0	2021	1	4	1	54
6	31.4366	76.8988	300.5	1.0	1.0	2021-01-01	547	Terra	MODIS	36	6.03	287.2	5.3	D	0	2021	1	4	1	54

[96]:
```
df.type.value_counts()
```

[96]:
```
type
0    182841
2      6501
3        28
Name: count, dtype: int64
```

[97]:
```
categorical_cols = df.select_dtypes(include='object').columns
```

[98]:
```
categorical_cols
```

[98]:
```
Index(['satellite', 'instrument', 'daynight'], dtype='object')
```

[99]:
```
# Select categorical columns for encoding
categorical_cols_to_encode = ['daynight', 'satellite', 'instrument']

#One-Hot Encoding
df_encoded = pd.get_dummies(df, columns=categorical_cols_to_encode,␣
 ↪drop_first=True)
```

[100]:
```
df_encoded.head(100)
```

[100]:

	latitude	longitude	brightness	scan	track	acq_date	acq_time	\
0	28.0993	96.9983	303.0	1.1	1.1	2021-01-01	409	
1	30.0420	79.6492	301.8	1.4	1.2	2021-01-01	547	
3	30.0408	80.0501	302.0	1.5	1.2	2021-01-01	547	
4	30.6565	78.9668	300.9	1.3	1.1	2021-01-01	547	
6	31.4366	76.8988	300.5	1.0	1.0	2021-01-01	547	
..	…	…	…	…	…	…	…	
116	23.7766	86.3997	313.8	1.0	1.0	2021-01-02	454	
117	23.6829	86.0831	310.4	1.1	1.0	2021-01-02	454	
118	23.6661	86.9215	308.2	1.0	1.0	2021-01-02	454	
119	23.8059	86.3222	313.5	1.0	1.0	2021-01-02	454	
120	23.8448	84.9512	310.7	1.2	1.1	2021-01-02	454	

	confidence	version	bright_t31	frp	type	year	month	day_of_week	\
0	44	6.03	292.6	8.6	0	2021	1	4	
1	37	6.03	287.4	9.0	0	2021	1	4	
3	46	6.03	287.7	10.7	0	2021	1	4	
4	43	6.03	287.6	9.0	0	2021	1	4	
6	36	6.03	287.2	5.3	0	2021	1	4	
..	…	…	…	…	…	…	…	…	
116	51	6.03	300.9	6.8	2	2021	1	5	
117	61	6.03	297.3	6.2	2	2021	1	5	
118	50	6.03	297.4	4.8	2	2021	1	5	
119	66	6.03	300.9	8.1	0	2021	1	5	

```
120          68     6.03       297.7   8.5      0  2021       1             5

     day_of_year  hour  satellite_Terra
0              1    40             True
1              1    54             True
3              1    54             True
4              1    54             True
6              1    54             True
..           …   …               …
116            2    45             True
117            2    45             True
118            2    45             True
119            2    45             True
120            2    45             True

[100 rows x 18 columns]
```

[101]:
```
df_encoded.type.value_counts()
```

[101]:
```
type
0    182841
2      6501
3        28
Name: count, dtype: int64
```

[102]:
```
# !pip install folium
import folium

india_map = folium.Map(location=[22.351115, 78.667743], zoom_start=5)
sample_df = df_encoded.sample(n=min(10000, len(df_encoded)), random_state=42)

for _, row in sample_df.iterrows():
    folium.CircleMarker(
        location=[row['latitude'], row['longitude']],
        radius=3,
        color='red',
        fill=True,
        fill_opacity=0.6,
        popup=f"FRP: {row['frp']:.2f}, Date: {row['acq_date'].
 ↪strftime('%Y-%m-%d')}"
    ).add_to(india_map)

display(india_map)
```

```
<folium.folium.Map at 0x7d53eef10850>
```

[103]:
```
scaler = StandardScaler()
numerical_cols_to_scale = ['brightness', 'scan', 'track', 'confidence',␣
 ↪'bright_t31', 'frp']
df_encoded[numerical_cols_to_scale] = scaler.
 ↪fit_transform(df_encoded[numerical_cols_to_scale])
df_encoded.head()
```

