

Problem Solution Using LSTM by LIPIKA SHARMA

Data Preprocessing

```
In [58]: # Import necessary libraries
```

```
In [59]: !pip install tensorflow
```

Requirement already satisfied: tensorflow in d:\new folder\lib\site-packages (2.17.0)
Requirement already satisfied: tensorflow-intel==2.17.0 in d:\new folder\lib\site-packages (from tensorflow) (2.17.0)
Requirement already satisfied: absl-py>=1.0.0 in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (2.1.0)
Requirement already satisfied: astunparse>=1.6.0 in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (1.6.3)
Requirement already satisfied: flatbuffers>=24.3.25 in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (24.3.25)
Requirement already satisfied: gast!=0.5.0,!0.5.1,!0.5.2,>=0.2.1 in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (0.6.0)
Requirement already satisfied: google-pasta>=0.1.1 in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (0.2.0)
Requirement already satisfied: h5py>=3.10.0 in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (3.11.0)
Requirement already satisfied: libclang>=13.0.0 in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (18.1.1)
Requirement already satisfied: ml-dtypes<0.5.0,>=0.3.1 in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (0.4.0)
Requirement already satisfied: opt-einsum>=2.3.2 in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (3.3.0)
Requirement already satisfied: packaging in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (23.1)
Requirement already satisfied: protobuf!=4.21.0,!4.21.1,!4.21.2,!4.21.3,!4.21.4,!4.21.5,<5.0.0dev,>=3.20.3 in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (3.20.3)
Requirement already satisfied: requests<3,>=2.21.0 in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (2.31.0)
Requirement already satisfied: setuptools in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (68.2.2)
Requirement already satisfied: six>=1.12.0 in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (1.16.0)
Requirement already satisfied: termcolor>=1.1.0 in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (2.4.0)
Requirement already satisfied: typing-extensions>=3.6.6 in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (4.9.0)
Requirement already satisfied: wrapt>=1.11.0 in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (1.14.1)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (1.65.1)
Requirement already satisfied: tensorboard<2.18,>=2.17 in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (2.17.0)
Requirement already satisfied: keras>=3.2.0 in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (3.4.1)

Requirement already satisfied: tensorflow-io-gcs-filesystem<=0.23.1 in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (0.31.0)

Requirement already satisfied: numpy<2.0.0,>=1.23.5 in d:\new folder\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (1.26.4)

Requirement already satisfied: wheel<1.0,>=0.23.0 in d:\new folder\lib\site-packages (from astunparse>=1.6.0->tensorflow-intel==2.17.0->tensorflow) (0.41.2)

Requirement already satisfied: rich in d:\new folder\lib\site-packages (from keras>=3.2.0->tensorflow-intel==2.17.0->tensorflow) (13.3.5)

Requirement already satisfied: namex in d:\new folder\lib\site-packages (from keras>=3.2.0->tensorflow-intel==2.17.0->tensorflow) (0.0.8)

Requirement already satisfied: optree in d:\new folder\lib\site-packages (from keras>=3.2.0->tensorflow-intel==2.17.0->tensorflow) (0.12.1)

Requirement already satisfied: charset-normalizer<4,>=2 in d:\new folder\lib\site-packages (from requests<3,>=2.21.0->tensorflow-intel==2.17.0->tensorflow) (2.0.4)

Requirement already satisfied: idna<4,>=2.5 in d:\new folder\lib\site-packages (from requests<3,>=2.21.0->tensorflow-intel==2.17.0->tensorflow) (3.4)

Requirement already satisfied: urllib3<3,>=1.21.1 in d:\new folder\lib\site-packages (from requests<3,>=2.21.0->tensorflow-intel==2.17.0->tensorflow) (2.0.7)

Requirement already satisfied: certifi>=2017.4.17 in d:\new folder\lib\site-packages (from requests<3,>=2.21.0->tensorflow-intel==2.17.0->tensorflow) (2024.6.2)

Requirement already satisfied: markdown>=2.6.8 in d:\new folder\lib\site-packages (from tensorboard<2.18,>=2.17->tensorflow-intel==2.17.0->tensorflow) (3.4.1)

Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in d:\new folder\lib\site-packages (from tensorboard<2.18,>=2.17->tensorflow-intel==2.17.0->tensorflow) (0.7.2)

