Anomaly Detection of FLC Stock Price Using LSTM based Auto Encoders

Kaggle REFERENCE for Base Code

[1] https://www.kaggle.com/code/neeoon/stock-market-manipulation-autoencoders/notebook

Other Similar Codes

[2] https://towardsdatascience.com/time-series-of-price-anomaly-detection-with-lstm-11a12ba4f6d9

[3] https://github.com/susanli2016/Machine-Learning-with-Python/blob/master/Timeseries%20anomaly%20detection%20using%20LSTM

[4] https://medium.com/@manthapavankumar11/anomaly-detection-in-time-series-data-with-the-help-of-lstm-auto-encoders-5f8affaae7a7

Section 1 - Introduction

Background on Auto Encoders

An autoencoder is an artificial neural network used for unsupervised learning of efficient codings. Its goal is to induce a representation (encoding) for a set of data by learning an approximation of the identity function of this data:

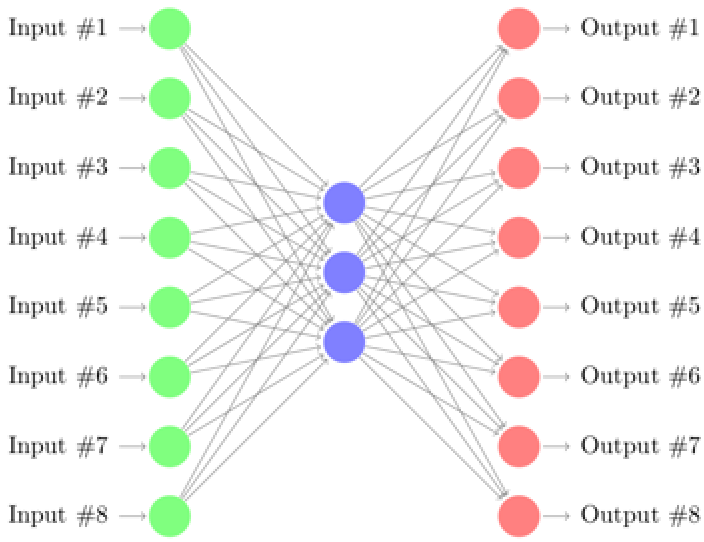
$$\mathrm{Id} : \mathcal{X} \to \mathcal{X}.$$

Architecturally, the simplest form of an autoencoder is a feedforward, non-recurrent neural network which is very similar to the multilayer perceptron (MLP), with an input layer, an output layer, and one or more hidden layers connecting them. The differences between autoencoders and MLPs are:

- In an autoencoder, the output layer has the same number of nodes as the input layer.
- Instead of being trained to predict a target value Y given inputs X, autoencoders are trained to reconstruct their own inputs X.

Architecture of an Autoencoder

(Image Ref: `https://philipperemy.github.io/anomaly-detection/![image-2.png](attachment:image-2.png)`)



The simplest form of an autoencoder is a feedforward neural network that resembles a multilayer perceptron (MLP). Its architecture consists of:

- Input Layer: Receives the input data.
- Hidden Layers: Encodes and decodes the data.
- Output Layer: Attempts to reconstruct the input.

How are Auto Encoders used for anomaly detection in Time Series data

Time series anomaly detection using autoencoders is a method for detecting unusual patterns in sequential data. An autoencoder is a type of neural network that can learn to encode the input data into a lower-dimensional representation and then decode it back to the original input. By training an autoencoder on a dataset of normal time series data, it can learn to reconstruct normal patterns in the data.

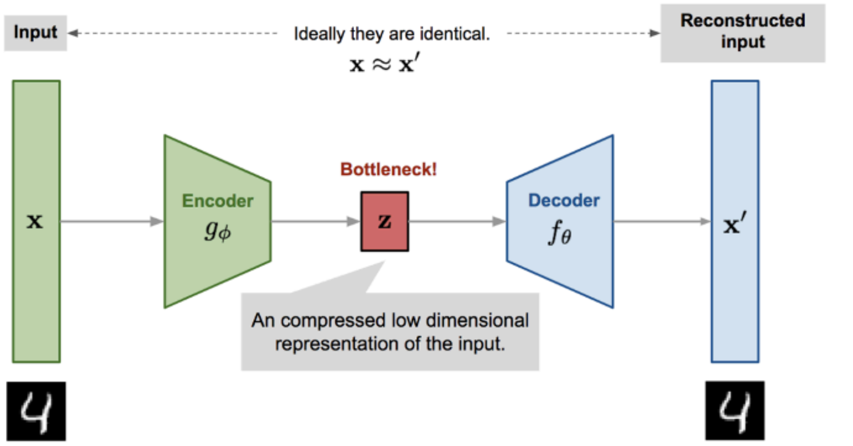
The trained autoencoder can be used to reconstruct new data points. If the difference between the original data point and its reconstructed version is above a certain threshold, the data point is considered anomalous. Different types of autoencoders can be used for time series anomaly detection, such as stacked autoencoders, convolutional autoencoders, or recurrent autoencoders and LSTM based ones

Application of Auto Encoder based anomaly detection in Time Series

Time series anomaly detection using autoencoders has been applied to a variety of domains, such as finance, healthcare, and industry. It can be used for detecting anomalous patterns in financial transactions, detecting unusual behaviour in sensor data, or detecting anomalies in medical time series data. However, it is important to note that autoencoders may not be the best choice for all types of anomaly detection tasks, and other methods such as support vector machines or clustering algorithms may be more appropriate in certain situations.