[103]:

	latitude	longitude	brightness	scan	track	acq_date	acq_time	\
0	28.0993	96.9983	-2.308455	-0.464860	0.059274	2021-01-01	409	
1	30.0420	79.6492	-2.445530	0.588678	0.936416	2021-01-01	547	
3	30.0408	80.0501	-2.422684	0.939857	0.936416	2021-01-01	547	
4	30.6565	78.9668	-2.548336	0.237499	0.059274	2021-01-01	547	
6	31.4366	76.8988	-2.594027	-0.816039	-0.817867	2021-01-01	547	

	confidence	version	bright_t31	frp	type	year	month	day_of_week	\
0	-1.319370	6.03	-1.754135	-0.735900	0	2021	1	4	
1	-1.818736	6.03	-2.471213	-0.683381	0	2021	1	4	
3	-1.176694	6.03	-2.429843	-0.460175	0	2021	1	4	
4	-1.390708	6.03	-2.443633	-0.683381	0	2021	1	4	
6	-1.890074	6.03	-2.498792	-1.169182	0	2021	1	4	

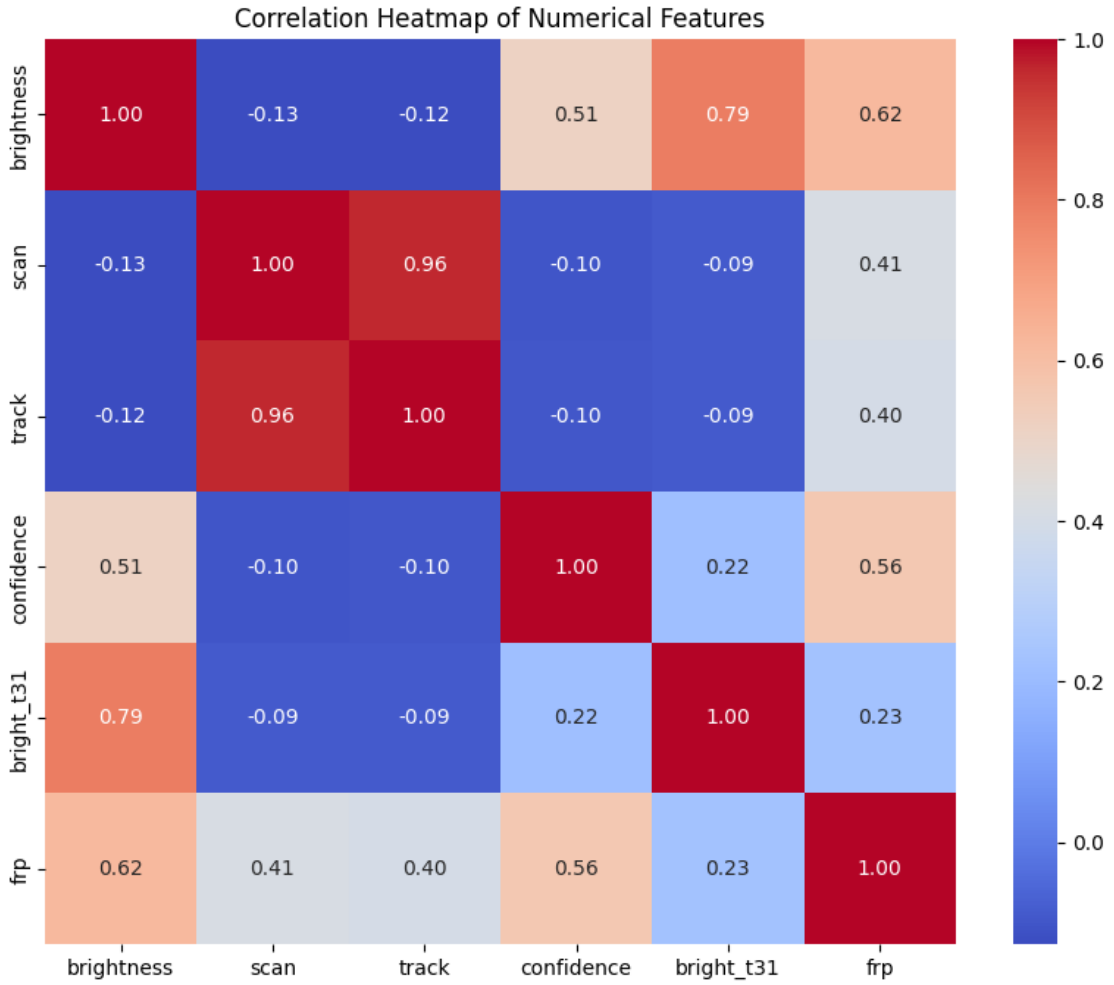
	day_of_year	hour	satellite_Terra
0	1	40	True
1	1	54	True
3	1	54	True
4	1	54	True
6	1	54	True

