In [ ]:
```python
# Predict the price of the Uber ride from a given pickup point to the agreed drop-off location.
# Perform following tasks:
# 1. Pre-process the dataset.
# 2. Identify outliers.
# 3. Check the correlation.
# 4. Implement linear regression and random forest regression models.
# 5. Evaluate the models and compare their respective scores like R2, RMSE, etc.
# Dataset link: https://www.kaggle.com/datasets/yasserh/uber-fares-datase
```

In [4]:
```python
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score, mean_squared_error

# Load the dataset
data = pd.read_csv("Uber.csv")

data
```

Out[4]:

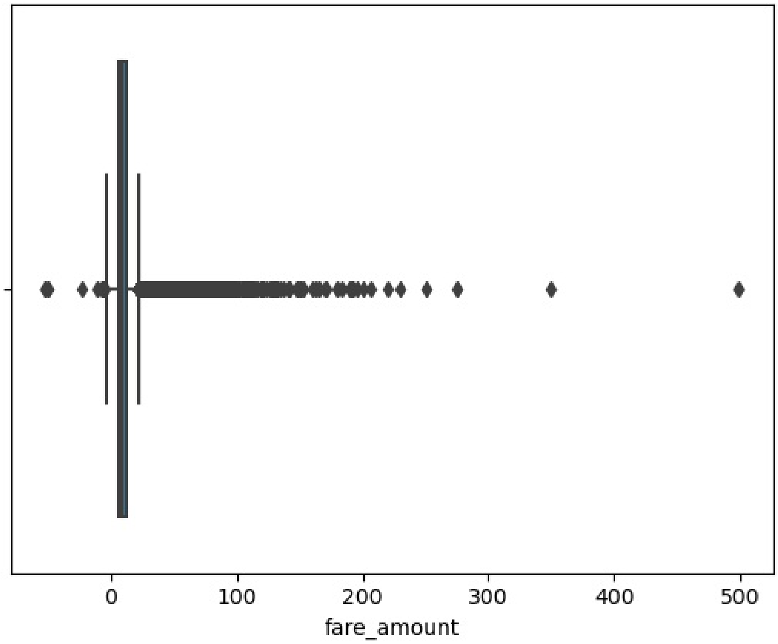
	Unnamed: 0	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff
0	24238194	2015-05-07 19:52:06.0000003	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.738354	-73.999512	4
1	27835199	2009-07-17 20:04:56.0000002	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.728225	-73.994710	4
2	44984355	2009-08-24 21:45:00.00000061	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.740770	-73.962565	4
3	25894730	2009-06-26 08:22:21.0000001	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.790844	-73.965316	4
4	17610152	2014-08-28 17:47:00.000000188	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.744085	-73.973082	4
...	...	...	...	...	...	...	...	
199995	42598914	2012-10-28 10:49:00.00000053	3.0	2012-10-28 10:49:00 UTC	-73.987042	40.739367	-73.986525	4
199996	16382965	2014-03-14 01:09:00.0000008	7.5	2014-03-14 01:09:00 UTC	-73.984722	40.736837	-74.006672	4
199997	27804658	2009-06-29 00:42:00.00000078	30.9	2009-06-29 00:42:00 UTC	-73.986017	40.756487	-73.858957	4
199998	20259894	2015-05-20 14:56:25.0000004	14.5	2015-05-20 14:56:25 UTC	-73.997124	40.725452	-73.983215	4
199999	11951496	2010-05-15 04:08:00.00000076	14.1	2010-05-15 04:08:00 UTC	-73.984395	40.720077	-73.985508	4

200000 rows × 9 columns

In [22]:
```python
# 1. Pre-process the dataset

# Remove unnecessary column
data["pickup_datetime"] = pd.to_datetime(data["pickup_datetime"])

missing_values = data.isnull().sum()
print("Missing values in the dataset:")
print(missing_values)

# Handle missing values
# We can choose to drop rows with missing values or fill them with appropriate values.

data.dropna(inplace=True)

# To fill missing values with the mean value of the column:
# data.fillna(data.mean(), inplace=True)

# Ensure there are no more missing values
missing_values = data.isnull().sum()
print("Missing values after handling:")
print(missing_values)

# 2. Identify outliers
# visualization to detect outliers.
```