Requirement already satisfied: werkzeug>=1.0.1 in d:\new folder\lib\site-packages (from tensorboard<2.18,>=2.17->tensorflow-intel==2.17.0->tensorflow) (2.2.3)

Requirement already satisfied: MarkupSafe>=2.1.1 in d:\new folder\lib\site-packages (from werkzeug>=1.0.1->tensorboard<2.18,>=2.17->tensorflow-intel==2.17.0->tensorflow) (2.1.3)

Requirement already satisfied: markdown-it-py<3.0.0,>=2.2.0 in d:\new folder\lib\site-packages (from rich->keras>=3.2.0->tensorflow-intel==2.17.0->tensorflow) (2.2.0)

Requirement already satisfied: pygments<3.0.0,>=2.13.0 in d:\new folder\lib\site-packages (from rich->keras>=3.2.0->tensorflow-intel==2.17.0->tensorflow) (2.15.1)

Requirement already satisfied: mdurl~0.1 in d:\new folder\lib\site-packages (from markdown-it-py<3.0.0,>=2.2.0->rich->keras>=3.2.0->tensorflow-intel==2.17.0->tensorflow) (0.1.0)

```
In [60]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error
from tensorflow.keras.models import Sequential
```

```
from tensorflow.keras.layers import LSTM, Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping
```

```
In [61]: # Load the data
data = pd.read_csv('Dispense.csv')
data.head()
```

```
Out[61]:
```

	Account	ATMID	caldate	Dispense	DT	MaxCapacity	CountTotalTxn
0	ABC	SPCN02020	01-01-2021	564500	0	2640000	157
1	ABC	TPCN10269	01-01-2021	509000	9	3520000	92
2	ABC	APCN00816	01-01-2021	64800	0	2640000	36
3	PQR	S1CN1142	01-01-2021	834500	0	3520000	101
4	PQR	S1CN2022	01-01-2021	825700	0	2860000	364

```
In [62]: # Convert caldate to datetime
data['caldate'] = pd.to_datetime(data['caldate'], format='%d-%m-%Y')
data = data.sort_values(by=['ATMID', 'caldate'])
```

Exploratory Data Analysis (EDA)

```
In [63]: # Summary statistics
data.describe()
```