[104]:
```
df_encoded.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 189370 entries, 0 to 271207
Data columns (total 18 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   latitude         189370 non-null  float64
 1   longitude        189370 non-null  float64
 2   brightness       189370 non-null  float64
 3   scan             189370 non-null  float64
 4   track            189370 non-null  float64
 5   acq_date         189370 non-null  datetime64[ns]
 6   acq_time         189370 non-null  int64
 7   confidence       189370 non-null  float64
 8   version          189370 non-null  float64
 9   bright_t31       189370 non-null  float64
 10  frp              189370 non-null  float64
 11  type             189370 non-null  int64
```

```
 12  year             189370 non-null  int32
 13  month            189370 non-null  int32
 14  day_of_week      189370 non-null  int32
 15  day_of_year      189370 non-null  int32
 16  hour             189370 non-null  int64
 17  satellite_Terra  189370 non-null  bool
dtypes: bool(1), datetime64[ns](1), float64(9), int32(4), int64(3)
memory usage: 23.3 MB
```

[105]:
```
# Heatmap of correlations btw numerical features
plt.figure(figsize=(10, 8))
correlation_matrix = df_encoded[['brightness', 'scan', 'track', 'confidence',␣
 ↪'bright_t31', 'frp']].corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap of Numerical Features')
plt.show()
```



[106]:
```
df_encoded.head()
```

[106]:

	latitude	longitude	brightness	scan	track	acq_date	acq_time	confidence	version	bright_t31	frp	type	year	month	day_of_week	day_of_year	hour	satellite_Terra
0	28.0993	96.9983	-2.308455	-0.464860	0.059274	2021-01-01	409	-1.319370	6.03	-1.754135	-0.735900	0	2021	1	4	1	40	True
1	30.0420	79.6492	-2.445530	0.588678	0.936416	2021-01-01	547	-1.818736	6.03	-2.471213	-0.683381	0	2021	1	4	1	54	True
3	30.0408	80.0501	-2.422684	0.939857	0.936416	2021-01-01	547	-1.176694	6.03	-2.429843	-0.460175	0	2021	1	4	1	54	True
4	30.6565	78.9668	-2.548336	0.237499	0.059274	2021-01-01	547	-1.390708	6.03	-2.443633	-0.683381	0	2021	1	4	1	54	True
6	31.4366	76.8988	-2.594027	-0.816039	-0.817867	2021-01-01	547	-1.890074	6.03	-2.498792	-1.169182	0	2021	1	4	1	54	True

[107]:
```
df_encoded.type.value_counts()
```

[107]:
```
type
0    182841
2      6501
3        28
Name: count, dtype: int64
```

[108]:
```
features = ['brightness', 'scan', 'track', 'confidence', 'bright_t31', 'frp']
target = 'type'

X = df_encoded[features]
y = df_encoded[target]
```

