Astra International (ASII.JK) Stock Price Prediction using LSTM

In this project, we will try to predict the stock price of PT. Astra International Tbk (Astra).

1. Business Understanding

Astra is an Indonesian conglomerate (Indonesia-investment.com, 2014). This company was established in 1957 in Jakarta as a general trading company. In 1990, Astra has listed its shares on the Indonesia Stock Exchange under the ticker code ASII (Astra.co.id, 2021).

The objective of this project is to accurately predict Astra stock price.

Since stock price data is time-series data, it is essential to use a model that can predict time-series data accurately. Several popular models can be used to predict time-series data such as Long Short-Term Memory (LSTM) Network, Autoregressive Integrated Moving Average (ARIMA), and Facebook Prophet. For instance, Bao et al. implemented LSTM model for stock price forecasting (Bao et al, 2017), Pai and Lin used ARIMA and Support Vector Machines (SVM) model in stock price forecasting (Pai and Lin, 2004), Papacharalampous et al. implemented a Facebook Prophet for time-series forecasting (Papacharalampous et al, 2018). However, in this simple project, we will use LSTM to predict the stock price.

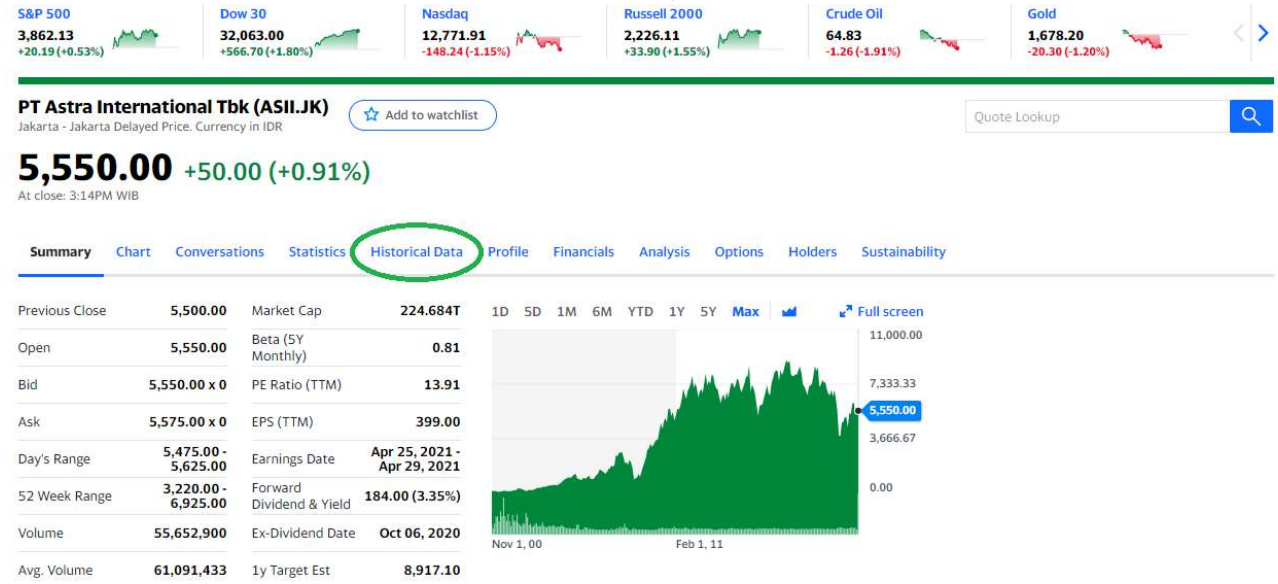
The LSTMs have recurrent connections; thus, the state of previous activations of the neuron from the previous time step is used as context for formulating an output (Brownlee, 2017). Besides, unlike other RNNs, LSTM has a unique formulation that allows it to avoid the problems that prevent the training and scaling of other RNNs. Therefore, it can achieve a better result. Those are the reasons why LSTM is gaining a lot of popularity for solving the time-series prediction case.

Are you ready? Let's predict ASII stock price! Note that we will use the LSTM model and the CRISP-DM reference model (adapted) as guidance to predict the ASII.JK stock price.

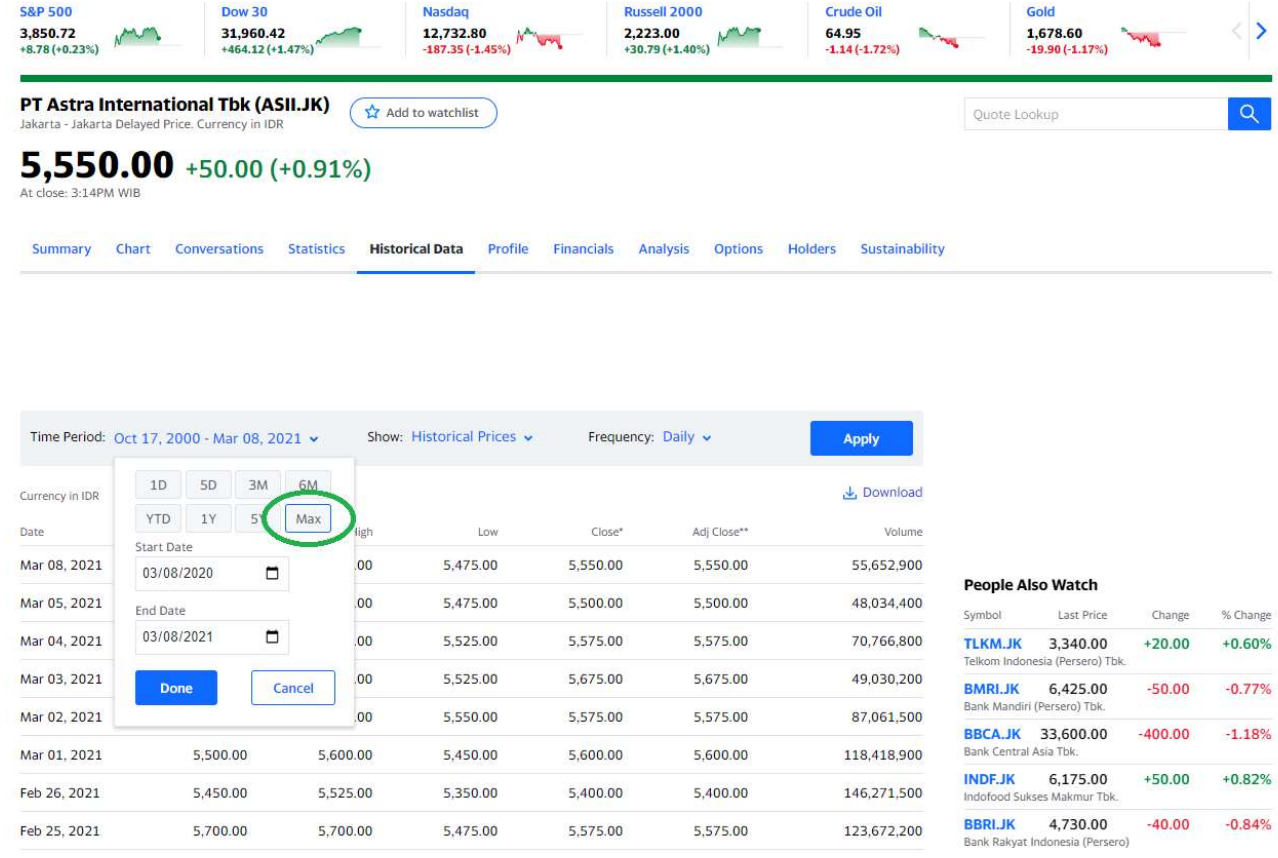
2. Data Acquisition

How to get the dataset? You can download the historical data on yahoo finance. Here's the link to access the ASII stock price: https://finance.yahoo.com/quote/ASII.JK?p=ASII.JK&.tsrc=fin-srch (https://finance.yahoo.com/quote/ASII.JK?p=ASII.JK&.tsrc=fin-srch)