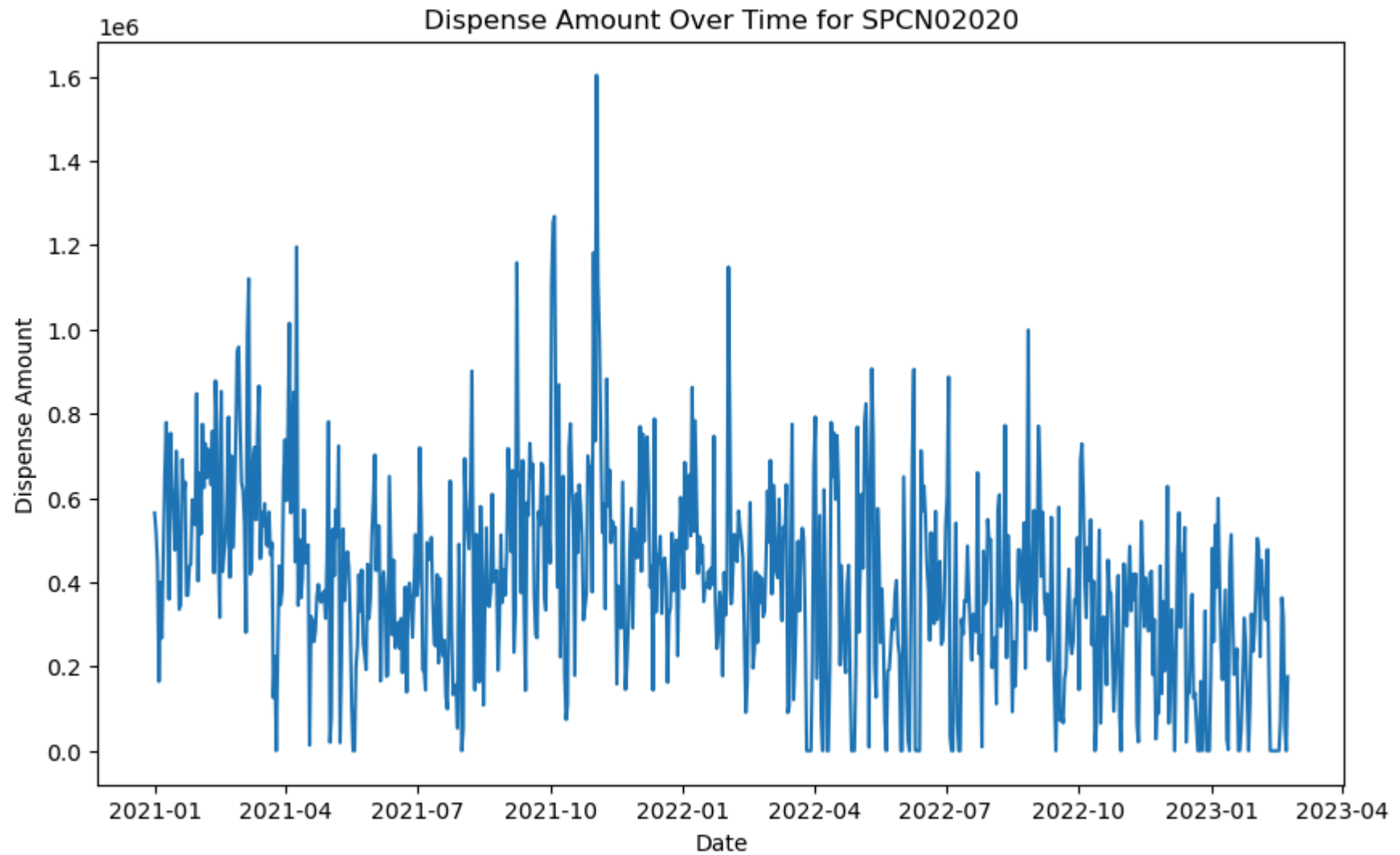
Out[63]:

