

Machine Learning 1 Report

```
150 def buildModel(x_train_data, y_train_data, no_steps, no_features, units=256, cell=LSTM, no_layers=2, dropout=0.3, loss='mean_absolute_error',
151               optimizer="rmsprop", no_epochs=25, size_batch=32):
152     # Use the sequential model type
153     model = Sequential()
154     print(cell)
155     # a for loop to add layers based on the specified number of layers
156     for i in range(no_layers):
157         if i == 0:
158             # The first layer, add a layer with return_sequences=True
159             # batch_input_shape helps determine the input shape as in the number of inputs
160             # the format of batch_input_shape is supposed to be
161             # batch_input_shape(batch_size, number of steps and number of features)
162             model.add(cell(units, return_sequences=True, batch_input_shape=(None, no_steps, no_features)))
163         elif i == no_layers - 1:
164             # The last layer, add a recurrent layer with return_sequences=False. This is false because we want
165             # one single final output instead of multiple, return_sequences can be true depending on the use
166             # case.
167             model.add(cell(units, return_sequences=False))
168         else:
169             # The layers in between first and last, add a layer with return_sequences=True
170             model.add(cell(units, return_sequences=True))
171
172     # a dropout layer is introduced, the function of this is to prevent overfitting
173     # if a dropout rate of 0.2 that means that 20% of the data in this layer will be
174     # dropped out or set to 0.
175     model.add(Dropout(dropout))
176
177     # Add a Dense layer with one output unit and linear activation for regression,
178     # linear activation, produces an output that is directly proportional to the input.
179     model.add(Dense(1, activation="linear"))
180
181     # Compile the model with specified loss, metrics, and optimizer
182     model.compile(loss=loss, metrics=['mean_absolute_error'], optimizer=optimizer)
183
184     model.fit(x_train_data, y_train_data, epochs=no_epochs, batch_size=size_batch)
185
186     # Return the constructed model
187     return model
```

The screenshot above contains the code which has been returned to function with my code. The code has been referenced from the example project in P1. I have understood the steps that was taken in P1 and used it in this development of the stock prediction v0.3. I have not included the need for the Bidirectional step in the model as it was not a part of the requirements for this task. Some research was done to figure out what the `return_sequences` and `batch_input_shape` parameter does.

```
model.add(cell(units, return_sequences=True, batch_input_shape=(None, no_steps, no_features)))
if i == no_layers - 1:
```

To summarize what the two parameters does is, when `return_sequences` is true it allows for the returning of more than one output into the next layer whereas if it is set to false, there is only one single output variable. Therefore, for the use case of this project the system only needs to output one value which is the value of the stock price at closing which is why the final layer has `return_sequences` set to false. An example of a use case where `return_sequences` is set to true is ChatGPT. ChatGPT outputs a sequence of characters which form sentences this would require the model to return a sequence rather than an individual variable or value.

As for the `batch_input_shape`, it helps determine the input shape or dimension meaning number of inputs.

There is a dropout parameter which is also used which in short determines the percentage of the overall data to be dropped from the dataset during that layer. In the context of the code above, after the final layer, 20% of the data is dropped by default unless set otherwise by the user within the parameters.py file.

```
175 model.add(Dropout(dropout))
```

In the parameters.py file the other parameters which the user can configure has also been added.

```
# =====  
  
# Building The Model  
unitSize = 256  
numberOfLayers = 4  
Optimizer = 'adam'  
Loss = 'mean_squared_error'  
# Deep Learning Type  
DLType = LSTM  
# Dropout Rate  
DORate = 0.2  
numberOfSteps = 100  
  
# =====  
|  
# =====  
  
# do you want to predict?  
predict = True  
Epochs = 50  
BatchSize = 32  
  
# =====
```

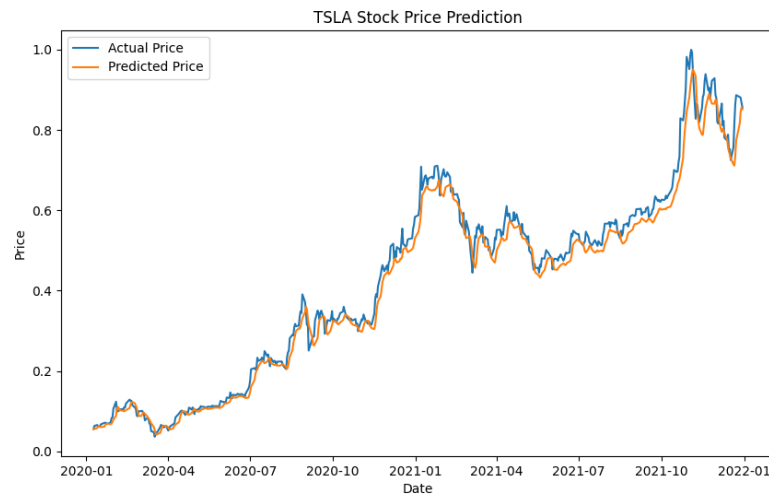
After setting the code up some experiments were conducted.