Schematic Explanation

(Image Ref : https://lilianweng.github.io/posts/2018-08-12-vae/![image.png]
(attachment:image.png))



The idea is quite straightforward:

- Due to the bottleneck architecture of the neural network, it is compelled to learn a compact representation from which it can reconstruct the original input.
- The model is trained exclusively on normal transactions, which it learns to reproduce with high accuracy.
- As a result, if an anomalous transaction is sufficiently different from normal transactions, the autoencoder will struggle to reconstruct it using its learned weights, leading to a high reconstruction loss.
- Any transaction with a reconstruction loss exceeding a specified threshold will be flagged as anomalous.

Section 2 : Code Demo

Imports

In [7]:
```
from tensorflow import keras
from sklearn.preprocessing import StandardScaler
import numpy as np
import tensorflow as tf
import pandas as pd
import plotly.graph_objects as go
import matplotlib.pyplot as plt
```

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LSTM, Dropout, RepeatVector, T
```

```
Matplotlib is building the font cache; this may take a moment.
```

Data Reads and Basic Data Cleaning

- Check for nulls
- Mean impute for Vol MA column
- Extract Date from Date Time format

In [8]:
```
# Read dataset
df = pd.read_csv("flc_unlabeled_time_series.csv")


# check Non Null count and Data type
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2170 entries, 0 to 2169
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   time       2170 non-null   object 
 1   open       2170 non-null   float64
 2   high       2170 non-null   float64
 3   low        2170 non-null   float64
 4   close      2170 non-null   float64
 5   Volume     2170 non-null   int64  
 6   Volume MA  2151 non-null   float64
dtypes: float64(5), int64(1), object(1)
memory usage: 118.8+ KB
```

In [9]:
```
# Mean impute for the column Volume MA
df['Volume MA'] = df['Volume MA'].fillna(df['Volume MA'].mean())

# extract Only the Date portion from a timestamp format
time = df['time'].str.split("T", expand = True)
df['time'] = time[0]

# check
df.head()
```

Out[9]:

	time	open	high	low	close	Volume	Volun
0	2013-08-06	4104.330818	4176.336622	4032.325014	4104.330818	6158668	1.36774
1	2013-08-07	4104.330818	4104.330818	3960.319210	4032.325014	4937960	1.36774
2	2013-08-08	4032.325014	4104.330818	3960.319210	3960.319210	2287341	1.36774
3	2013-08-09	3960.319210	4032.325014	3888.313406	3960.319210	2425496	1.36774
4	2013-08-12	3960.319210	3960.319210	3816.307603	3816.307603	3534864	1.36774

Get time range

- Print the Start and the End of the Date Range

In [10]:

```
# Print Start Value of Date Range
print("Start", df['time'].min())

# Print Start Value of Date Range
print("End",  df['time'].max())
```

```
Start 2013-08-06
End 2022-05-04
```

Extract necessary columns from dataframe

- We exttract only the `time` and `close` columns

In [11]:

```
df = df[['time', 'close']]
print(df['time'].min(), df['time'].max())
df.head()
df.info()
```