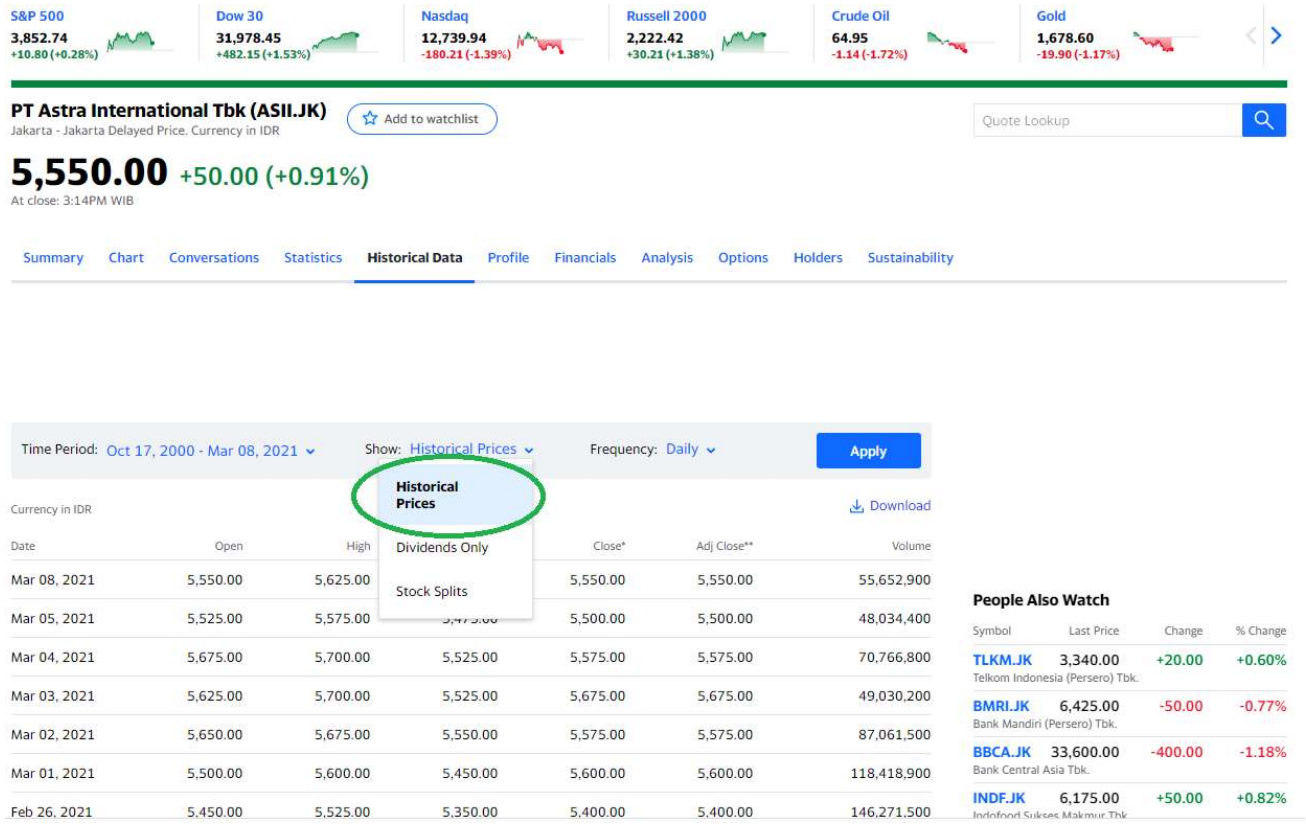
1. Click on the "Historical Data" to see all the ASII stock price data.



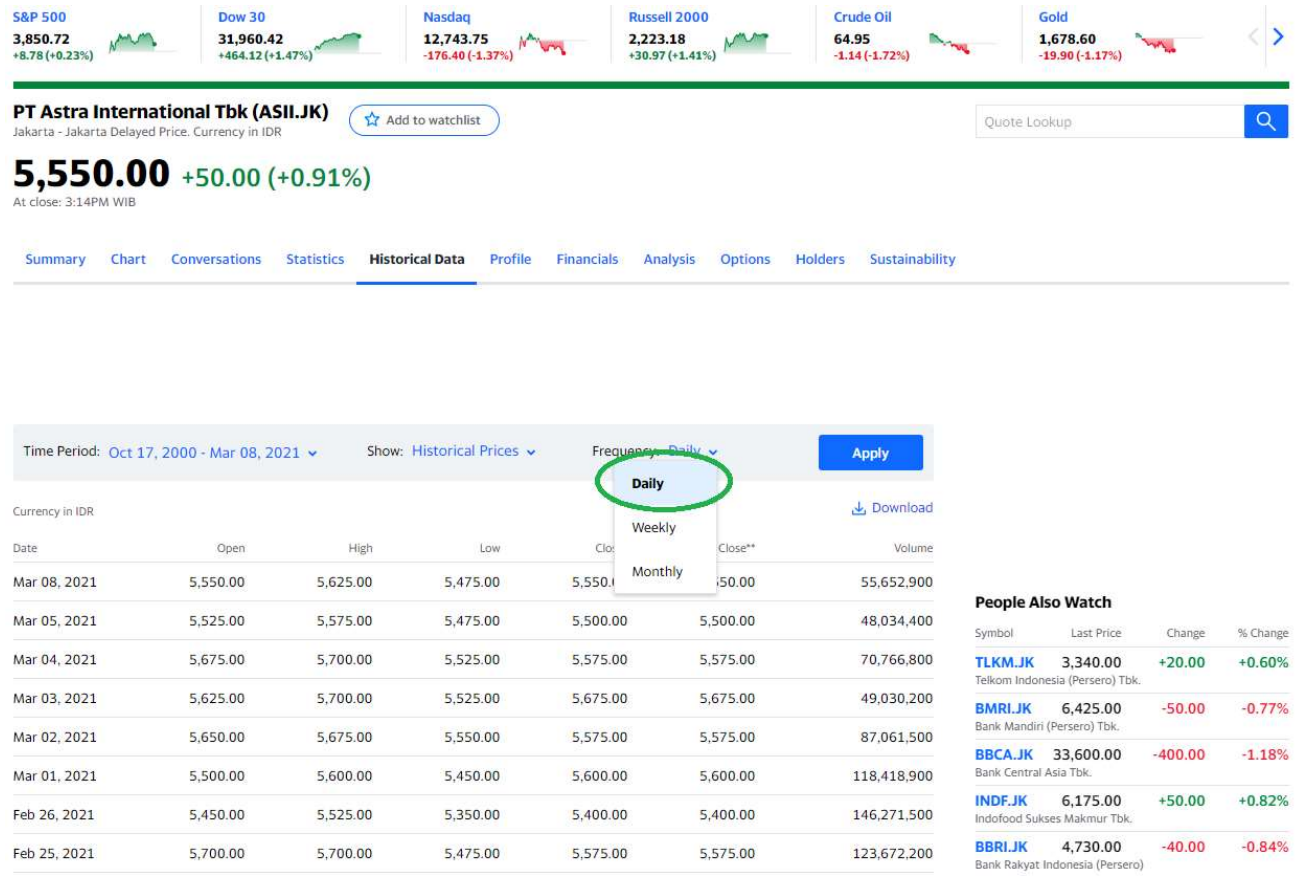
1. Chose the time period as "MAX".



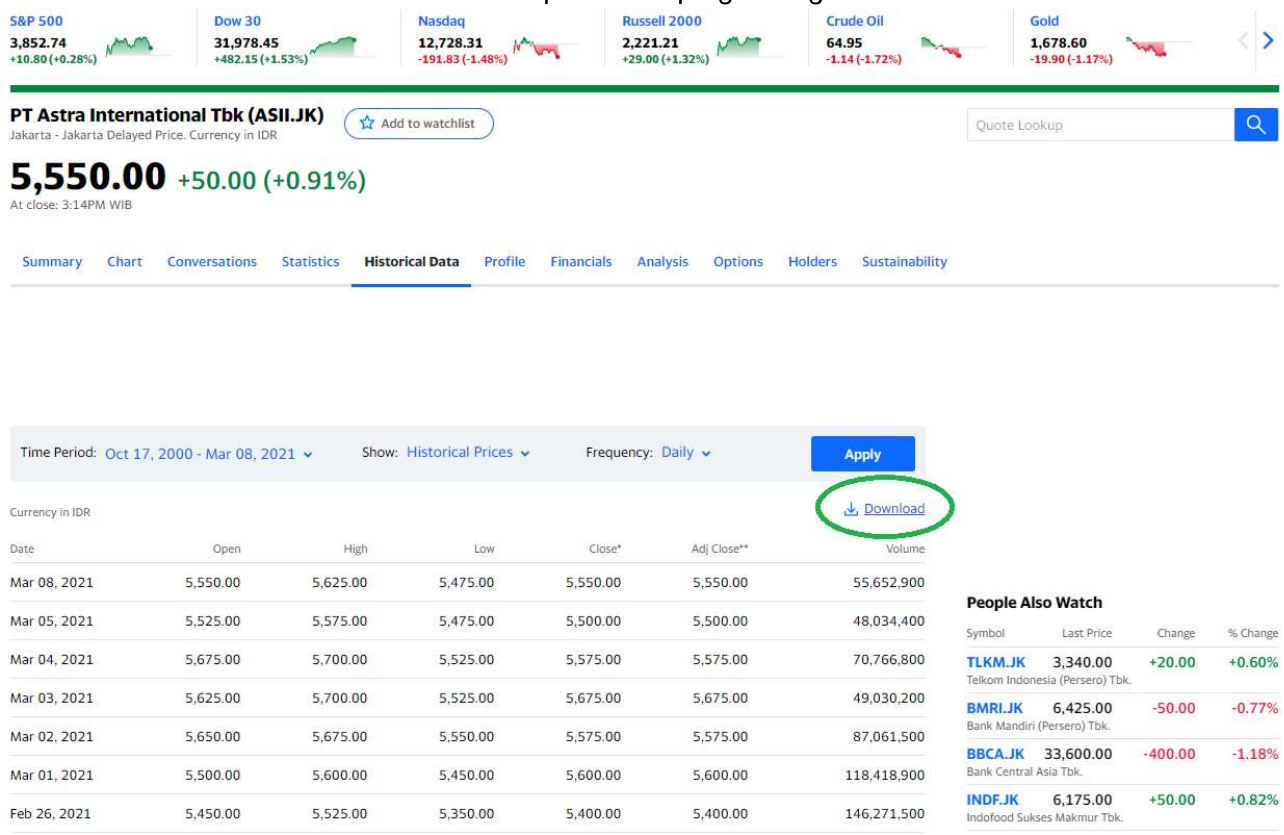
1. Show the "Historical Prices"



1. Show frequency data in "Daily". Thus, it will provide the stock price of ASII until the latest day on daily basis.



1. Click "Download". Voila! Now the download process is progressing.



After the download is finished, you will have the .csv file containing data such as date, open, high, low, close, adj close, and volume.