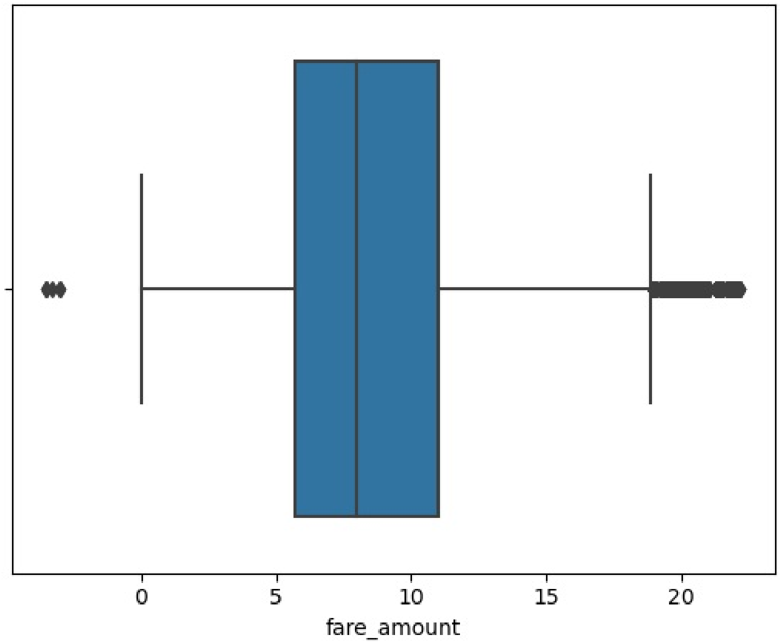
```python
sns.boxplot(x=data["fare_amount"])
plt.show()
```

```
Missing values in the dataset:
key                  0
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    1
dropoff_latitude     1
passenger_count      0
dtype: int64
Missing values after handling:
key                  0
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    0
dropoff_latitude     0
passenger_count      0
dtype: int64
```