```
2013-08-06 2022-05-04
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2170 entries, 0 to 2169
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   time    2170 non-null   object 
 1   close   2170 non-null   float64
dtypes: float64(1), object(1)
memory usage: 34.0+ KB
```

Plotting data

- Plot the closing price Vs Date

In [31]:
```
fig = go.Figure()
fig.add_trace(go.Scatter(x=df['time'], y=df['close'], name='Close price'))
fig.update_layout(showlegend=True, title='FLC. Stock Price 2013-2022')
fig.show()
```

- It's obvious that after 2021, there's a spike in close price of FLC Stock
- We'll assume there're no anomaly before the 2021 point.

Prepare Train and Test Data

- Train - All data upto and including 2021-01-01
- Test - All data beyond 2021-01-01

In [13]:
```
train = df.loc[df['time'] <= '2021-01-01']
test = df.loc[df['time'] > '2021-01-01']
train.shape, test.shape
```

Out[13]: ((1841, 2), (329, 2))

Scaling data

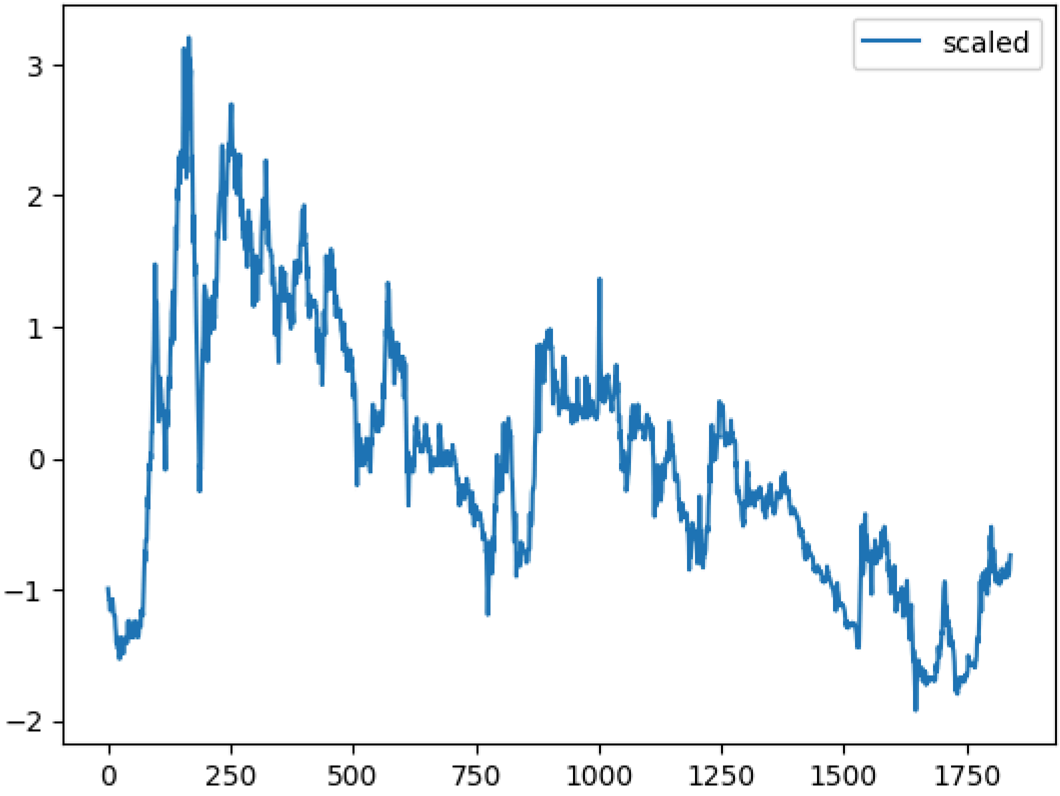
- A standard scaler is fit onto the training data
- The fitted scaler is then used to scale the train and test data

In [14]:
```
# Initiate Standard Scaler
scaler = StandardScaler()

# Fit scaler on Train Data
scaler = scaler.fit(train[['close']])

# Scale using fitted model on train data
train['close'] = scaler.transform(train[['close']])

# Scale using fitted model on test data
test['close'] = scaler.transform(test[['close']])
```

```
/var/folders/1m/07kgjdg97477jnhwzd0w8gyh0000gn/T/ipykernel_57141/35504918.
py:8: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

/var/folders/1m/07kgjdg97477jnhwzd0w8gyh0000gn/T/ipykernel_57141/35504918.
py:11: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

Plot Scaled Data

In [15]:
```
import matplotlib.pyplot as plt


plt.plot(train['close'], label = 'scaled')
plt.legend()
plt.show()
```



Prepare X and y data

Notes

- We have 1841 sequential values of closing stock prices as per Train data set
- A rolling block of 30 sequential values is selected as X data : The next value is treated as the corresponding 'y' data

In [16]:
```
# Set Time Steps
TIME_STEPS=30

# define function to create X , Y data
def create_sequences(X, y, time_steps=TIME_STEPS):
    X_out, y_out = [], []
    for i in range(len(X)-time_steps):
        X_out.append(X.iloc[i:(i+time_steps)].values)
        y_out.append(y.iloc[i+time_steps])

    return np.array(X_out), np.array(y_out)

# Create X Train and y Train
X_train, y_train = create_sequences(train[['close']], train['close'])

# Create X  Test and y Test
X_test, y_test = create_sequences(test[['close']], test['close'])

# Check shape
print("Training input shape: ", X_train.shape)
print("Testing input shape: ", X_test.shape)
```

```
Training input shape:  (1811, 30, 1)
Testing input shape:  (299, 30, 1)
```

Set random seed

In [17]:
```
np.random.seed(21)
tf.random.set_seed(21)
```

Building model

Define Auto Encoders with LSTM

Model Definition

`model = Sequential()`

- Initializes a sequential model, which allows stacking layers one after another.