In terms of the experiments, I have conducted using this model. I decided to alter the Deep Learning Type and the number of layers. In the experiment I used two different models: LSTM and GRU with Epochs Set to 50 on all of the tests. The number of layers used are 2, 4, and 6.

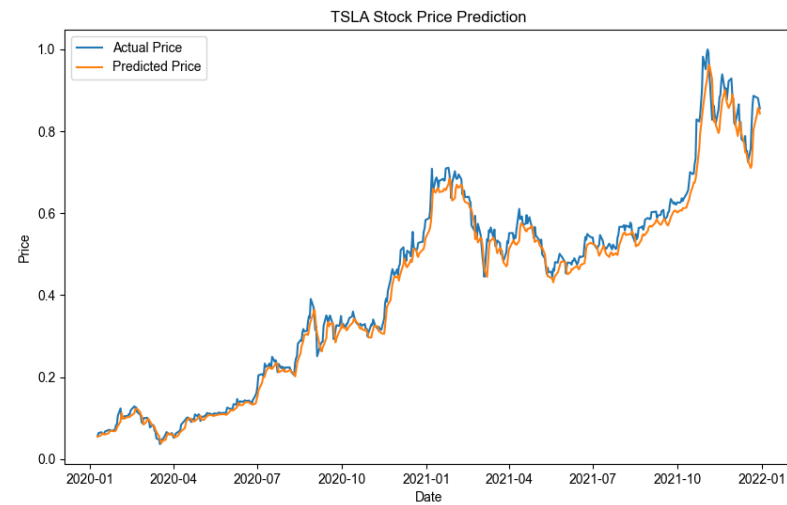
Below I have attached screenshots of the results.

2 Layers

LSTM



GRU

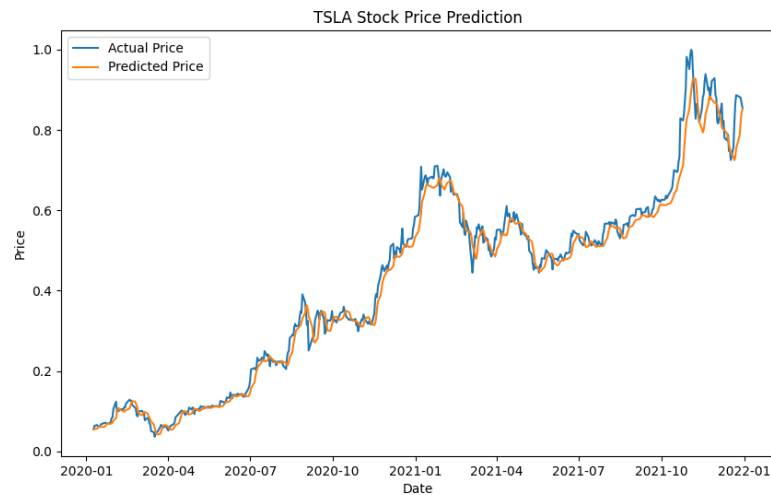


Observation

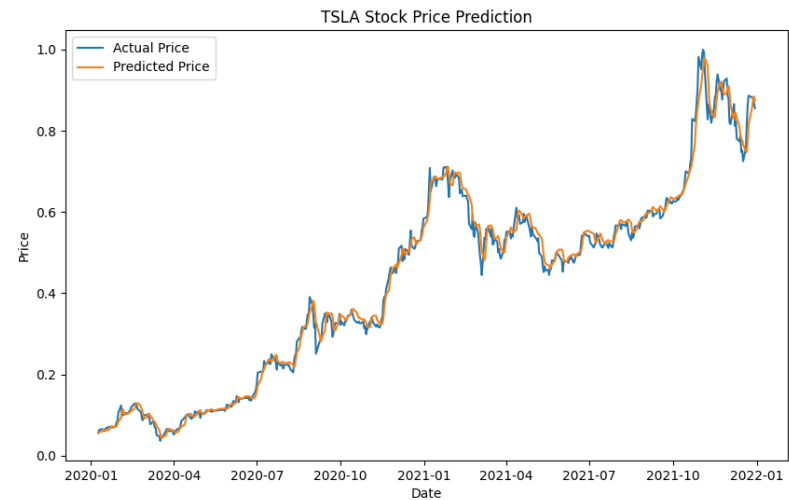
From this two-layer model, the graph is already functioning quite decently, with the predicted price closely following the actual price. When comparing the models, it seems that the GRU model performs better than the LSTM model as the line from the model when compared to the actual price follows more closely than the LSTM model, it seems that the GRU model reacts better to the fluctuation and changes in price whereas LSTM seems to smoothen the graph more.