	caldate	Dispense	DT	MaxCapacity	CountTotalTxn
count	14593	1.459300e+04	14593.000000	1.459300e+04	14593.000000
mean	2022-02-24 13:07:26.762146304	4.027993e+05	158.538614	3.279753e+06	105.322963
min	2021-01-01 00:00:00	0.000000e+00	0.000000	2.420000e+06	0.000000
25%	2021-08-28 00:00:00	1.685000e+05	0.000000	2.860000e+06	45.000000
50%	2022-03-07 00:00:00	3.653000e+05	0.000000	3.520000e+06	98.000000
75%	2022-09-02 00:00:00	5.780000e+05	64.000000	3.520000e+06	146.000000
max	2023-02-22 00:00:00	2.151800e+06	1440.000000	3.740000e+06	561.000000
std	NaN	3.036762e+05	356.073765	3.974770e+05	76.727151

```
In [66]: # Handle missing values
data.ffmpeg(inplace=True)
```

```
In [67]: import matplotlib.pyplot as plt
import seaborn as sns

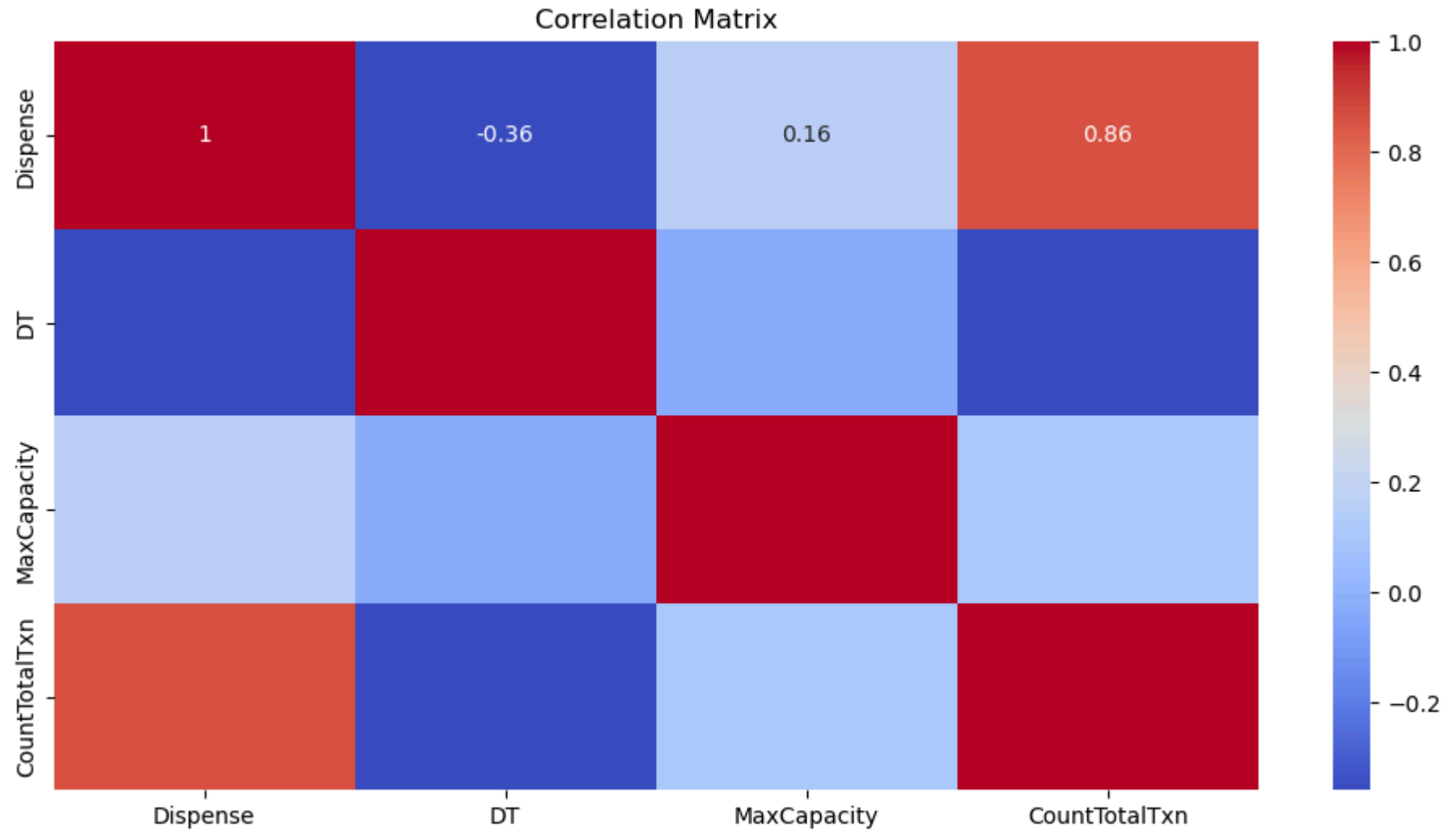
# Dispense amount over time for a sample ATM
sample_atm = data[data['ATMID'] == 'SPCN02020']
plt.figure(figsize=(10, 6))
plt.plot(sample_atm['caldate'], sample_atm['Dispense'])
plt.title('Dispense Amount Over Time for SPCN02020')
plt.xlabel('Date')
plt.ylabel('Dispense Amount')
plt.show()
```



```
In [68]: # Select only numeric columns
numeric_data = data.select_dtypes(include=[np.number])

# Correlation matrix
plt.figure(figsize=(12, 6))
sns.heatmap(numeric_data.corr(), annot=True, cmap='coolwarm')
```

```
plt.title('Correlation Matrix')  
plt.show()
```



Feature Engineering

```
In [69]: def create_features(df):  
         df['year'] = df['caldate'].dt.year
```

```

df['month'] = df['caldate'].dt.month
df['day'] = df['caldate'].dt.day
df['weekday'] = df['caldate'].dt.weekday
return df

data = create_features(data)

# Normalize the dispense amount
scaler = StandardScaler()
data['Dispense_scaled'] = scaler.fit_transform(data[['Dispense']])