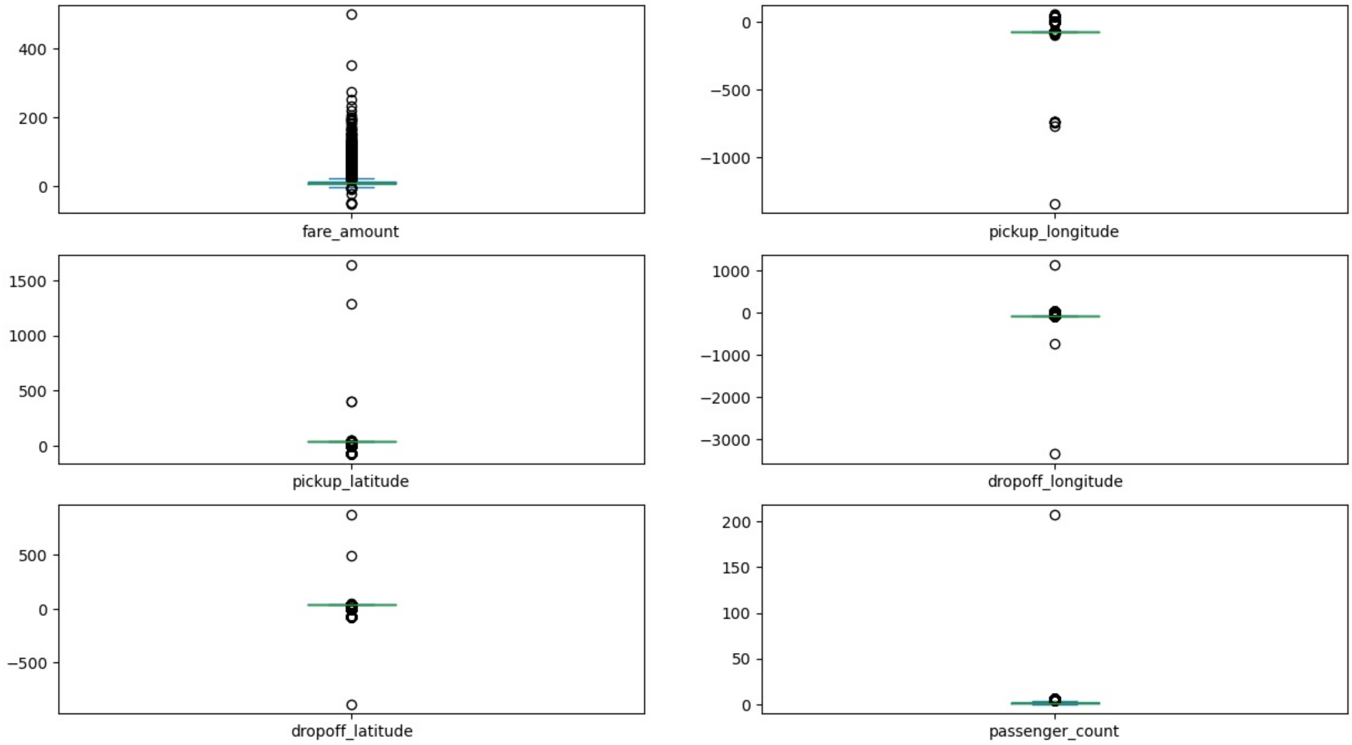
In [55]:

```python
# Calculate the IQR for the 'fare_amount' column
Q1 = data["fare_amount"].quantile(0.25)
Q3 = data["fare_amount"].quantile(0.75)
IQR = Q3 - Q1

# Define a threshold (e.g., 1.5 times the IQR) to identify outliers
threshold = 1.5
lower_bound = Q1 - threshold * IQR
upper_bound = Q3 + threshold * IQR

# Remove outliers
data_no_outliers = data[(data["fare_amount"] >= lower_bound) & (data["fare_amount"] <= upper_bound)]

# Visualize the 'fare_amount' distribution without outliers
sns.boxplot(x=data_no_outliers["fare_amount"])
plt.show()
```