Encoder Definition

`model.add(LSTM(128, activation='tanh', input_shape=(X_train.shape[1], X_train.shape[2])))`

- Adds an LSTM layer with:
  - 128 units: Number of neurons in the layer.
  - Activation = 'tanh': Hyperbolic tangent activation function, standard for LSTM layers.
  - Input shape = (X_train.shape[1], X_train.shape[2]):
    - X_train.shape[1]: Number of time steps (sequence length).
    - X_train.shape[2]: Number of features for each time step.
- This layer processes sequential data, encodes it, and reduces the dimensionality (latent space representation).

Drop Out Layer

`model.add(Dropout(rate=0.2))`

- Adds a dropout layer with a dropout rate of 20%. This helps prevent overfitting by randomly setting 20% of the weights to zero during training.

Bottleneck

`RepeatVector(n=X_train.shape[1])`

- Duplicates the latent vector (output from the encoder) across all time steps.
- This prepares the compressed representation for the decoder, effectively matching the time steps of the input sequence.

Decoder

`LSTM(units=128, return_sequences=True)'

- Adds another LSTM layer with 128 units.
- `return_sequences=True:` Ensures the LSTM outputs a sequence for each time step, required for reconstructing the input sequence.

'Dropout(rate=0.2)'

- Adds another dropout layer to prevent overfitting in the decoder.

Output- Time Distributed Layer

`TimeDistributed:`

- Ensures the Dense layer is applied to each time step independently.

`Dense(units=X_train.shape[2]):`

- Outputs the same number of features as the input for each time step.
- Reconstructs the input data.

Compile the Model

`model.compile(optimizer=keras.optimizers.Adam(learning_rate=0.001), loss="mse")`

`Optimizer = Adam:`

- Adaptive optimization algorithm.

`Learning rate = 0.001`

- (default for Adam).

`Loss = 'mse':`

- Mean squared error (MSE) is used to measure reconstruction error (difference between input and reconstructed sequence).

Summary

`model.summary()`

Prints a summary of the model, including the number of layers, shapes of inputs/outputs, and the total number of trainable parameters.

In [18]:
```
model = Sequential()
model.add(LSTM(128, activation = 'tanh', input_shape=(X_train.shape[1], X
model.add(Dropout(rate=0.2))
model.add(RepeatVector(X_train.shape[1]))
model.add(LSTM(128, activation = 'tanh', return_sequences=True))
model.add(Dropout(rate=0.2))
model.add(TimeDistributed(Dense(X_train.shape[2])))
model.compile(optimizer=keras.optimizers.Adam(learning_rate=0.001), loss=
model.summary()
```

```
/Users/anishroychowdhury/anaconda3/envs/LLM/lib/python3.12/site-packages/k
eras/src/layers/rnn/rnn.py:200: UserWarning:

Do not pass an `input_shape`/`input_dim` argument to a layer. When using S
equential models, prefer using an `Input(shape)` object as the first layer
in the model instead.
```

Model: "sequential"

Layer (type)	Output Shape	
lstm (LSTM)	(None, 128)	
dropout (Dropout)	(None, 128)	
repeat_vector (RepeatVector)	(None, 30, 128)	
lstm_1 (LSTM)	(None, 30, 128)	
dropout_1 (Dropout)	(None, 30, 128)	
time_distributed (TimeDistributed)	(None, 30, 1)	

Total params: 198,273 (774.50 KB)
Trainable params: 198,273 (774.50 KB)
Non-trainable params: 0 (0.00 B)

Train Model

`history = model.fit()`

- Purpose: Trains the model on the input data `(X_train, y_train)` for a specified number of epochs, while tracking performance metrics.

`epochs=100`

- Specifies the maximum number of passes through the entire training dataset.
- Higher epochs can improve learning but may lead to overfitting if unchecked.

`batch_size=32`

- Batch size is the number of samples the model processes before updating weights.
- Smaller batch sizes provide more updates per epoch (finer adjustments to the model's weights), but they increase training time.

`validation_split=0.1`

- Reserves 10% of the training data (X_train and y_train) as a validation set.
- The model evaluates its performance on this subset after each epoch to monitor generalization and tune hyperparameters.

`callbacks=[keras.callbacks.EarlyStopping(monitor='val_loss', patience=5, mode='min')]`

EarlyStopping halts training early if the monitored metric (here, val_loss) stops improving.

- `monitor='val_loss'` : Watches the validation loss during training.
- `patience=5:` Training stops if validation loss doesn't improve for 5 consecutive epochs.
- `mode='min':` Looks for a minimum in the validation loss (smaller loss is better).

`shuffle=False`

- Prevents shuffling of training data before each epoch.
- **Reason to avoid shuffling:**
  - In time-series data, the temporal order is crucial and should remain intact during training.
  - Shuffling would destroy this sequential dependency.

  `history = ...`

- The history object stores the model's performance metrics (loss, validation loss, etc.) for each epoch.
- You can use history.history to extract these metrics for visualization or further analysis.