```

Model Selection and Training (LSTM Approach)

```

In [70]: # Creating sequences for LSTM
def create_sequences(df, seq_length):
    sequences = []
    for i in range(len(df) - seq_length):
        sequence = df['Dispense_scaled'].values[i:i+seq_length]
        label = df['Dispense_scaled'].values[i+seq_length]
        sequences.append((sequence, label))
    return sequences

seq_length = 30 # Using the past 30 days to predict the next day
atm_sequences = {}

for atm_id in data['ATMID'].unique():
    atm_data = data[data['ATMID'] == atm_id]
    atm_sequences[atm_id] = create_sequences(atm_data, seq_length)

# Preparing the data for LSTM
X, y = [], []
for atm_id in atm_sequences:
    atm_X, atm_y = zip(*atm_sequences[atm_id])
    X.extend(atm_X)
    y.extend(atm_y)

X = np.array(X)
y = np.array(y)

```



```
In [71]: # Split into train and test sets
split_idx = int(0.8 * len(X))
X_train, X_test = X[:split_idx], X[split_idx:]
y_train, y_test = y[:split_idx], y[split_idx:]

# Reshape input to be 3D for LSTM [samples, time steps, features]
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))

# Build the LSTM model
model = Sequential()
model.add(LSTM(50, return_sequences=True, input_shape=(seq_length, 1)))
model.add(LSTM(50, return_sequences=False))
model.add(Dropout(0.2))
model.add(Dense(1))

model.compile(optimizer='adam', loss='mean_squared_error')
model.summary()
```

D:\New folder\Lib\site-packages\keras\src\layers\rnn\rnn.py:204: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.

```
super().__init__(**kwargs)
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
lstm_4 (LSTM)	(None, 30, 50)	10,400
lstm_5 (LSTM)	(None, 50)	20,200
dropout_2 (Dropout)	(None, 50)	0
dense_2 (Dense)	(None, 1)	51

Total params: 30,651 (119.73 KB)

Trainable params: 30,651 (119.73 KB)

Non-trainable params: 0 (0.00 B)

```
In [72]: # Train the model
early_stop = EarlyStopping(monitor='val_loss', patience=5)
history = model.fit(X_train, y_train, epochs=50, batch_size=32, validation_split=0.2, callbacks=[early_stop])

# Evaluate the model
y_pred = model.predict(X_test)
y_pred_inv = scaler.inverse_transform(y_pred)
y_test_inv = scaler.inverse_transform(y_test.reshape(-1, 1))

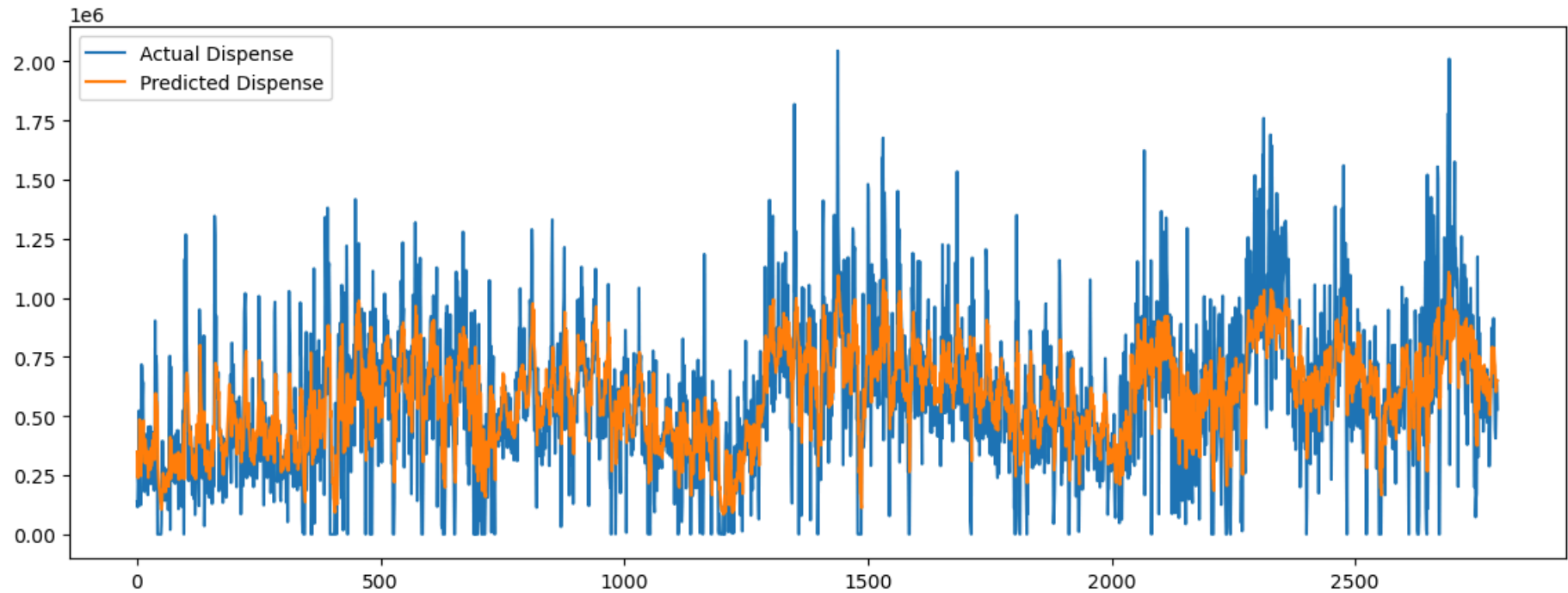
mse = mean_squared_error(y_test_inv, y_pred_inv)
print(f'Mean Squared Error: {mse}')
```