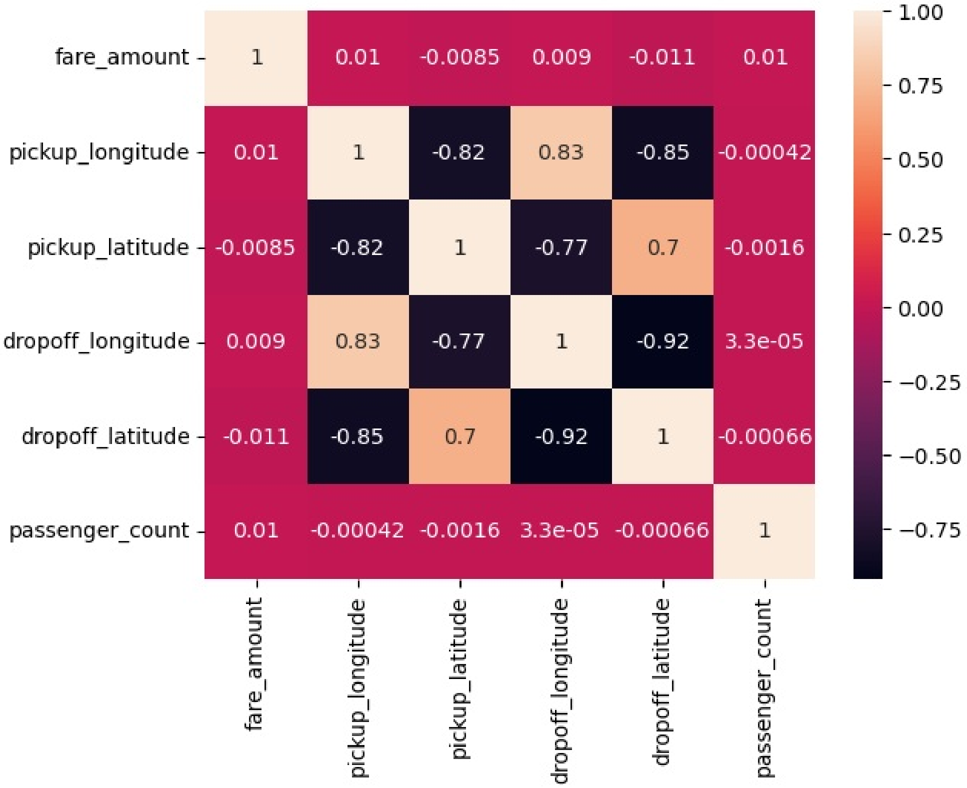


In [53]:
```python
data.plot(kind="box",subplots=True, layout=(7, 2), figsize=(15, 20))
```

Out[53]:
```
fare_amount            AxesSubplot(0.125,0.786098;0.352273x0.0939024)
pickup_longitude    AxesSubplot(0.547727,0.786098;0.352273x0.0939024)
pickup_latitude        AxesSubplot(0.125,0.673415;0.352273x0.0939024)
dropoff_longitude   AxesSubplot(0.547727,0.673415;0.352273x0.0939024)
dropoff_latitude       AxesSubplot(0.125,0.560732;0.352273x0.0939024)
passenger_count     AxesSubplot(0.547727,0.560732;0.352273x0.0939024)
dtype: object
```



In [23]:
```python
# 3. Check the correlation
# Determine the correlation between features and the target variable (fare_amount).
correlation_matrix = data.corr()
sns.heatmap(correlation_matrix, annot=True)
plt.show()
```



In [24]:
```
# 4. Implement linear regression and random forest regression models
# Split the data into features and target variable
X = data[['pickup_longitude', 'pickup_latitude', 'dropoff_longitude', 'dropoff_latitude', 'passenger_count']]
y = data['fare_amount']  #Target

y
```

Out[24]:
```
0          7.5
1          7.7
2         12.9
3          5.3
4         16.0
          ...
199995     3.0
199996     7.5
199997    30.9
199998    14.5
199999    14.1
Name: fare_amount, Length: 199999, dtype: float64
```

In [25]:
```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [26]:
```
# Create and train the linear regression model
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)
```

Out[26]:
```
LinearRegression()
```

In [34]:
```
# Create and train the random forest regression model
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
```

Out[34]:
```
RandomForestRegressor(random_state=42)
```

In [36]:
```
# 5. Evaluate the models
# Predict the values
y_pred_lr = lr_model.predict(X_test)
y_pred_lr
print("Linear Model:",y_pred_lr)
y_pred_rf = rf_model.predict(X_test)
print("Random Forest Model:", y_pred_rf)
```

```
Linear Model: [11.29237916 11.29171388 11.5718662  ... 11.29183291 11.43252639
 11.29190248]
Random Forest Model: [ 9.262   5.043  12.547  ...  6.8087 11.279   8.315 ]
```

In [32]:
```
# Calculate R-squared (R2) and Root Mean Squared Error (RMSE) for both models
r2_lr = r2_score(y_test, y_pred_lr)
rmse_lr = np.sqrt(mean_squared_error(y_test, y_pred_lr))
```

In [33]:
```
# Compare the scores
print("Linear Regression - R2:", r2_lr)
print("Linear Regression - RMSE:", rmse_lr)
```

```
Linear Regression - R2: 0.00034152697863043535
Linear Regression - RMSE: 10.197470623964248
```

In [41]:
```
r2_rf = r2_score(y_test, y_pred_rf)
rmse_rf = np.sqrt(mean_squared_error(y_test, y_pred_rf))

print("Random Forest Regression R2:", r2_rf)
print("Random Forest Regression RMSE:",rmse_rf)
```

```
Random Forest Regression R2: 0.7011790407391916
Random Forest Regression RMSE: 5.575350372469675
```

In [ ]:
```
# Overall Analysis

# The Random Forest Regression model has significantly improved the predictive performance.
# An R-squared (R2) value of approximately 0.701 and a Root Mean Squared Error (RMSE)
# of approximately 5.575 indicate that the Random Forest model is capturing a substantial portion
# of the variance in the target variable and providing more accurate predictions compared to the linear regress
```

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