[109]:
```
X
```

[109]:

	brightness	scan	track	confidence	bright_t31	frp
0	-2.308455	-0.464860	0.059274	-1.319370	-1.754135	-0.735900
1	-2.445530	0.588678	0.936416	-1.818736	-2.471213	-0.683381
3	-2.422684	0.939857	0.936416	-1.176694	-2.429843	-0.460175
4	-2.548336	0.237499	0.059274	-1.390708	-2.443633	-0.683381
6	-2.594027	-0.816039	-0.817867	-1.890074	-2.498792	-1.169182
…	…	…	…	…	…	…
271199	-0.423680	1.642216	1.813557	-0.605991	0.369517	0.327610

```
271200   -0.846327  3.398112  2.690698   -1.319370   -0.085551  0.209442
271201   -0.789212  1.993395  1.813557   -1.105356   -0.306191 -0.079412
271204   -0.115262  1.993395  1.813557    0.678093    0.093718  1.679975
271207   -1.051939  0.237499  0.059274   -0.605991   -0.223451 -0.985366

[189370 rows x 6 columns]
```

[110]:
```
y
```

[110]:
```
0         0
1         0
3         0
4         0
6         0
         ..
271199    0
271200    0
271201    0
271204    0
271207    0
Name: type, Length: 189370, dtype: int64
```

[111]:
```
!pip install -U imbalanced-learn
from imblearn.over_sampling import SMOTE
```

```
Requirement already satisfied: imbalanced-learn in
/usr/local/lib/python3.11/dist-packages (0.13.0)
Requirement already satisfied: numpy<3,>=1.24.3 in
/usr/local/lib/python3.11/dist-packages (from imbalanced-learn) (2.0.2)
Requirement already satisfied: scipy<2,>=1.10.1 in
/usr/local/lib/python3.11/dist-packages (from imbalanced-learn) (1.16.1)
Requirement already satisfied: scikit-learn<2,>=1.3.2 in
/usr/local/lib/python3.11/dist-packages (from imbalanced-learn) (1.6.1)
Requirement already satisfied: sklearn-compat<1,>=0.1 in
/usr/local/lib/python3.11/dist-packages (from imbalanced-learn) (0.1.3)
Requirement already satisfied: joblib<2,>=1.1.1 in
/usr/local/lib/python3.11/dist-packages (from imbalanced-learn) (1.5.1)
Requirement already satisfied: threadpoolctl<4,>=2.0.0 in
/usr/local/lib/python3.11/dist-packages (from imbalanced-learn) (3.6.0)
```

[112]:
```
# Initialize SMOTE #week 2
smote = SMOTE(random_state=42)

X_resampled, y_resampled = smote.fit_resample(X, y)  #SMOT

print("Distribution of target variable after SMOTE:")
print(y_resampled.value_counts())
```

```
Distribution of target variable after SMOTE:
type
0    182841
2    182841
3    182841
Name: count, dtype: int64
```

[113]:
```
X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled,␣
↪test_size=0.25, random_state=42, stratify=y_resampled)
```

[114]:
```
print("Shape of X_train:", X_train.shape)
print("Shape of X_test:", X_test.shape)
print("Shape of y_train:", y_train.shape)
print("Shape of y_test:", y_test.shape)
```

```
Shape of X_train: (411392, 6)
Shape of X_test: (137131, 6)
Shape of y_train: (411392,)
Shape of y_test: (137131,)
```

[115]:
```
# Import Logistic Regression to Train from SKlearn
loreg = LogisticRegression(max_iter=200)
loreg.fit(X_train,y_train)
loreg_pred = loreg.predict(X_test)
score = accuracy_score(y_test,loreg_pred)
cr = classification_report(y_test,loreg_pred)

print("Logistic Regression")
print ("Accuracy Score value: {:.4f}".format(score))
print (cr)
```