In [19]:
```
history = model.fit(X_train,
                    y_train,
                    epochs=100,
                    batch_size=32,
                    validation_split=0.1,
                    callbacks=[keras.callbacks.EarlyStopping(monitor='val
                    shuffle=False)
```

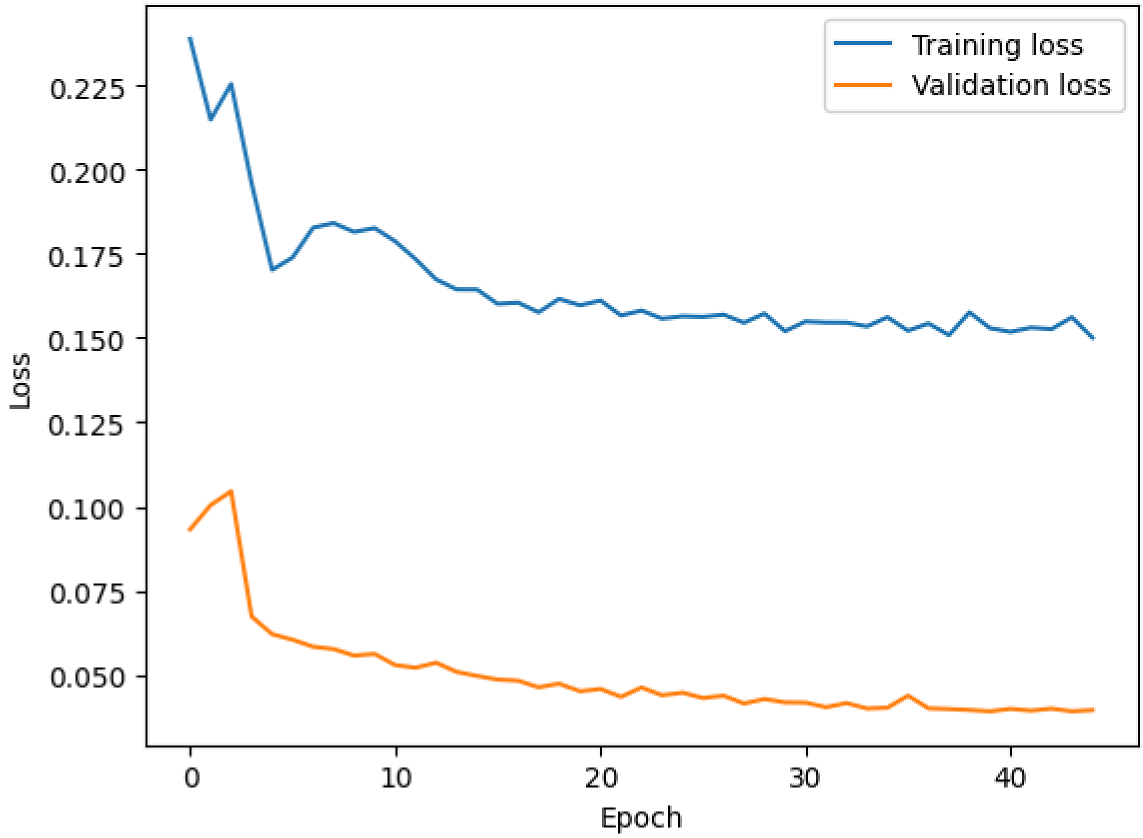
```
Epoch 1/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 3s 37ms/step - loss: 0.5177 - val_loss: 0.0932
Epoch 2/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 35ms/step - loss: 0.3873 - val_loss: 0.1004
Epoch 3/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 40ms/step - loss: 0.4144 - val_loss: 0.1045
Epoch 4/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 41ms/step - loss: 0.3562 - val_loss: 0.0673
Epoch 5/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 39ms/step - loss: 0.3041 - val_loss: 0.0620
Epoch 6/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 41ms/step - loss: 0.3053 - val_loss: 0.0604
Epoch 7/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 42ms/step - loss: 0.3161 - val_loss: 0.0583
Epoch 8/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 42ms/step - loss: 0.3231 - val_loss: 0.0576
Epoch 9/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 42ms/step - loss: 0.3202 - val_loss: 0.0557
Epoch 10/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 42ms/step - loss: 0.3170 - val_loss: 0.0562
Epoch 11/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 41ms/step - loss: 0.3097 - val_loss: 0.0529
Epoch 12/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 42ms/step - loss: 0.3050 - val_loss: 0.0520
Epoch 13/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 40ms/step - loss: 0.2958 - val_loss: 0.0536
Epoch 14/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 42ms/step - loss: 0.2902 - val_loss: 0.0508
Epoch 15/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 43ms/step - loss: 0.2903 - val_loss: 0.0496
Epoch 16/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 42ms/step - loss: 0.2825 - val_loss: 0.0486
Epoch 17/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 42ms/step - loss: 0.2847 - val_loss: 0.0482
Epoch 18/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 42ms/step - loss: 0.2804 - val_loss: 0.0462
Epoch 19/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 42ms/step - loss: 0.2868 - val_loss: 0.0473
Epoch 20/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 42ms/step - loss: 0.2849 - val_loss: 0.0451
Epoch 21/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 42ms/step - loss: 0.2886 - val_loss: 0.0457
Epoch 22/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 42ms/step - loss: 0.2796 - val_loss: 0.0434
Epoch 23/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 43ms/step - loss: 0.2847 - val_loss: 0.0462
Epoch 24/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 42ms/step - loss: 0.2782 - val_loss: 0.0439
Epoch 25/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 43ms/step - loss: 0.2778 - val_loss: 0.0446
Epoch 26/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 43ms/step - loss: 0.2793 - val_loss: 0.0431
Epoch 27/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 44ms/step - loss: 0.2797 - val_loss: 0.0437
Epoch 28/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 42ms/step - loss: 0.2766 - val_loss: 0.0414
Epoch 29/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 43ms/step - loss: 0.2835 - val_loss: 0.0428
Epoch 30/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 43ms/step - loss: 0.2739 - val_loss: 0.0418
```

```
Epoch 31/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 42ms/step - loss: 0.2767 - val_loss: 0.0417
Epoch 32/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 43ms/step - loss: 0.2784 - val_loss: 0.0403
Epoch 33/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 43ms/step - loss: 0.2777 - val_loss: 0.0415
Epoch 34/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 43ms/step - loss: 0.2760 - val_loss: 0.0399
Epoch 35/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 43ms/step - loss: 0.2807 - val_loss: 0.0402
Epoch 36/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 43ms/step - loss: 0.2771 - val_loss: 0.0437
Epoch 37/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 42ms/step - loss: 0.2785 - val_loss: 0.0400
Epoch 38/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 42ms/step - loss: 0.2733 - val_loss: 0.0398
Epoch 39/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 42ms/step - loss: 0.2818 - val_loss: 0.0395
Epoch 40/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 41ms/step - loss: 0.2731 - val_loss: 0.0391
Epoch 41/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 43ms/step - loss: 0.2727 - val_loss: 0.0398
Epoch 42/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 43ms/step - loss: 0.2727 - val_loss: 0.0393
Epoch 43/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 43ms/step - loss: 0.2722 - val_loss: 0.0399
Epoch 44/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 42ms/step - loss: 0.2834 - val_loss: 0.0391
Epoch 45/100
51/51 ━━━━━━━━━━━━━━━━━━━━ 2s 43ms/step - loss: 0.2682 - val_loss: 0.0395
```