Note that in this project I use ASII stock price data from 17th of October 2000 until 5th of March 2021. The pictures above mentioned only illustrate the process of data acquisition.

Now we have the dataset. Let's explore this dataset!

3. Data Understanding

In [1]:

```
#import the libraries
import matplotlib.pyplot as plt
import keras
import pandas as pd
import numpy as np
from keras.models import Sequential
from keras.layers import Dense, LSTM, Dropout
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error, mean_absolute_error
from sklearn.model_selection import train_test_split
from keras.callbacks import EarlyStopping

%matplotlib inline
pd.set_option('display.max_columns', None)

# Data viz by using Plotly
import plotly.express as px
import plotly.graph_objects as go

# ignore warnings
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

```
Using TensorFlow backend.
```

In [2]:

```
# importing the dataset
inputdir = 'asiistockprice' #data was donloaded on 8 Mar 2021
#asii = pd.read_csv('ASII.JK.csv')
asii = pd.read_csv(inputdir+'/ASII.JK.csv')
```

In [3]:

```
# cheking missing values
asii[asii.isnull().any(axis=1)]
```

Out[3]:

	Date	Open	High	Low	Close	Adj Close	Volume
4688	2019-06-19	NaN	NaN	NaN	NaN	NaN	NaN

In [4]:

```
# identify how many missing values in each feature
asii.isnull().sum()
```

Out[4]:

```
Date         0
Open         1
High         1
Low          1
Close        1
Adj Close    1
Volume       1
dtype: int64
```

In [5]:

```
# drop missing values from the dataset
asii = asii.dropna()
```

In [6]:

```
# check the shape of dataset
asii.shape
```

Out[6]:

```
(5110, 7)
```

In [7]:

```
# check the dataset
asii.tail()
```

Out[7]:

	Date	Open	High	Low	Close	Adj Close	Volume
5106	2021-03-01	5500.0	5600.0	5450.0	5600.0	5600.0	118418900.0
5107	2021-03-02	5650.0	5675.0	5550.0	5575.0	5575.0	87061500.0
5108	2021-03-03	5625.0	5700.0	5525.0	5675.0	5675.0	49030200.0
5109	2021-03-04	5675.0	5700.0	5525.0	5575.0	5575.0	70766800.0
5110	2021-03-05	5525.0	5575.0	5475.0	5500.0	5500.0	48034400.0

In [8]:

```
# check the info of dataset
asii.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5110 entries, 0 to 5110
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Date       5110 non-null   object 
 1   Open       5110 non-null   float64
 2   High       5110 non-null   float64
 3   Low        5110 non-null   float64
 4   Close      5110 non-null   float64
 5   Adj Close  5110 non-null   float64
 6   Volume     5110 non-null   float64
dtypes: float64(6), object(1)
memory usage: 319.4+ KB
```

In [9]:

```
# describe of the dataset
asii.describe()
```

Out[9]:

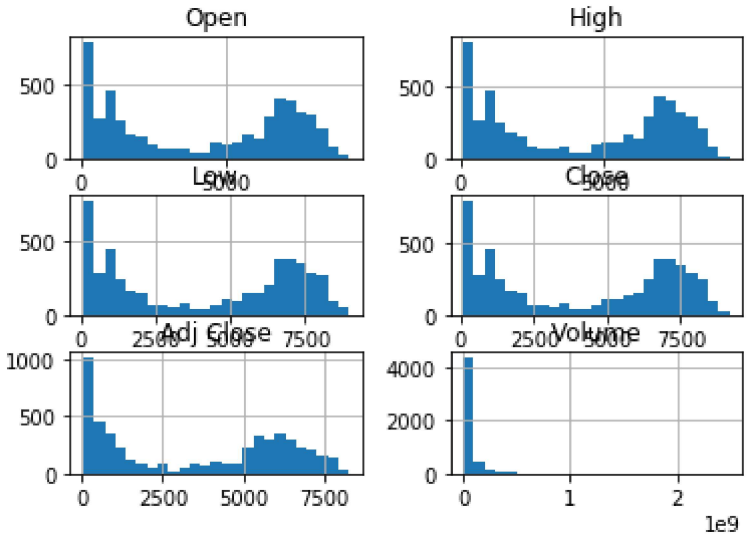
	Open	High	Low	Close	Adj Close	Volume
count	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	5.110000e+03
mean	4164.369534	4214.692055	4110.037662	4162.452002	3487.004051	6.330208e+07
std	3058.450393	3088.898983	3023.776667	3056.231198	2762.520885	1.271598e+08
min	86.940796	90.804832	85.008781	88.872810	50.086323	0.000000e+00
25%	1020.000000	1035.000000	1000.000000	1015.000000	625.521606	1.682555e+07
50%	4815.000000	4870.000000	4730.000000	4810.000000	3756.409790	3.221595e+07
75%	7100.000000	7157.500000	7000.000000	7098.750000	6073.216797	6.107175e+07
max	9250.000000	9350.000000	8975.000000	9150.000000	8269.624023	2.485057e+09

In [10]:

```
# checking the features
asii.hist(bins=25)
```

Out[10]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x000001EE72F7B84
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001EE7504EC8
8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000001EE75089BC
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001EE750C0D0
8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000001EE750F9E0
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001EE75131F0
8>]],
      dtype=object)
```



In [11]:

```
# format the raw date feature into a measureable format
asii['Date'] = pd.to_datetime(asii['Date'], format="%Y-%m-%dT%H:%M:%S")
```

In [12]:

```
# check the dataset
asii.head()
```

Out[12]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	2000-10-17	189.724136	192.815369	187.405716	187.792114	105.834579	30266285.0
1	2000-10-18	187.792114	188.951324	181.609665	181.996063	102.568069	45082402.0
2	2000-10-19	183.928085	187.405716	179.291245	186.246506	104.963516	43730189.0
3	2000-10-20	193.201767	195.133789	175.813614	177.745636	100.172661	212012808.0
4	2000-10-23	177.745636	181.609665	173.881592	175.813614	99.083794	84723602.0

In [13]:

```
# visualize the dataset by using Plotly
fig = go.Figure(data=[go.Candlestick(x= asii['Date'],
                open= asii['Open'], high= asii['High'],
                low= asii['Low'], close= asii['Close'])
                      ])

fig.update_layout(
    title='ASII.JK Stock Price',
    yaxis_title='ASII Stock',
    shapes = [dict(
        x0='2020-01-27', x1='2020-01-27', y0=0, y1=1, xref='x', yref='paper',
        line_width=2)],
    annotations=[dict(
        x='2020-01-27', y=0.05, xref='x', yref='paper',
        showarrow=False, xanchor='right', text='Increase Period Begins')]
)

fig.update_yaxes(title_text = 'Stock Price', tickprefix = 'IDR ')

fig.show()
```

In [14]:

```
# Visualize the dataset by using Matplotlib
fig, ax = plt.subplots(figsize=(16, 4))
plt.plot(asii['Date'], asii['Close'], color = 'blue', label = 'Real price')
plt.title('ASII Stock Price')
plt.xlabel('Time')
plt.ylabel('Stock Price')
plt.legend()
plt.show()
```

By implementing this kind of data visualization, we can see when the stock price tends to increase or decrease. It helps us to find out the root causes if the market is volatile. In addition, we can select the point that we want to observe.