```
Epoch 1/50
280/280 ————— 12s 22ms/step - loss: 0.5938 - val_loss: 0.3643
Epoch 2/50
280/280 ————— 5s 19ms/step - loss: 0.5053 - val_loss: 0.3531
Epoch 3/50
280/280 ————— 5s 19ms/step - loss: 0.4685 - val_loss: 0.3384
Epoch 4/50
280/280 ————— 10s 18ms/step - loss: 0.4781 - val_loss: 0.3365
Epoch 5/50
280/280 ————— 5s 17ms/step - loss: 0.4486 - val_loss: 0.3303
Epoch 6/50
280/280 ————— 5s 18ms/step - loss: 0.4596 - val_loss: 0.3371
Epoch 7/50
280/280 ————— 5s 18ms/step - loss: 0.4813 - val_loss: 0.3304
Epoch 8/50
280/280 ————— 6s 21ms/step - loss: 0.4771 - val_loss: 0.3401
Epoch 9/50
280/280 ————— 10s 21ms/step - loss: 0.4696 - val_loss: 0.3382
Epoch 10/50
280/280 ————— 10s 18ms/step - loss: 0.4565 - val_loss: 0.3333
88/88 ————— 1s 11ms/step
Mean Squared Error: 60678255268.89817
```

Visualization

```
In [73]: # Visualization of actual vs predicted
plt.figure(figsize=(14, 5))
```

```
plt.plot(y_test_inv, label='Actual Dispense')
plt.plot(y_pred_inv, label='Predicted Dispense')
plt.legend()
plt.show()
```



Forecasting

```
In [75]: # Forecasting next 7 days
def forecast_next_days(model, data, seq_length, n_days):
    forecasts = []
    input_seq = data.reshape((1, seq_length, 1)) # Reshape to match the input format of the model
    for _ in range(n_days):
        next_dispense = model.predict(input_seq)
        next_dispense = next_dispense.reshape((1, 1, 1)) # Reshape next_dispense to match the dimensions
        forecasts.append(next_dispense[0, 0, 0])
        input_seq = np.append(input_seq[:, 1:, :], next_dispense, axis=1)
    return forecasts
```