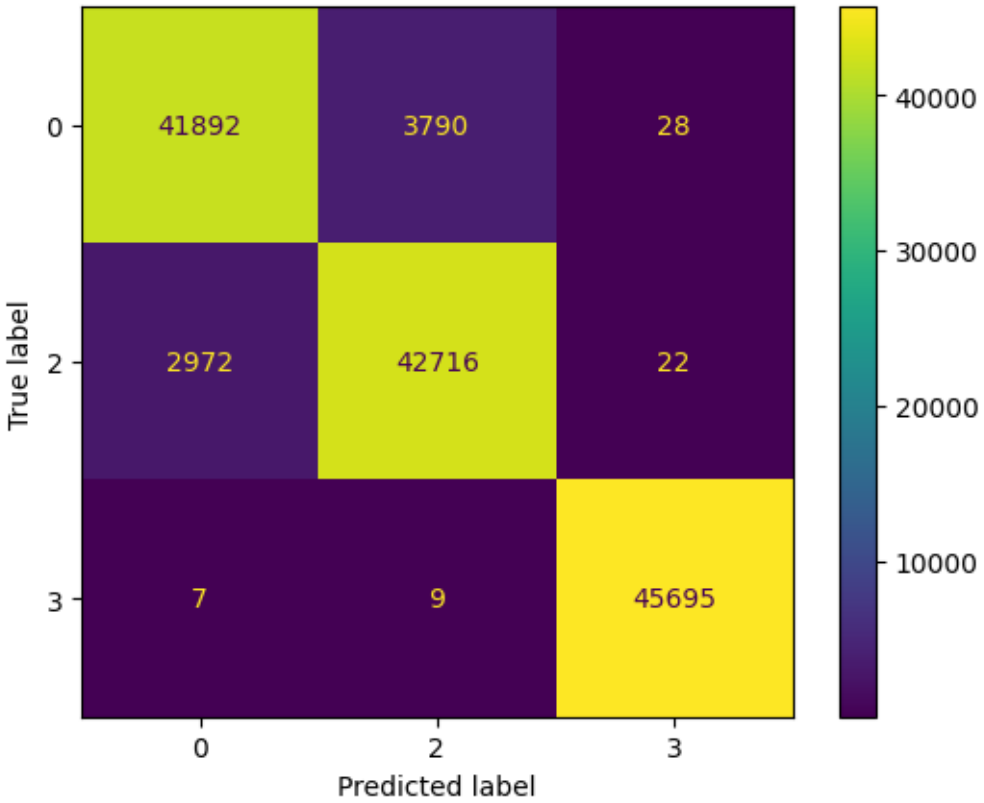
```
Logistic Regression
Accuracy Score value: 0.5858
              precision    recall  f1-score   support

           0       0.62      0.51      0.56     45710
           2       0.48      0.48      0.48     45710
           3       0.65      0.76      0.70     45711

    accuracy                           0.59    137131
   macro avg       0.58      0.59      0.58    137131
weighted avg       0.58      0.59      0.58    137131
```

[116]:
```
from sklearn.tree import DecisionTreeClassifier
dtc = DecisionTreeClassifier()
dtc.fit(X_train,y_train)
dtc_pred = dtc.predict(X_test)
```

```
score = accuracy_score(y_test,dtc_pred)
cr = classification_report(y_test,dtc_pred)

print("Decision Tree")
print ("Accuracy Score value: {:.4f}".format(score))
print (cr)
```

```
Decision Tree
Accuracy Score value: 0.9502
              precision    recall  f1-score   support

           0       0.93      0.92      0.92     45710
           2       0.92      0.93      0.93     45710
           3       1.00      1.00      1.00     45711

    accuracy                           0.95    137131
   macro avg       0.95      0.95      0.95    137131
weighted avg       0.95      0.95      0.95    137131
```