4. Data Preparation

We will use the 'Close' stock price of ASII.JK

In [15]:

```
# select the train set and test set
train_set = asii.iloc[:4500, 4:5].values
test_set = asii.iloc[4500:, 4:5].values
```

In [16]:

```
# checking the train set
train_set
```

Out[16]:

```
array([[ 187.792114],
       [ 181.996063],
       [ 186.246506],
       ...,
       [7200.      ],
       [7350.      ],
       [7375.      ]])
```

In [17]:

```
# Feature Scaling
sc = MinMaxScaler(feature_range = (0, 1))
train_set_scaled = sc.fit_transform(train_set)
```

In [18]:

```
# Creating a data structure of train set
X_train = []
y_train = []

for i in range(60, 4500):
    X_train.append(train_set_scaled[i-50:i, 0])
    y_train.append(train_set_scaled[i, 0])
X_train, y_train = np.array(X_train), np.array(y_train)
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
```

In [19]:

```
# Creating a data structure of test set
dataset_train = asii.iloc[:4500, 4:5]
dataset_test = asii.iloc[4500:, 4:5]

dataset_total = pd.concat((dataset_train, dataset_test), axis = 0)

inputs = dataset_total[len(dataset_total) - len(dataset_test) - 60:].values
inputs = inputs.reshape(-1,1)
inputs = sc.transform(inputs)

X_test = []
y_test = []

for i in range(60, 670):
    X_test.append(inputs[i-50:i, 0])
    y_test.append(inputs[i, 0])

X_test, y_test = np.array(X_test), np.array(y_test)
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
print(X_test.shape)
```

```
(610, 50, 1)
```

5. Modelling and Validation

In [20]:

```
model = Sequential()

n_unit = 100

#Adding the first LSTM layer and some Dropout regularisation
model.add(LSTM(units = n_unit, return_sequences = True, input_shape = (X_train.shape[1
], 1)))
model.add(Dropout(0.2))

# Adding a second LSTM layer and some Dropout regularisation
model.add(LSTM(units = n_unit, return_sequences = True))
model.add(Dropout(0.2))

# Adding a third LSTM layer and some Dropout regularisation
model.add(LSTM(units = n_unit, return_sequences = True))
model.add(Dropout(0.2))

# Adding a fourth LSTM layer and some Dropout regularisation
model.add(LSTM(units = n_unit))
model.add(Dropout(0.2))

# Adding the output layer
model.add(Dense(units = 1))

# Compiling the RNN
model.compile(optimizer = 'adam', loss = 'mean_squared_error', metrics=['mae', 'mse','a
ccuracy'])
```

In [21]:

```
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (None, 50, 100)           40800
_________________________________________________________________
dropout_1 (Dropout)          (None, 50, 100)           0
_________________________________________________________________
lstm_2 (LSTM)                (None, 50, 100)           80400
_________________________________________________________________
dropout_2 (Dropout)          (None, 50, 100)           0
_________________________________________________________________
lstm_3 (LSTM)                (None, 50, 100)           80400
_________________________________________________________________
dropout_3 (Dropout)          (None, 50, 100)           0
_________________________________________________________________
lstm_4 (LSTM)                (None, 100)               80400
_________________________________________________________________
dropout_4 (Dropout)          (None, 100)               0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 101
=================================================================
Total params: 282,101
Trainable params: 282,101
Non-trainable params: 0
_________________________________________________________________
```