```
# Forecast for each ATM
forecast_results = {}
for atm_id in data['ATMID'].unique():
    atm_data = data[data['ATMID'] == atm_id]
    atm_seq = atm_data['Dispense_scaled'].values[-seq_length:]
    forecast = forecast_next_days(model, atm_seq, seq_length, 7)
    forecast_inv = scaler.inverse_transform(np.array(forecast).reshape(-1, 1))
    forecast_results[atm_id] = forecast_inv
```

1/1	0s	31ms/step
1/1	0s	31ms/step
1/1	0s	36ms/step
1/1	0s	24ms/step
1/1	0s	25ms/step
1/1	0s	31ms/step
1/1	0s	26ms/step
1/1	0s	24ms/step
1/1	0s	31ms/step
1/1	0s	27ms/step
1/1	0s	28ms/step
1/1	0s	28ms/step
1/1	0s	33ms/step
1/1	0s	30ms/step
1/1	0s	26ms/step
1/1	0s	32ms/step
1/1	0s	34ms/step
1/1	0s	32ms/step
1/1	0s	32ms/step
1/1	0s	39ms/step
1/1	0s	40ms/step
1/1	0s	41ms/step
1/1	0s	70ms/step
1/1	0s	28ms/step
1/1	0s	27ms/step
1/1	0s	25ms/step
1/1	0s	29ms/step
1/1	0s	23ms/step
1/1	0s	26ms/step
1/1	0s	27ms/step
1/1	0s	27ms/step
1/1	0s	23ms/step
1/1	0s	24ms/step
1/1	0s	26ms/step
1/1	0s	24ms/step
1/1	0s	30ms/step
1/1	0s	28ms/step
1/1	0s	27ms/step
1/1	0s	30ms/step
1/1	0s	26ms/step
1/1	0s	30ms/step

1/1	0s	30ms/step
1/1	0s	26ms/step
1/1	0s	28ms/step
1/1	0s	32ms/step
1/1	0s	25ms/step
1/1	0s	27ms/step
1/1	0s	27ms/step
1/1	0s	27ms/step
1/1	0s	28ms/step
1/1	0s	26ms/step
1/1	0s	29ms/step
1/1	0s	28ms/step
1/1	0s	29ms/step
1/1	0s	30ms/step
1/1	0s	30ms/step
1/1	0s	35ms/step
1/1	0s	34ms/step
1/1	0s	32ms/step
1/1	0s	30ms/step
1/1	0s	35ms/step
1/1	0s	34ms/step
1/1	0s	30ms/step
1/1	0s	29ms/step
1/1	0s	28ms/step
1/1	0s	28ms/step
1/1	0s	32ms/step
1/1	0s	32ms/step
1/1	0s	31ms/step
1/1	0s	23ms/step
1/1	0s	25ms/step
1/1	0s	29ms/step
1/1	0s	25ms/step
1/1	0s	29ms/step
1/1	0s	29ms/step
1/1	0s	27ms/step
1/1	0s	32ms/step
1/1	0s	70ms/step
1/1	0s	28ms/step
1/1	0s	25ms/step
1/1	0s	24ms/step

1/1	0s	28ms/step
1/1	0s	26ms/step
1/1	0s	25ms/step
1/1	0s	26ms/step
1/1	0s	36ms/step
1/1	0s	28ms/step
1/1	0s	27ms/step
1/1	0s	29ms/step
1/1	0s	25ms/step
1/1	0s	30ms/step
1/1	0s	29ms/step
1/1	0s	29ms/step
1/1	0s	26ms/step
1/1	0s	31ms/step
1/1	0s	32ms/step
1/1	0s	28ms/step
1/1	0s	33ms/step
1/1	0s	34ms/step
1/1	0s	33ms/step
1/1	0s	32ms/step
1/1	0s	32ms/step
1/1	0s	33ms/step
1/1	0s	33ms/step
1/1	0s	31ms/step
1/1	0s	27ms/step
1/1	0s	29ms/step
1/1	0s	26ms/step
1/1	0s	27ms/step
1/1	0s	28ms/step
1/1	0s	25ms/step
1/1	0s	25ms/step
1/1	0s	24ms/step
1/1	0s	26ms/step
1/1	0s	32ms/step
1/1	0s	35ms/step
1/1	0s	43ms/step
1/1	0s	42ms/step
1/1	0s	50ms/step
1/1	0s	42ms/step
1/1	0s	32ms/step
1/1	0s	39ms/step

```

1/1 _____ 0s 32ms/step
1/1 _____ 0s 31ms/step
1/1 _____ 0s 36ms/step
1/1 _____ 0s 34ms/step
1/1 _____ 0s 30ms/step
1/1 _____ 0s 36ms/step
1/1 _____ 0s 32ms/step
1/1 _____ 0s 32ms/step
1/1 _____ 0s 39ms/step
1/1 _____ 0s 36ms/step
1/1 _____ 0s 28ms/step
1/1 _____ 0s 32ms/step
1/1 _____ 0s 35ms/step
1/1 _____ 0s 38ms/step
1/1 _____ 0s 32ms/step
1/1 _____ 0s 33ms/step
1/1 _____ 0s 39ms/step
1/1 _____ 0s 40ms/step
1/1 _____ 0s 37ms/step
1/1 _____ 0s 37ms/step
1/1 _____ 0s 33ms/step
1/1 _____ 0s 34ms/step
1/1 _____ 0s 41ms/step
1/1 _____ 0s 38ms/step

```

```

In [76]: import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler

```

```

In [77]: # Assuming `data` is your DataFrame and `model` is your trained model

# Define forecast_next_days function
def forecast_next_days(model, atm_seq, seq_length, forecast_days):
    # Dummy implementation for illustration; replace with your actual function
    return [0.5] * forecast_days

# Initialize and fit the MinMaxScaler on the original 'Dispense_scaled' column
scaler = MinMaxScaler()
scaler.fit(data['Dispense_scaled'].values.reshape(-1, 1))

```



```
# Length of the sequence used for prediction
seq_length = 30
```

```
In [78]: # Forecast for each ATM
forecast_results = {}
for atm_id in data['ATMID'].unique():
    atm_data = data[data['ATMID'] == atm_id]

    # Ensure there are enough data points to form a sequence
    if len(atm_data) >= seq_length:
        atm_seq = atm_data['Dispense_scaled'].values[-seq_length:]

        # Check the shape of atm_seq
        if atm_seq.shape[0] == seq_length:
            forecast = forecast_next_days(model, atm_seq, seq_length, 7)

            # Ensure forecast is a numpy array
            forecast = np.array(forecast).reshape(-1, 1)

            # Check if forecast can be inverse transformed
            if forecast.shape[1] == 1:
                forecast_inv = scaler.inverse_transform(forecast)
                forecast_results[atm_id] = forecast_inv
            else:
                print(f"Error: Forecast shape {forecast.shape} is not suitable for inverse transform")
        else:
            print(f"Error: ATM {atm_id} sequence length {atm_seq.shape[0]} does not match {seq_length}")
    else:
        print(f"Error: Not enough data for ATM {atm_id}")

# Check the forecast results
print(forecast_results)
```

```
{'APAN11109': array([[2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416]]), 'APAN22403': array([[2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416]]), 'APAN23217': array([[2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416]]), 'APAN35706': array([[2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416]]), 'APCN00816': array([[2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416]]), 'S1CN1142': array([[2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416]]), 'S1CN2011': array([[2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416],
    [2.21658416]]),
```

```
[2.21658416],  
[2.21658416]]), 'S1CN2022': array([[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416]]), 'S1CN2820': array([[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416]]), 'S1CN3514': array([[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416]]), 'SPCN02020': array([[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416]]), 'SPCND067': array([[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416]]), 'SPCNG376': array([[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416]]), 'T1BH000003039': array([[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],
```

```
[2.21658416],  
[2.21658416],  
[2.21658416]]), 'T1BH00011116': array([[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416]]), 'T1BH000274012': array([[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416]]), 'T1BH000603091': array([[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416]]), 'T1BH007252090': array([[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416]]), 'T1NH000575414': array([[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416]]), 'T1NY000166081': array([[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416]]), 'TPCN10269': array([[2.21658416],  
[2.21658416],  
[2.21658416],
```

```
[2.21658416],  
[2.21658416],  
[2.21658416],  
[2.21658416]]})}
```

Save the Final Result

```
In [79]: import numpy as np  
import pandas as pd  
  
# Assuming forecast_results is a dictionary with ATM IDs as keys and 2D forecast arrays as values  
flattened_results = {atm_id: forecast.flatten() for atm_id, forecast in forecast_results.items()}  
  
# Convert the flattened results dictionary to a DataFrame  
forecast_df = pd.DataFrame.from_dict(flattened_results, orient='index')  
forecast_df.columns = [f'Day_{i+1}' for i in range(forecast_df.shape[1])]  
  
# Save the DataFrame to a CSV file  
forecast_df.to_csv('atm_dispense_forecasts.csv', index=True)  
  
# Save the Jupyter Notebook and Python script  
# (In Jupyter Notebook, use the following code to save the notebook)  
# !jupyter nbconvert --to script atm_dispense_forecast.ipynb  
  
# Save the model in the native Keras format  
model.save('atm_dispense_model.keras')
```