Loss Analysis

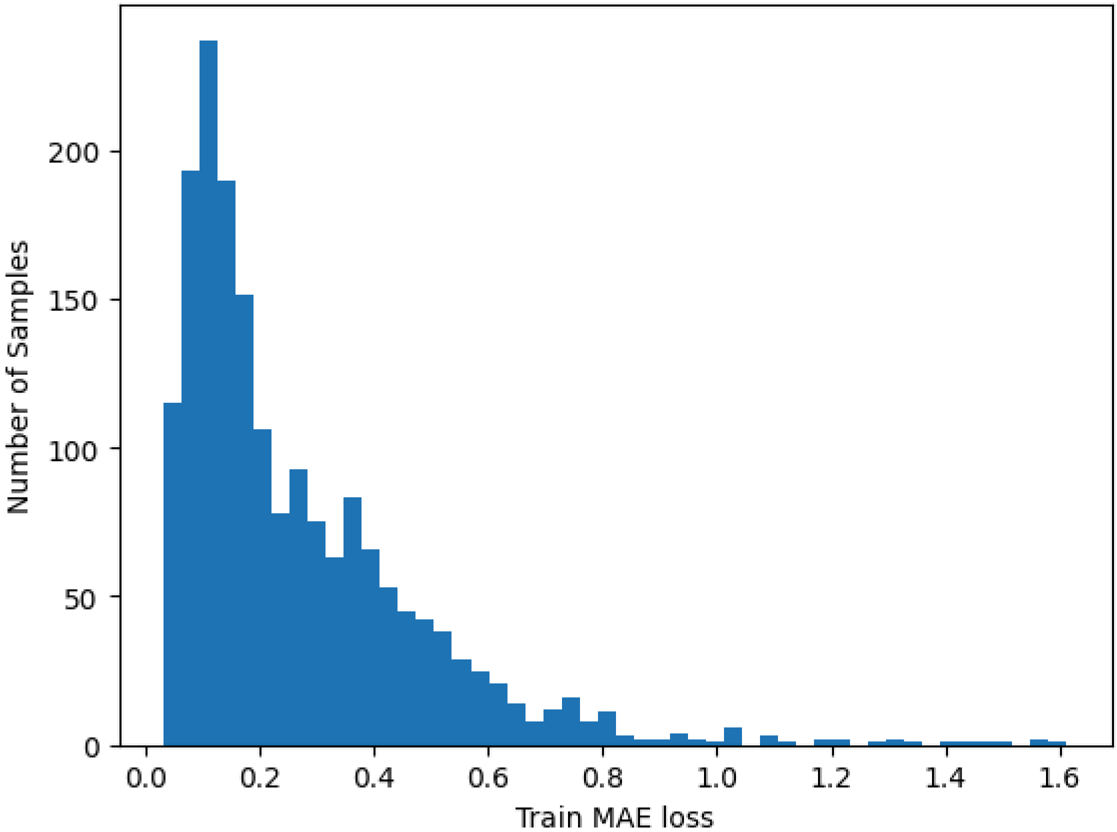
- Plot training and validation loss
- Histogram plot of MAE Loss on train data
- Set threshold of loss to max value of train loss
- Histogram plot of MAE Loss on test data