In [22]:

```
# Fitting the LSTM Network to the Training set
history = model.fit(X_train, y_train, epochs = 100, batch_size = 32, validation_data=(X
_test, y_test))
```

```
Train on 4440 samples, validate on 610 samples
Epoch 1/100
4440/4440 [==============================] - 20s 5ms/step - loss: 0.0097 -
mae: 0.0542 - mse: 0.0097 - accuracy: 9.0090e-04 - val_loss: 0.0026 - val_
mae: 0.0377 - val_mse: 0.0026 - val_accuracy: 0.0000e+00
Epoch 2/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0024 -
mae: 0.0322 - mse: 0.0024 - accuracy: 9.0090e-04 - val_loss: 0.0027 - val_
mae: 0.0391 - val_mse: 0.0027 - val_accuracy: 0.0000e+00
Epoch 3/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0021 -
mae: 0.0306 - mse: 0.0021 - accuracy: 9.0090e-04 - val_loss: 0.0025 - val_
mae: 0.0385 - val_mse: 0.0025 - val_accuracy: 0.0000e+00
Epoch 4/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0020 -
mae: 0.0299 - mse: 0.0020 - accuracy: 9.0090e-04 - val_loss: 0.0026 - val_
mae: 0.0393 - val_mse: 0.0026 - val_accuracy: 0.0000e+00
Epoch 5/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0019 -
mae: 0.0291 - mse: 0.0019 - accuracy: 9.0090e-04 - val_loss: 0.0028 - val_
mae: 0.0418 - val_mse: 0.0028 - val_accuracy: 0.0000e+00
Epoch 6/100
4440/4440 [==============================] - 19s 4ms/step - loss: 0.0023 -
mae: 0.0321 - mse: 0.0023 - accuracy: 9.0090e-04 - val_loss: 0.0022 - val_
mae: 0.0353 - val_mse: 0.0022 - val_accuracy: 0.0000e+00
Epoch 7/100
4440/4440 [==============================] - 19s 4ms/step - loss: 0.0018 -
mae: 0.0284 - mse: 0.0018 - accuracy: 9.0090e-04 - val_loss: 0.0016 - val_
mae: 0.0298 - val_mse: 0.0016 - val_accuracy: 0.0000e+00
Epoch 8/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0019 -
mae: 0.0298 - mse: 0.0019 - accuracy: 9.0090e-04 - val_loss: 0.0016 - val_
mae: 0.0296 - val_mse: 0.0016 - val_accuracy: 0.0000e+00
Epoch 9/100
4440/4440 [==============================] - 19s 4ms/step - loss: 0.0017 -
mae: 0.0278 - mse: 0.0017 - accuracy: 9.0090e-04 - val_loss: 0.0022 - val_
mae: 0.0361 - val_mse: 0.0022 - val_accuracy: 0.0000e+00
Epoch 10/100
4440/4440 [==============================] - 19s 4ms/step - loss: 0.0017 -
mae: 0.0277 - mse: 0.0017 - accuracy: 9.0090e-04 - val_loss: 0.0014 - val_
mae: 0.0277 - val_mse: 0.0014 - val_accuracy: 0.0000e+00
Epoch 11/100
4440/4440 [==============================] - 19s 4ms/step - loss: 0.0015 -
mae: 0.0269 - mse: 0.0015 - accuracy: 9.0090e-04 - val_loss: 0.0016 - val_
mae: 0.0301 - val_mse: 0.0016 - val_accuracy: 0.0000e+00
Epoch 12/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0018 -
mae: 0.0292 - mse: 0.0018 - accuracy: 9.0090e-04 - val_loss: 0.0022 - val_
mae: 0.0378 - val_mse: 0.0022 - val_accuracy: 0.0000e+00
Epoch 13/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0014 -
mae: 0.0257 - mse: 0.0014 - accuracy: 9.0090e-04 - val_loss: 0.0016 - val_
mae: 0.0306 - val_mse: 0.0016 - val_accuracy: 0.0000e+00
Epoch 14/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0016 -
mae: 0.0279 - mse: 0.0016 - accuracy: 9.0090e-04 - val_loss: 0.0011 - val_
mae: 0.0243 - val_mse: 0.0011 - val_accuracy: 0.0000e+00
Epoch 15/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0015 -
mae: 0.0270 - mse: 0.0015 - accuracy: 9.0090e-04 - val_loss: 0.0018 - val_
mae: 0.0343 - val_mse: 0.0018 - val_accuracy: 0.0000e+00
```

```
Epoch 16/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0014 -
mae: 0.0270 - mse: 0.0014 - accuracy: 9.0090e-04 - val_loss: 0.0011 - val_
mae: 0.0251 - val_mse: 0.0011 - val_accuracy: 0.0000e+00
Epoch 17/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0013 -
mae: 0.0257 - mse: 0.0013 - accuracy: 9.0090e-04 - val_loss: 0.0016 - val_
mae: 0.0314 - val_mse: 0.0016 - val_accuracy: 0.0000e+00
Epoch 18/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0012 -
mae: 0.0250 - mse: 0.0012 - accuracy: 9.0090e-04 - val_loss: 9.2311e-04 -
val_mae: 0.0222 - val_mse: 9.2311e-04 - val_accuracy: 0.0000e+00
Epoch 19/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0013 -
mae: 0.0256 - mse: 0.0013 - accuracy: 9.0090e-04 - val_loss: 8.7399e-04 -
val_mae: 0.0216 - val_mse: 8.7399e-04 - val_accuracy: 0.0000e+00
Epoch 20/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0012 -
mae: 0.0251 - mse: 0.0012 - accuracy: 9.0090e-04 - val_loss: 8.5093e-04 -
val_mae: 0.0212 - val_mse: 8.5093e-04 - val_accuracy: 0.0000e+00
Epoch 21/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0013 -
mae: 0.0257 - mse: 0.0013 - accuracy: 9.0090e-04 - val_loss: 0.0014 - val_
mae: 0.0301 - val_mse: 0.0014 - val_accuracy: 0.0000e+00
Epoch 22/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0012 -
mae: 0.0254 - mse: 0.0012 - accuracy: 9.0090e-04 - val_loss: 8.2811e-04 -
val_mae: 0.0213 - val_mse: 8.2811e-04 - val_accuracy: 0.0000e+00
Epoch 23/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0012 -
mae: 0.0255 - mse: 0.0012 - accuracy: 9.0090e-04 - val_loss: 9.0438e-04 -
val_mae: 0.0224 - val_mse: 9.0438e-04 - val_accuracy: 0.0000e+00
Epoch 24/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0012 -
mae: 0.0254 - mse: 0.0012 - accuracy: 9.0090e-04 - val_loss: 7.8449e-04 -
val_mae: 0.0209 - val_mse: 7.8449e-04 - val_accuracy: 0.0000e+00
Epoch 25/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0012 -
mae: 0.0256 - mse: 0.0012 - accuracy: 9.0090e-04 - val_loss: 9.1703e-04 -
val_mae: 0.0231 - val_mse: 9.1703e-04 - val_accuracy: 0.0000e+00
Epoch 26/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0011 -
mae: 0.0239 - mse: 0.0011 - accuracy: 9.0090e-04 - val_loss: 6.7512e-04 -
val_mae: 0.0192 - val_mse: 6.7512e-04 - val_accuracy: 0.0000e+00
Epoch 27/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0011 -
mae: 0.0246 - mse: 0.0011 - accuracy: 9.0090e-04 - val_loss: 0.0010 - val_
mae: 0.0254 - val_mse: 0.0010 - val_accuracy: 0.0000e+00
Epoch 28/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0011 -
mae: 0.0240 - mse: 0.0011 - accuracy: 9.0090e-04 - val_loss: 5.9146e-04 -
val_mae: 0.0178 - val_mse: 5.9146e-04 - val_accuracy: 0.0000e+00
Epoch 29/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0010 -
mae: 0.0236 - mse: 0.0010 - accuracy: 9.0090e-04 - val_loss: 5.8603e-04 -
val_mae: 0.0177 - val_mse: 5.8603e-04 - val_accuracy: 0.0000e+00
Epoch 30/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0011 -
mae: 0.0243 - mse: 0.0011 - accuracy: 9.0090e-04 - val_loss: 9.0777e-04 -
val_mae: 0.0235 - val_mse: 9.0777e-04 - val_accuracy: 0.0000e+00
Epoch 31/100
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4440/4440 [==============================] - 18s 4ms/step - loss: 0.0011 -
mae: 0.0236 - mse: 0.0011 - accuracy: 9.0090e-04 - val_loss: 9.7785e-04 -
val_mae: 0.0252 - val_mse: 9.7785e-04 - val_accuracy: 0.0000e+00
Epoch 32/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0011 -
mae: 0.0250 - mse: 0.0011 - accuracy: 9.0090e-04 - val_loss: 6.2537e-04 -
val_mae: 0.0187 - val_mse: 6.2537e-04 - val_accuracy: 0.0000e+00
Epoch 33/100
4440/4440 [==============================] - 18s 4ms/step - loss: 9.6742e-
04 - mae: 0.0230 - mse: 9.6742e-04 - accuracy: 9.0090e-04 - val_loss: 5.50
27e-04 - val_mae: 0.0172 - val_mse: 5.5027e-04 - val_accuracy: 0.0000e+00
Epoch 34/100
4440/4440 [==============================] - 18s 4ms/step - loss: 0.0010 -
mae: 0.0238 - mse: 0.0010 - accuracy: 9.0090e-04 - val_loss: 7.7748e-04 -
val_mae: 0.0222 - val_mse: 7.7748e-04 - val_accuracy: 0.0000e+00
Epoch 35/100
4440/4440 [==============================] - 18s 4ms/step - loss: 9.9388e-
04 - mae: 0.0236 - mse: 9.9388e-04 - accuracy: 9.0090e-04 - val_loss: 5.15
61e-04 - val_mae: 0.0167 - val_mse: 5.1561e-04 - val_accuracy: 0.0000e+00
Epoch 36/100
4440/4440 [==============================] - 18s 4ms/step - loss: 9.6585e-
04 - mae: 0.0231 - mse: 9.6585e-04 - accuracy: 9.0090e-04 - val_loss: 7.66
24e-04 - val_mae: 0.0220 - val_mse: 7.6624e-04 - val_accuracy: 0.0000e+00
Epoch 37/100
4440/4440 [==============================] - 18s 4ms/step - loss: 9.8993e-
04 - mae: 0.0235 - mse: 9.8993e-04 - accuracy: 9.0090e-04 - val_loss: 4.58
17e-04 - val_mae: 0.0158 - val_mse: 4.5817e-04 - val_accuracy: 0.0000e+00
Epoch 38/100
4440/4440 [==============================] - 17s 4ms/step - loss: 0.0010 -
mae: 0.0244 - mse: 0.0010 - accuracy: 9.0090e-04 - val_loss: 4.9564e-04 -
val_mae: 0.0167 - val_mse: 4.9564e-04 - val_accuracy: 0.0000e+00
Epoch 39/100
4440/4440 [==============================] - 18s 4ms/step - loss: 8.9863e-
04 - mae: 0.0223 - mse: 8.9863e-04 - accuracy: 9.0090e-04 - val_loss: 6.91
70e-04 - val_mae: 0.0205 - val_mse: 6.9170e-04 - val_accuracy: 0.0000e+00
Epoch 40/100
4440/4440 [==============================] - 18s 4ms/step - loss: 8.9380e-
04 - mae: 0.0226 - mse: 8.9380e-04 - accuracy: 9.0090e-04 - val_loss: 7.35
32e-04 - val_mae: 0.0213 - val_mse: 7.3532e-04 - val_accuracy: 0.0000e+00
Epoch 41/100
4440/4440 [==============================] - 18s 4ms/step - loss: 9.2686e-
04 - mae: 0.0226 - mse: 9.2686e-04 - accuracy: 9.0090e-04 - val_loss: 4.97
25e-04 - val_mae: 0.0168 - val_mse: 4.9725e-04 - val_accuracy: 0.0000e+00
Epoch 42/100
4440/4440 [==============================] - 18s 4ms/step - loss: 9.7706e-
04 - mae: 0.0236 - mse: 9.7706e-04 - accuracy: 9.0090e-04 - val_loss: 4.60
26e-04 - val_mae: 0.0158 - val_mse: 4.6026e-04 - val_accuracy: 0.0000e+00
Epoch 43/100
4440/4440 [==============================] - 18s 4ms/step - loss: 8.6126e-
04 - mae: 0.0218 - mse: 8.6126e-04 - accuracy: 9.0090e-04 - val_loss: 4.69
20e-04 - val_mae: 0.0162 - val_mse: 4.6920e-04 - val_accuracy: 0.0000e+00
Epoch 44/100
4440/4440 [==============================] - 18s 4ms/step - loss: 9.3490e-
04 - mae: 0.0232 - mse: 9.3490e-04 - accuracy: 9.0090e-04 - val_loss: 4.32
43e-04 - val_mae: 0.0156 - val_mse: 4.3243e-04 - val_accuracy: 0.0000e+00
Epoch 45/100
4440/4440 [==============================] - 18s 4ms/step - loss: 9.3583e-
04 - mae: 0.0229 - mse: 9.3583e-04 - accuracy: 9.0090e-04 - val_loss: 4.90
83e-04 - val_mae: 0.0167 - val_mse: 4.9083e-04 - val_accuracy: 0.0000e+00
Epoch 46/100
4440/4440 [==============================] - 18s 4ms/step - loss: 9.3557e-
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04 - mae: 0.0227 - mse: 9.3557e-04 - accuracy: 9.0090e-04 - val_loss: 4.23
33e-04 - val_mae: 0.0153 - val_mse: 4.2333e-04 - val_accuracy: 0.0000e+00
Epoch 47/100
4440/4440 [==============================] - 18s 4ms/step - loss: 9.0035e-
04 - mae: 0.0227 - mse: 9.0035e-04 - accuracy: 9.0090e-04 - val_loss: 0.00
10 - val_mae: 0.0266 - val_mse: 0.0010 - val_accuracy: 0.0000e+00
Epoch 48/100
4440/4440 [==============================] - 18s 4ms/step - loss: 9.5318e-
04 - mae: 0.0234 - mse: 9.5318e-04 - accuracy: 9.0090e-04 - val_loss: 8.67
98e-04 - val_mae: 0.0242 - val_mse: 8.6798e-04 - val_accuracy: 0.0000e+00
Epoch 49/100
4440/4440 [==============================] - 18s 4ms/step - loss: 9.4944e-
04 - mae: 0.0234 - mse: 9.4944e-04 - accuracy: 9.0090e-04 - val_loss: 4.39
76e-04 - val_mae: 0.0158 - val_mse: 4.3976e-04 - val_accuracy: 0.0000e+00
Epoch 50/100
4440/4440 [==============================] - 18s 4ms/step - loss: 8.9009e-
04 - mae: 0.0224 - mse: 8.9009e-04 - accuracy: 9.0090e-04 - val_loss: 7.46
17e-04 - val_mae: 0.0218 - val_mse: 7.4617e-04 - val_accuracy: 0.0000e+00
Epoch 51/100
4440/4440 [==============================] - 18s 4ms/step - loss: 8.8067e-
04 - mae: 0.0224 - mse: 8.8067e-04 - accuracy: 9.0090e-04 - val_loss: 4.64
25e-04 - val_mae: 0.0163 - val_mse: 4.6425e-04 - val_accuracy: 0.0000e+00
Epoch 52/100
4440/4440 [==============================] - 18s 4ms/step - loss: 9.0397e-
04 - mae: 0.0230 - mse: 9.0397e-04 - accuracy: 9.0090e-04 - val_loss: 5.63
07e-04 - val_mae: 0.0184 - val_mse: 5.6307e-04 - val_accuracy: 0.0000e+00
Epoch 53/100
4440/4440 [==============================] - 18s 4ms/step - loss: 8.2749e-
04 - mae: 0.0218 - mse: 8.2749e-04 - accuracy: 9.0090e-04 - val_loss: 0.00
17 - val_mae: 0.0365 - val_mse: 0.0017 - val_accuracy: 0.0000e+00
Epoch 54/100
4440/4440 [==============================] - 18s 4ms/step - loss: 8.4823e-
04 - mae: 0.0221 - mse: 8.4823e-04 - accuracy: 9.0090e-04 - val_loss: 7.08
44e-04 - val_mae: 0.0219 - val_mse: 7.0844e-04 - val_accuracy: 0.0000e+00
Epoch 55/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.8068e-
04 - mae: 0.0210 - mse: 7.8068e-04 - accuracy: 9.0090e-04 - val_loss: 3.91
36e-04 - val_mae: 0.0150 - val_mse: 3.9136e-04 - val_accuracy: 0.0000e+00
Epoch 56/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.8925e-
04 - mae: 0.0211 - mse: 7.8925e-04 - accuracy: 9.0090e-04 - val_loss: 3.71
75e-04 - val_mae: 0.0142 - val_mse: 3.7175e-04 - val_accuracy: 0.0000e+00
Epoch 57/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.7727e-
04 - mae: 0.0211 - mse: 7.7727e-04 - accuracy: 9.0090e-04 - val_loss: 3.89
35e-04 - val_mae: 0.0149 - val_mse: 3.8935e-04 - val_accuracy: 0.0000e+00
Epoch 58/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.7582e-
04 - mae: 0.0212 - mse: 7.7582e-04 - accuracy: 9.0090e-04 - val_loss: 4.32
56e-04 - val_mae: 0.0157 - val_mse: 4.3256e-04 - val_accuracy: 0.0000e+00
Epoch 59/100
4440/4440 [==============================] - 18s 4ms/step - loss: 8.0526e-
04 - mae: 0.0214 - mse: 8.0526e-04 - accuracy: 9.0090e-04 - val_loss: 4.20
70e-04 - val_mae: 0.0154 - val_mse: 4.2070e-04 - val_accuracy: 0.0000e+00
Epoch 60/100
4440/4440 [==============================] - 18s 4ms/step - loss: 8.2467e-
04 - mae: 0.0217 - mse: 8.2467e-04 - accuracy: 9.0090e-04 - val_loss: 3.90
68e-04 - val_mae: 0.0150 - val_mse: 3.9068e-04 - val_accuracy: 0.0000e+00
Epoch 61/100
4440/4440 [==============================] - 18s 4ms/step - loss: 8.0598e-
04 - mae: 0.0216 - mse: 8.0598e-04 - accuracy: 9.0090e-04 - val_loss: 3.77
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12e-04 - val_mae: 0.0148 - val_mse: 3.7712e-04 - val_accuracy: 0.0000e+00
Epoch 62/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.6747e-
04 - mae: 0.0211 - mse: 7.6747e-04 - accuracy: 9.0090e-04 - val_loss: 3.28
52e-04 - val_mae: 0.0135 - val_mse: 3.2852e-04 - val_accuracy: 0.0000e+00
Epoch 63/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.3035e-
04 - mae: 0.0205 - mse: 7.3035e-04 - accuracy: 9.0090e-04 - val_loss: 5.58
88e-04 - val_mae: 0.0188 - val_mse: 5.5888e-04 - val_accuracy: 0.0000e+00
Epoch 64/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.8506e-
04 - mae: 0.0215 - mse: 7.8506e-04 - accuracy: 9.0090e-04 - val_loss: 3.56
76e-04 - val_mae: 0.0141 - val_mse: 3.5676e-04 - val_accuracy: 0.0000e+00
Epoch 65/100
4440/4440 [==============================] - 17s 4ms/step - loss: 8.0829e-
04 - mae: 0.0215 - mse: 8.0829e-04 - accuracy: 9.0090e-04 - val_loss: 3.10
61e-04 - val_mae: 0.0131 - val_mse: 3.1061e-04 - val_accuracy: 0.0000e+00
Epoch 66/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.7989e-
04 - mae: 0.0211 - mse: 7.7989e-04 - accuracy: 9.0090e-04 - val_loss: 4.44
29e-04 - val_mae: 0.0163 - val_mse: 4.4429e-04 - val_accuracy: 0.0000e+00
Epoch 67/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.8685e-
04 - mae: 0.0215 - mse: 7.8685e-04 - accuracy: 9.0090e-04 - val_loss: 5.60
09e-04 - val_mae: 0.0189 - val_mse: 5.6009e-04 - val_accuracy: 0.0000e+00
Epoch 68/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.8577e-
04 - mae: 0.0213 - mse: 7.8577e-04 - accuracy: 9.0090e-04 - val_loss: 6.27
03e-04 - val_mae: 0.0204 - val_mse: 6.2703e-04 - val_accuracy: 0.0000e+00
Epoch 69/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.5642e-
04 - mae: 0.0210 - mse: 7.5642e-04 - accuracy: 9.0090e-04 - val_loss: 5.51
86e-04 - val_mae: 0.0187 - val_mse: 5.5186e-04 - val_accuracy: 0.0000e+00
Epoch 70/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.6749e-
04 - mae: 0.0212 - mse: 7.6749e-04 - accuracy: 9.0090e-04 - val_loss: 4.11
05e-04 - val_mae: 0.0158 - val_mse: 4.1105e-04 - val_accuracy: 0.0000e+00
Epoch 71/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.2623e-
04 - mae: 0.0208 - mse: 7.2623e-04 - accuracy: 9.0090e-04 - val_loss: 3.26
72e-04 - val_mae: 0.0136 - val_mse: 3.2672e-04 - val_accuracy: 0.0000e+00
Epoch 72/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.5872e-
04 - mae: 0.0211 - mse: 7.5872e-04 - accuracy: 9.0090e-04 - val_loss: 4.95
03e-04 - val_mae: 0.0175 - val_mse: 4.9503e-04 - val_accuracy: 0.0000e+00
Epoch 73/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.5816e-
04 - mae: 0.0210 - mse: 7.5816e-04 - accuracy: 9.0090e-04 - val_loss: 6.19
92e-04 - val_mae: 0.0208 - val_mse: 6.1992e-04 - val_accuracy: 0.0000e+00
Epoch 74/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.5863e-
04 - mae: 0.0211 - mse: 7.5863e-04 - accuracy: 9.0090e-04 - val_loss: 3.81
51e-04 - val_mae: 0.0149 - val_mse: 3.8151e-04 - val_accuracy: 0.0000e+00
Epoch 75/100
4440/4440 [==============================] - 18s 4ms/step - loss: 6.9409e-
04 - mae: 0.0202 - mse: 6.9409e-04 - accuracy: 9.0090e-04 - val_loss: 3.42
35e-04 - val_mae: 0.0140 - val_mse: 3.4235e-04 - val_accuracy: 0.0000e+00
Epoch 76/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.2277e-
04 - mae: 0.0206 - mse: 7.2277e-04 - accuracy: 9.0090e-04 - val_loss: 6.10
51e-04 - val_mae: 0.0203 - val_mse: 6.1051e-04 - val_accuracy: 0.0000e+00
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Epoch 77/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.2063e-
04 - mae: 0.0206 - mse: 7.2063e-04 - accuracy: 9.0090e-04 - val_loss: 3.33
37e-04 - val_mae: 0.0140 - val_mse: 3.3337e-04 - val_accuracy: 0.0000e+00
Epoch 78/100
4440/4440 [==============================] - 18s 4ms/step - loss: 6.8534e-
04 - mae: 0.0201 - mse: 6.8534e-04 - accuracy: 9.0090e-04 - val_loss: 3.59
93e-04 - val_mae: 0.0144 - val_mse: 3.5993e-04 - val_accuracy: 0.0000e+00
Epoch 79/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.3691e-
04 - mae: 0.0207 - mse: 7.3691e-04 - accuracy: 9.0090e-04 - val_loss: 6.29
29e-04 - val_mae: 0.0213 - val_mse: 6.2929e-04 - val_accuracy: 0.0000e+00
Epoch 80/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.2512e-
04 - mae: 0.0208 - mse: 7.2512e-04 - accuracy: 9.0090e-04 - val_loss: 5.18
83e-04 - val_mae: 0.0180 - val_mse: 5.1883e-04 - val_accuracy: 0.0000e+00
Epoch 81/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.0856e-
04 - mae: 0.0204 - mse: 7.0856e-04 - accuracy: 9.0090e-04 - val_loss: 3.63
61e-04 - val_mae: 0.0148 - val_mse: 3.6361e-04 - val_accuracy: 0.0000e+00
Epoch 82/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.5106e-
04 - mae: 0.0209 - mse: 7.5106e-04 - accuracy: 9.0090e-04 - val_loss: 2.83
31e-04 - val_mae: 0.0127 - val_mse: 2.8331e-04 - val_accuracy: 0.0000e+00
Epoch 83/100
4440/4440 [==============================] - 17s 4ms/step - loss: 7.0226e-
04 - mae: 0.0203 - mse: 7.0226e-04 - accuracy: 9.0090e-04 - val_loss: 6.36
66e-04 - val_mae: 0.0211 - val_mse: 6.3666e-04 - val_accuracy: 0.0000e+00
Epoch 84/100
4440/4440 [==============================] - 18s 4ms/step - loss: 6.4887e-
04 - mae: 0.0197 - mse: 6.4887e-04 - accuracy: 9.0090e-04 - val_loss: 3.06
88e-04 - val_mae: 0.0135 - val_mse: 3.0688e-04 - val_accuracy: 0.0000e+00
Epoch 85/100
4440/4440 [==============================] - 18s 4ms/step - loss: 6.8600e-
04 - mae: 0.0201 - mse: 6.8600e-04 - accuracy: 9.0090e-04 - val_loss: 4.16
17e-04 - val_mae: 0.0162 - val_mse: 4.1617e-04 - val_accuracy: 0.0000e+00
Epoch 86/100
4440/4440 [==============================] - 18s 4ms/step - loss: 6.8263e-
04 - mae: 0.0199 - mse: 6.8263e-04 - accuracy: 9.0090e-04 - val_loss: 3.39
69e-04 - val_mae: 0.0140 - val_mse: 3.3969e-04 - val_accuracy: 0.0000e+00
Epoch 87/100
4440/4440 [==============================] - 18s 4ms/step - loss: 6.7105e-
04 - mae: 0.0197 - mse: 6.7105e-04 - accuracy: 9.0090e-04 - val_loss: 2.89
99e-04 - val_mae: 0.0131 - val_mse: 2.8999e-04 - val_accuracy: 0.0000e+00
Epoch 88/100
4440/4440 [==============================] - 17s 4ms/step - loss: 6.5131e-
04 - mae: 0.0196 - mse: 6.5131e-04 - accuracy: 9.0090e-04 - val_loss: 3.73
14e-04 - val_mae: 0.0147 - val_mse: 3.7314e-04 - val_accuracy: 0.0000e+00
Epoch 89/100
4440/4440 [==============================] - 18s 4ms/step - loss: 6.7375e-
04 - mae: 0.0199 - mse: 6.7375e-04 - accuracy: 9.0090e-04 - val_loss: 7.00
04e-04 - val_mae: 0.0223 - val_mse: 7.0004e-04 - val_accuracy: 0.0000e+00
Epoch 90/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.2786e-
04 - mae: 0.0208 - mse: 7.2786e-04 - accuracy: 9.0090e-04 - val_loss: 0.00
15 - val_mae: 0.0350 - val_mse: 0.0015 - val_accuracy: 0.0000e+00
Epoch 91/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.2419e-
04 - mae: 0.0208 - mse: 7.2419e-04 - accuracy: 9.0090e-04 - val_loss: 4.20
82e-04 - val_mae: 0.0166 - val_mse: 4.2082e-04 - val_accuracy: 0.0000e+00
Epoch 92/100
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4440/4440 [==============================] - 17s 4ms/step - loss: 7.0072e-
04 - mae: 0.0205 - mse: 7.0072e-04 - accuracy: 9.0090e-04 - val_loss: 3.10
93e-04 - val_mae: 0.0138 - val_mse: 3.1093e-04 - val_accuracy: 0.0000e+00
Epoch 93/100
4440/4440 [==============================] - 18s 4ms/step - loss: 6.1833e-
04 - mae: 0.0192 - mse: 6.1833e-04 - accuracy: 9.0090e-04 - val_loss: 3.18
32e-04 - val_mae: 0.0141 - val_mse: 3.1832e-04 - val_accuracy: 0.0000e+00
Epoch 94/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.0861e-
04 - mae: 0.0203 - mse: 7.0861e-04 - accuracy: 9.0090e-04 - val_loss: 4.29
80e-04 - val_mae: 0.0168 - val_mse: 4.2980e-04 - val_accuracy: 0.0000e+00
Epoch 95/100
4440/4440 [==============================] - 18s 4ms/step - loss: 6.5670e-
04 - mae: 0.0196 - mse: 6.5670e-04 - accuracy: 9.0090e-04 - val_loss: 3.57
47e-04 - val_mae: 0.0150 - val_mse: 3.5747e-04 - val_accuracy: 0.0000e+00
Epoch 96/100
4440/4440 [==============================] - 18s 4ms/step - loss: 6.0156e-
04 - mae: 0.0189 - mse: 6.0156e-04 - accuracy: 9.0090e-04 - val_loss: 2.57
56e-04 - val_mae: 0.0121 - val_mse: 2.5756e-04 - val_accuracy: 0.0000e+00
Epoch 97/100
4440/4440 [==============================] - 18s 4ms/step - loss: 6.5000e-
04 - mae: 0.0196 - mse: 6.5000e-04 - accuracy: 9.0090e-04 - val_loss: 3.18
73e-04 - val_mae: 0.0137 - val_mse: 3.1873e-04 - val_accuracy: 0.0000e+00
Epoch 98/100
4440/4440 [==============================] - 18s 4ms/step - loss: 6.1983e-
04 - mae: 0.0193 - mse: 6.1983e-04 - accuracy: 9.0090e-04 - val_loss: 2.90
44e-04 - val_mae: 0.0130 - val_mse: 2.9044e-04 - val_accuracy: 0.0000e+00
Epoch 99/100
4440/4440 [==============================] - 18s 4ms/step - loss: 7.1169e-
04 - mae: 0.0206 - mse: 7.1169e-04 - accuracy: 9.0090e-04 - val_loss: 3.82
13e-04 - val_mae: 0.0153 - val_mse: 3.8213e-04 - val_accuracy: 0.0000e+00
Epoch 100/100
4440/4440 [==============================] - 17s 4ms/step - loss: 7.2541e-
04 - mae: 0.0205 - mse: 7.2541e-04 - accuracy: 9.0090e-04 - val_loss: 4.75
84e-04 - val_mae: 0.0180 - val_mse: 4.7584e-04 - val_accuracy: 0.0000e+00
```

In [23]:

```
# Getting the predicted stock price
predicted_stock_price = model.predict(X_test)
predicted_stock_price = sc.inverse_transform(predicted_stock_price)
```

In [24]:

```
# check the prediction shape
predicted_stock_price.shape
```

Out[24]:

```
(610, 1)
```

In [25]:

```
# check the test set shape
dataset_test.values.shape
```

Out[25]:

```
(610, 1)
```

In [26]:

```
# create a new dataframe for visualization
date = pd.DataFrame(asii['Date'][4500:])
test_value = pd.DataFrame(dataset_test.values, columns=['Real price'])
pred_value = pd.DataFrame(predicted_stock_price, columns=['Predicted price'])
```

In [27]:

```
# reset index
date = date.reset_index()
```

In [28]:

```
# combine the desired value into one dataframe
pred_stock = pd.concat([date, test_value, pred_value], axis=1)
pred_stock = pred_stock.drop(columns=['index'])
pred_stock
```

Out[28]:

	Date	Real price	Predicted price
0	2018-09-28	7350.0	7505.325684
1	2018-10-01	7325.0	7492.707031
2	2018-10-02	7200.0	7483.139160
3	2018-10-03	7200.0	7397.719727
4	2018-10-04	7075.0	7384.062012
...	...	...	...
605	2021-03-01	5600.0	5531.662109
606	2021-03-02	5575.0	5636.507324
607	2021-03-03	5675.0	5662.985840
608	2021-03-04	5575.0	5738.117188
609	2021-03-05	5500.0	5686.202637

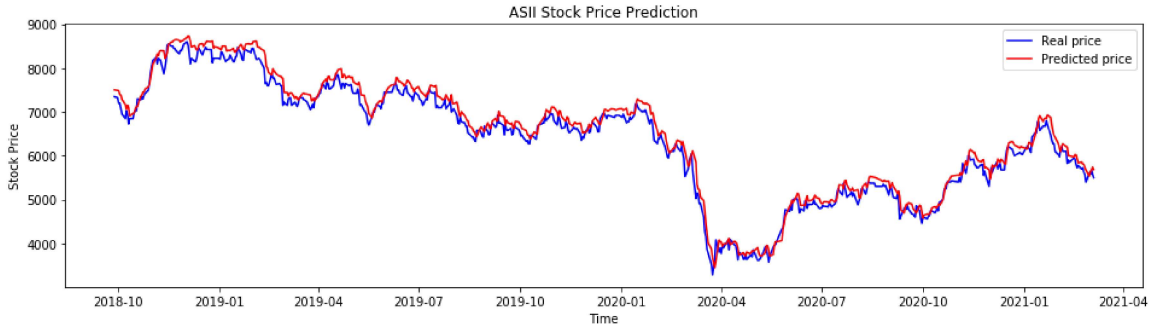
610 rows × 3 columns

In [29]:

```
# visualize the stock price prediction by using Plotly
fig = px.line(pred_stock, x = 'Date', y = pred_stock.columns,
              hover_data={'Date': '|%B %d, %Y'},
              title='ASII.JK Stock Price Prediction')

fig.update_xaxes(
    dtick='M1',
    tickformat='%b\n%Y',
    ticklabelmode='period')

fig.update_yaxes(title_text = 'Stock Price', tickprefix = 'IDR ')

fig.show()
```

In [30]:

```
# Visualize the results by using Matplotlib
fig, ax = plt.subplots(figsize=(16, 4))
plt.plot(asii['Date'][4500:], dataset_test.values, color = 'blue', label = 'Real price'
)
plt.plot(asii['Date'][4500:], predicted_stock_price, color = 'red', label = 'Predicted
 price')
plt.title('ASII Stock Price Prediction')
plt.xlabel('Time')
plt.ylabel('Stock Price')
plt.legend()
plt.show()
```



Wow! Quite impressive!