4 Layers

LSTM



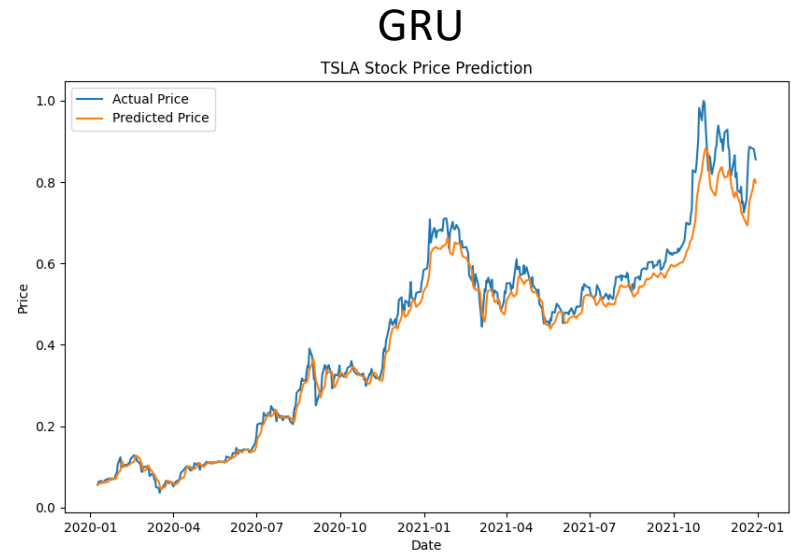
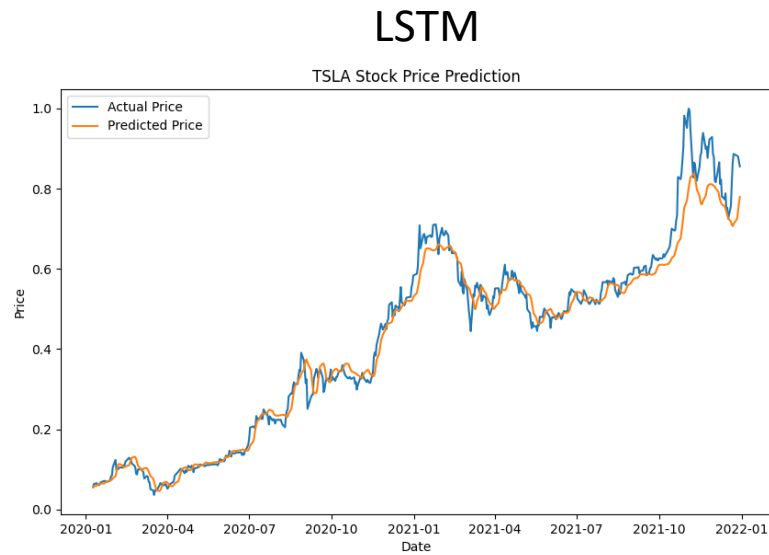
GRU



Observation

Now with an increase of two layers in the model, creating a four-layer model. This model has by far created the most accurate line when compared to the actual prices. With the GRU model again outperforming the LSTM model in terms of following the actual price line. The line of the predicted graph from the GRU model, as can be seen on the graph, the predicted line is basically on the same line as the actual price line.

6 Layers



Observation

As can be seen in this graph, once an additional two layers is added for some reason the predicted price is unable to match the actual price as accurately as the models which was made in the 4 Layers. The model seems to lose the accuracy it has.

References

Cloud, S. (2023, August 25). Understanding the batch_input_shape tuple in Keras LSTM for data scientists. Saturn Cloud Blog.
<https://saturncloud.io/blog/understanding-the-batchinputshape-tuple-in-keras-lstm-for-data-scientists/>