In [20]:
```
# Plotting training & validation loss

plt.plot(history.history['loss'], label='Training loss')
plt.plot(history.history['val_loss'], label='Validation loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend();
```



In [21]:
```
# Plotting MAE loss on train data

X_train_pred = model.predict(X_train)
train_mae_loss = np.mean(np.abs(X_train_pred - X_train), axis=1)

plt.hist(train_mae_loss, bins=50)
plt.xlabel('Train MAE loss')
plt.ylabel('Number of Samples');

# Set reconstruction error threshold
threshold = np.max(train_mae_loss)

print('Reconstruction error threshold:',threshold)
```

```
57/57 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step
Reconstruction error threshold: 1.611732148761672
```

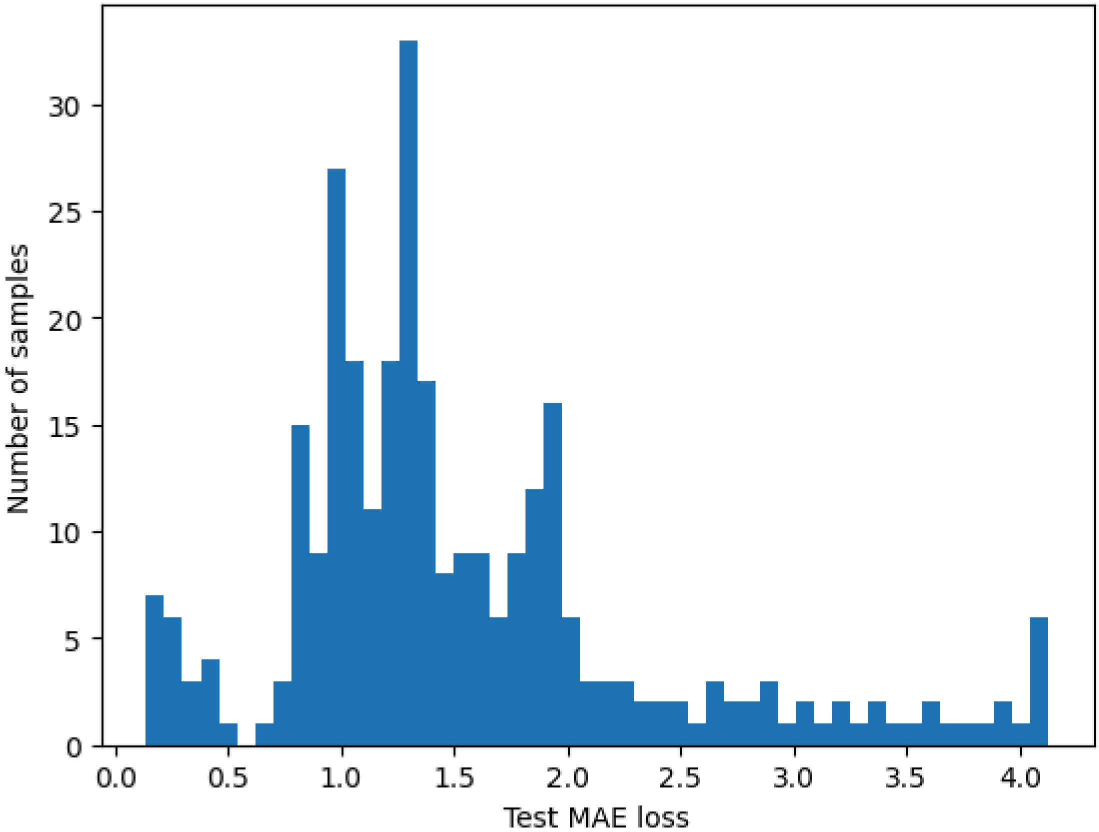


In [22]:

```
# Plotting MAE loss on test data

X_test_pred = model.predict(X_test, verbose=1)
test_mae_loss = np.mean(np.abs(X_test_pred-X_test), axis=1)

plt.hist(test_mae_loss, bins=50)
plt.xlabel('Test MAE loss')
plt.ylabel('Number of samples')
```

```
10/10 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step
```