The COVID-19 pandemic has started in January 2020. Therefore, there was a huge drop in ASII stock price in April 2020 due to the COVID-19 partial lockdown in several areas of Indonesia. It affects the performance of the company directly. After the implementation of health protocols in Indonesia, the stock market seems to bounce back on track. Hope the performance can be normal in the future or even better.

Let's evaluate this model now~

6. Evaluation

In [31]:

```
hist = pd.DataFrame(history.history)
hist['epoch'] = history.epoch
hist.tail()
```

Out[31]:

	val_loss	val_mae	val_mse	val_accuracy	loss	mae	mse	accuracy	epc
95	0.000258	0.012131	0.000258	0.0	0.000602	0.018852	0.000602	0.000901	
96	0.000319	0.013651	0.000319	0.0	0.000650	0.019622	0.000650	0.000901	
97	0.000290	0.012983	0.000290	0.0	0.000620	0.019281	0.000620	0.000901	
98	0.000382	0.015322	0.000382	0.0	0.000712	0.020574	0.000712	0.000901	
99	0.000476	0.018011	0.000476	0.0	0.000725	0.020499	0.000725	0.000901	

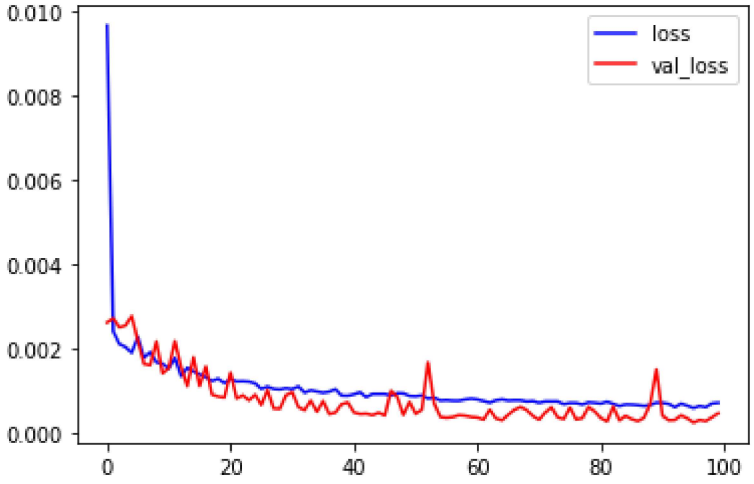
In [32]:

```
print(history.history.keys())
```

```
dict_keys(['val_loss', 'val_mae', 'val_mse', 'val_accuracy', 'loss', 'ma
e', 'mse', 'accuracy'])
```

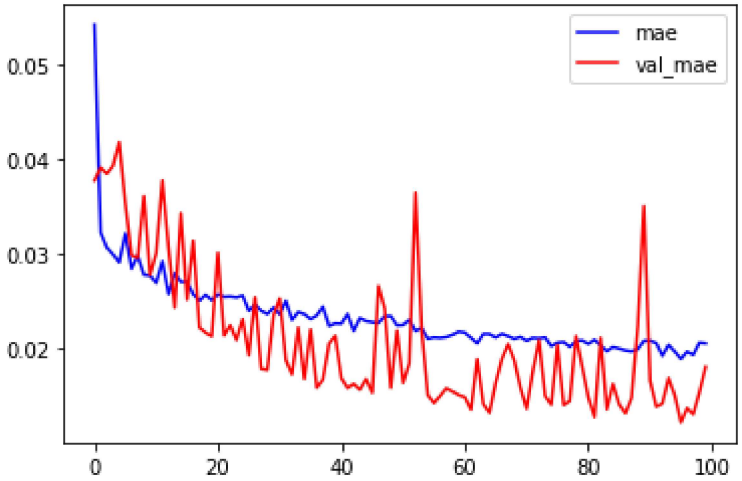
In [33]:

```
# Loss Graph
plt.plot(history.epoch, history.history['loss'] , label = "loss", color = 'blue')
plt.plot(history.epoch, history.history['val_loss'] , label = "val_loss", color = 'red'
)
plt.legend()
plt.show()
```



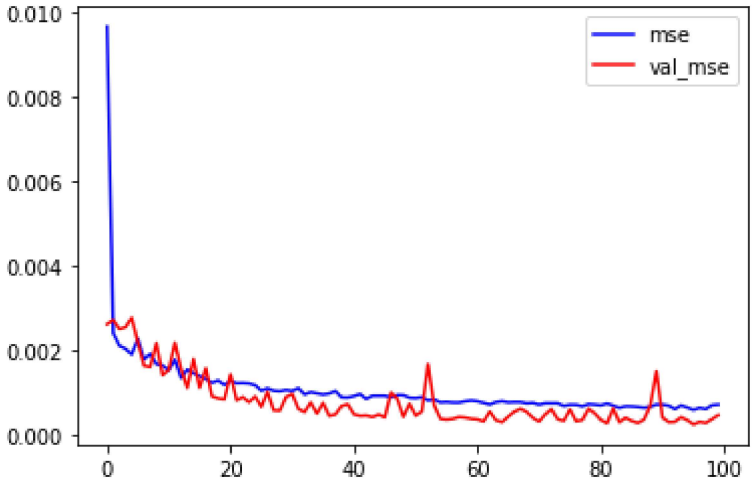
In [34]:

```
# Mean Absolute Error (MAE) Graph
plt.plot(history.epoch, history.history['mae'] , label="mae", color = 'blue')
plt.plot(history.epoch, history.history['val_mae'] , label = "val_mae", color = 'red')
plt.legend()
plt.show()
```



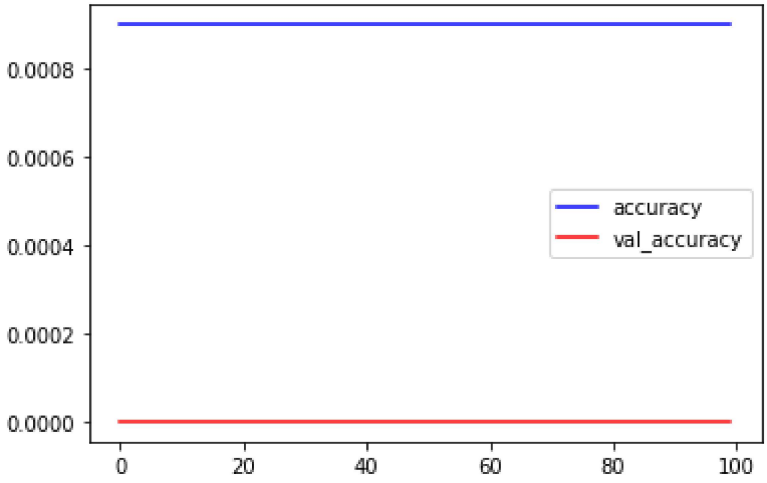
In [35]:

```
# Mean Squared Error (MSE) Graph
plt.plot(history.epoch, history.history['mse'] , label="mse", color = 'blue')
plt.plot(history.epoch, history.history['val_mse'] , label = "val_mse", color = 'red')
plt.legend()
plt.show()
```



In [36]:

```
# Accuracy Graph
plt.plot(history.epoch, history.history['accuracy'] , label="accuracy", color = 'blue')
plt.plot(history.epoch, history.history['val_accuracy'] , label = "val_accuracy", color
= 'red')
plt.legend()
plt.show()
```



Noice! the validation accuracy is even lower than the train accuracy.

In [37]:

```
# Now evaluating the model
print('Evaluate on test data')
score = model.evaluate(X_test, y_test, batch_size=16, verbose = 0)
print("%s: %.2f%%" % ("loss", score[0]*100))
print("%s: %.2f%%" % ("mae", score[1]*100))
print("%s: %.2f%%" % ("mse", score[2]*100))
print("%s: %.2f%%" % ("acc", score[3]*100))
#print("test loss, test mae, test mse, test acc:", score)
```

```
Evaluate on test data
loss: 0.05%
mae: 1.80%
mse: 0.05%
acc: 0.00%
```

Conclusion

Here are some conclusions that we can draw after evaluating the result:

1. LSTM Network can accurately predict the stock price time-series data of Astra because it has a unique formulation that allows it to avoid the problems that prevent the training and scaling of other RNNs
2. The model will generalize better and accurately for the new data if we feed a larger train set to the model.
3. Data visualization helps in analyzing the stock price; thus, the right decisions can be formulated.

Future development: training different time-series models to predict the stock price and compare the result of the different models.

7. Deployment

In this stock prediction project, we did not go into the deployment part.

Note that in this part you will have to apply the conclusion to the business domain. Several activities should be conducted in this phase as below:

1. Plan deployment
2. Plan monitoring and maintenance
3. Produce final report
4. Review project

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