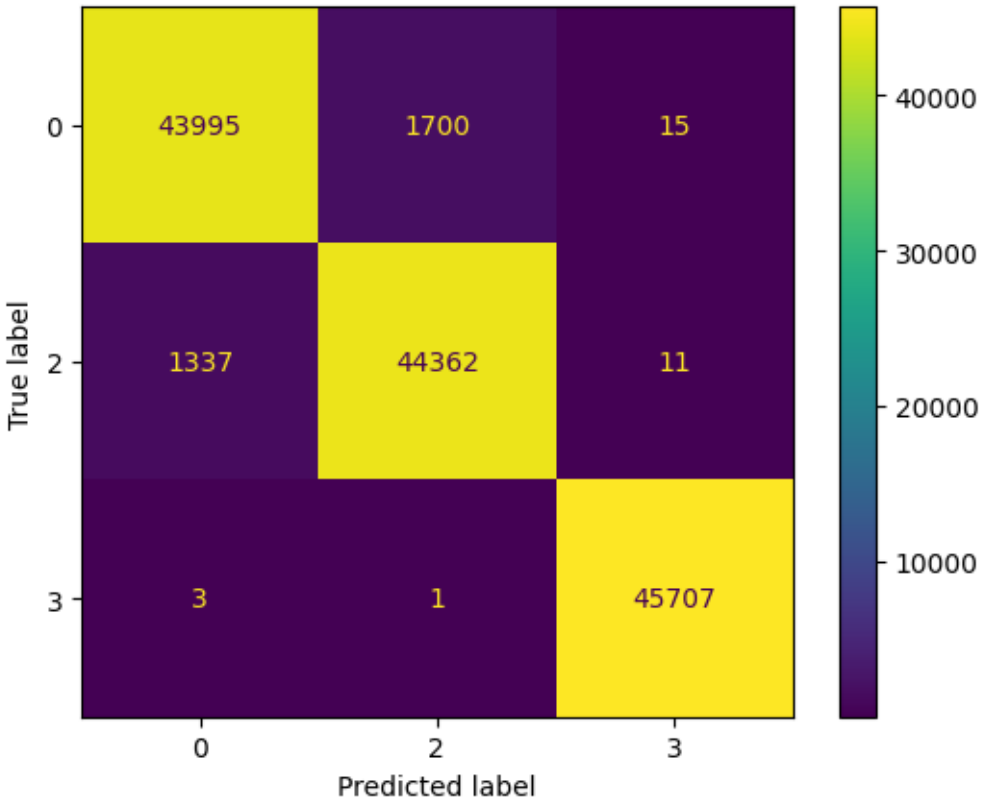
[117]:
```
dt_cm = ConfusionMatrixDisplay.from_estimator(dtc, X_test, y_test)
```



[118]:
```
rfc = RandomForestClassifier()
rfc.fit(X_train,y_train)
rfc_pred = rfc.predict(X_test)
score = accuracy_score(y_test,rfc_pred)
cr = classification_report(y_test,rfc_pred)

print("Random Forest")
print ("Accuracy Score value: {:.4f}".format(score))
print (cr)
```

```
Random Forest
Accuracy Score value: 0.9776
              precision    recall  f1-score   support

           0       0.97      0.96      0.97     45710
           2       0.96      0.97      0.97     45710
           3       1.00      1.00      1.00     45711

    accuracy                           0.98    137131
   macro avg       0.98      0.98      0.98    137131
weighted avg       0.98      0.98      0.98    137131
```

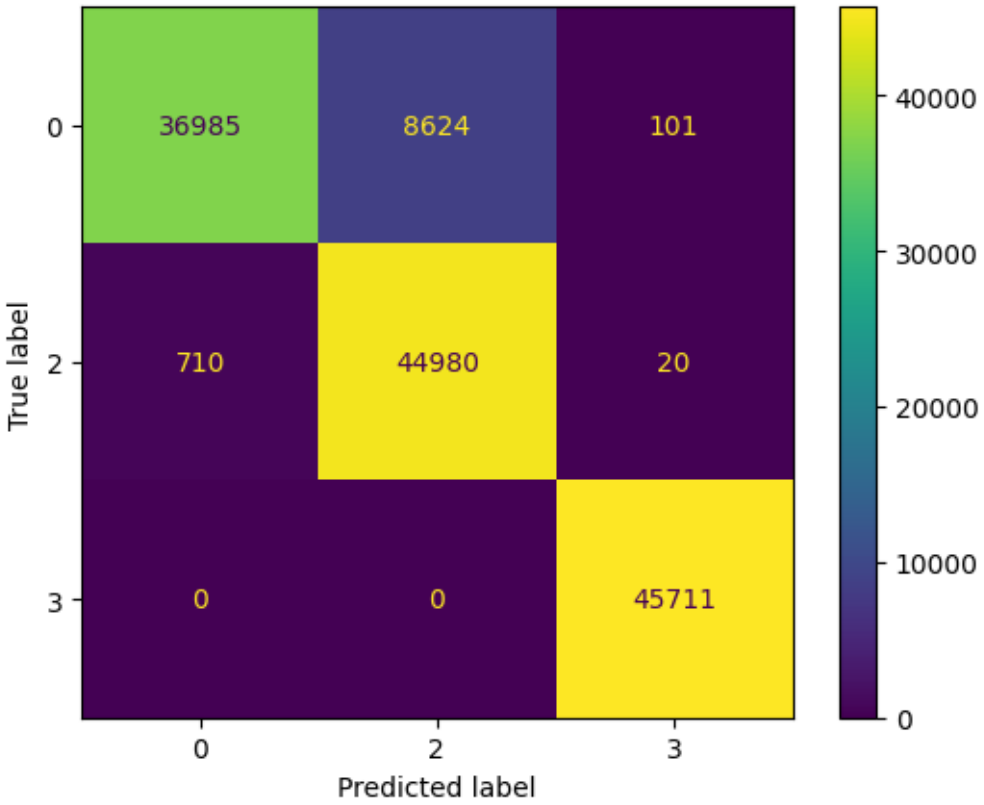
[119]:
```
rf_cm = ConfusionMatrixDisplay.from_estimator(rfc, X_test, y_test)
```



[120]:
```
# KNeighborsClassifier to Train from SKlearn
knnc = KNeighborsClassifier()
knnc.fit(X_train,y_train)
knn_pred = knnc.predict(X_test)
score = accuracy_score(y_test,knn_pred)
cr = classification_report(y_test,knn_pred)

print("KNeighbors Classifier")
print ("Accuracy Score value: {:.4f}".format(score))
print (cr)
```

```
KNeighbors Classifier
Accuracy Score value: 0.9311
              precision    recall  f1-score   support

           0       0.98      0.81      0.89     45710
           2       0.84      0.98      0.91     45710
           3       1.00      1.00      1.00     45711

    accuracy                           0.93    137131
   macro avg       0.94      0.93      0.93    137131
weighted avg       0.94      0.93      0.93    137131
```

[121]:
```
knn_cm = ConfusionMatrixDisplay.from_estimator(knnc, X_test, y_test)
```



[122]:
```
# Collect the accuracies of each model
model_accuracies = {
    "Logistic Regression": accuracy_score(y_test, loreg_pred),
    "Decision Tree": accuracy_score(y_test, dtc_pred),
    "Random Forest": accuracy_score(y_test, rfc_pred),
    "KNeighbors Classifier": accuracy_score(y_test, knn_pred)
}

# Find the best model
best_model_name = max(model_accuracies, key=model_accuracies.get)
best_model_accuracy = model_accuracies[best_model_name]

print("Model Accuracies:")
for model, accuracy in model_accuracies.items():
    print(f"{model}: {accuracy:.4f}")

print(f"\nBest Model: {best_model_name} with Accuracy: {best_model_accuracy:.
  ↪4f}")
```

```
Model Accuracies:
Logistic Regression: 0.5858
```

```
Decision Tree: 0.9502
Random Forest: 0.9776
KNeighbors Classifier: 0.9311

Best Model: Random Forest with Accuracy: 0.9776
```

[123]:
```python
import joblib
best_model = rfc

joblib.dump(best_model, 'best_fire_detection_model.pkl')
joblib.dump(scaler, 'scaler.pkl')

print("Best model and scaler saved successfully.")
```

```
Best model and scaler saved successfully.
```

[ ]:
```python

```