Out[22]: `Text(0, 0.5, 'Number of samples')`



Data preparation for plotting anomalies

- Subset the test data top include data points post the initial count of TIMESTEPS
- set threshold to be a constant value
- create a Boolean feature : 'anomaly' if loss exceeds threshold

In [23]:
```
# feature engineering for plotting anomalies

anomaly_df = pd.DataFrame(test[TIME_STEPS:])
anomaly_df['loss'] = test_mae_loss
anomaly_df['threshold'] = threshold
anomaly_df['anomaly'] = anomaly_df['loss'] > anomaly_df['threshold']
anomaly_df['close'] = test[TIME_STEPS:]['close']

# check
anomaly_df.head()
```

Out[23]:

	time	close	loss	threshold	anomaly
1871	2021-02-22	0.272766	0.413385	1.611732	False
1872	2021-02-23	0.175629	0.396643	1.611732	False
1873	2021-02-24	0.118490	0.357662	1.611732	False
1874	2021-02-25	0.147060	0.326786	1.611732	False
1875	2021-02-26	0.255624	0.297873	1.611732	False

In [25]:
```
# Specify file path
file_path = "anomaly.csv"
```

```
# Save DataFrame to local drive as a CSV file
anomaly_df.to_csv(file_path, index=False)

# display saved path
print(f"DataFrame saved to {file_path}")
```

```
DataFrame saved to anomaly.csv
```

RESTART CODE FROM HERE IF Training has been completed and feature engineered Anomaly DF has been created

Read back the feature engineered Anomaly dataframe from drive storage

In [27]:
```
# Read the DataFrame back
file_path = "anomaly.csv"
df_loaded = pd.read_csv(file_path)
print("DataFrame loaded from file:")

df_loaded.head()
```

```
DataFrame loaded from file:
```

Out[27]:

	time	close	loss	threshold	anomaly
0	2021-02-22	0.272766	0.413385	1.611732	False
1	2021-02-23	0.175629	0.396643	1.611732	False
2	2021-02-24	0.118490	0.357662	1.611732	False
3	2021-02-25	0.147060	0.326786	1.611732	False
4	2021-02-26	0.255624	0.297873	1.611732	False

Plot Test Loss with anomaly threshold

In [28]:
```
# Initiate Figure
fig = go.Figure()

# Plot Loss in recontsruction vs date  for test data
fig.add_trace(go.Scatter(x=df_loaded['time'], y=df_loaded['loss'], name='

# plot a horizontal line across all the test data at threshold level
fig.add_trace(go.Scatter(x=df_loaded['time'], y=df_loaded['threshold'], n

# Set Title and legend
fig.update_layout(showlegend=True, title='Test loss vs. Threshold')

# Display figure
fig.show()
```

Subset the anomalous data rows based on Boolean feature

In [29]:
```
# subset
anomalies = df_loaded.loc[df_loaded['anomaly'] == True]

# check
anomalies.head()
```

Out[29]:

	time	close	loss	threshold	anomaly
88	2021-06-29	4.461061	1.632374	1.611732	True
89	2021-06-30	4.261074	1.667337	1.611732	True
90	2021-07-01	4.318213	1.713220	1.611732	True
91	2021-07-02	4.118226	1.741794	1.611732	True
92	2021-07-05	3.689683	1.784559	1.611732	True

Mark Anomaly points on Actual data

In [30]:
```
import plotly.graph_objects as go
import numpy as np

# Initiate figure
```

```
fig = go.Figure()

# Inverse transform closing prices and plot vs timeline
close_prices_scaled = df_loaded['close'].values.reshape(-1, 1)  # Reshape
close_prices_original = scaler.inverse_transform(close_prices_scaled).fla
fig.add_trace(go.Scatter(
    x=df_loaded['time'],
    y=close_prices_original,
    name='Close price',
    line=dict(color='blue')
))

# Inverse transform anomaly prices and plot
anomaly_prices_scaled = anomalies['close'].values.reshape(-1, 1)  # Resha
anomaly_prices_original = scaler.inverse_transform(anomaly_prices_scaled)
fig.add_trace(go.Scatter(
    x=anomalies['time'],
    y=anomaly_prices_original,
    mode='markers',
    name='Anomaly',
    marker=dict(
        color='red',
        size=10,
        symbol='circle'
    )
))

# Define layout
fig.update_layout(
    title='Stock Price Anomalies Detection',
    title_x=0.5,  # Center the title
    xaxis_title='Time',
    yaxis_title='Price',
    showlegend=True,
    template='plotly_white',  # Clean white background
    legend=dict(
        yanchor="top",
        y=0.99,
        xanchor="left",
        x=0.01
    )
)

# Show the plot
fig.show()
```

In [ ]: