Task 4: Machine Learning 1

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Requirements / Deliverables –

- Implement a function that constructs deep learning (DL) models based on user-defined parameters, such as the number of layers, types of layers (e.g., LSTM, GRU), and their configurations.
- The purpose was to provide a flexible tool for experimenting with various DL architectures without manually coding each model variation.

Result –

Implementation Steps:

Function Design:

- The create_dl_model function was designed to dynamically create deep learning models using the Keras. It accepts multiple parameters like layer_types, layer_sizes, dropout_rates, return_sequences, and activation_functions, enabling the construction of custom architectures depending on user input.

Dynamic Layer Configuration:

A key feature is the loop that adds layers iteratively based on the input configuration:

```
for i in range(n_layers):
    layer_type = layer_types[i].upper()
    units = layer_sizes[i]
    dropout_rate = dropout_rates[i] if i < len(dropout_rates) else 0.0
    return_seq = return_sequences[i]
    activation = activation_functions[i]
```

- **Challenge**: Ensuring that each layer type (LSTM, GRU, Dense) was correctly configured based on the input parameters required careful validation and alignment of list lengths to avoid index errors.

Dropout layers were conditionally added to mitigate overfitting, especially important for time series models where recurrent layers can easily overfit. Deciding the optimal placement and rate for Dropout required balancing regularization without excessively hindering learning capacity.

- **Reference**: Regularization techniques were reviewed from Towards Data Science.

Error Handling:

- The function includes error handling to catch unsupported layer types and mismatched configurations:

```
else:
    raise ValueError(f"Unsupported layer type: {layer_type}")
```

Provides clear feedback to guide the user when incorrect parameters are passed.

Layer Creation Logic:

This block dynamically configures each specified layer type, determining whether sequences should be returned (critical for stacked recurrent layers) and setting the appropriate activation functions.

```
if layer_type == 'LSTM':
    x = LSTM(units, return_sequences=return_seq)(x)
elif layer_type == 'GRU':
    x = GRU(units, return_sequences=return_seq)(x)
elif layer_type == 'RNN':
    x = SimpleRNN(units, return_sequences=return_seq)(x)
elif layer_type == 'DENSE':
    x = Dense(units, activation=activation)(x)
```

Model Compilation:

```
model.compile(optimizer=optimizer, loss=loss_function)
```

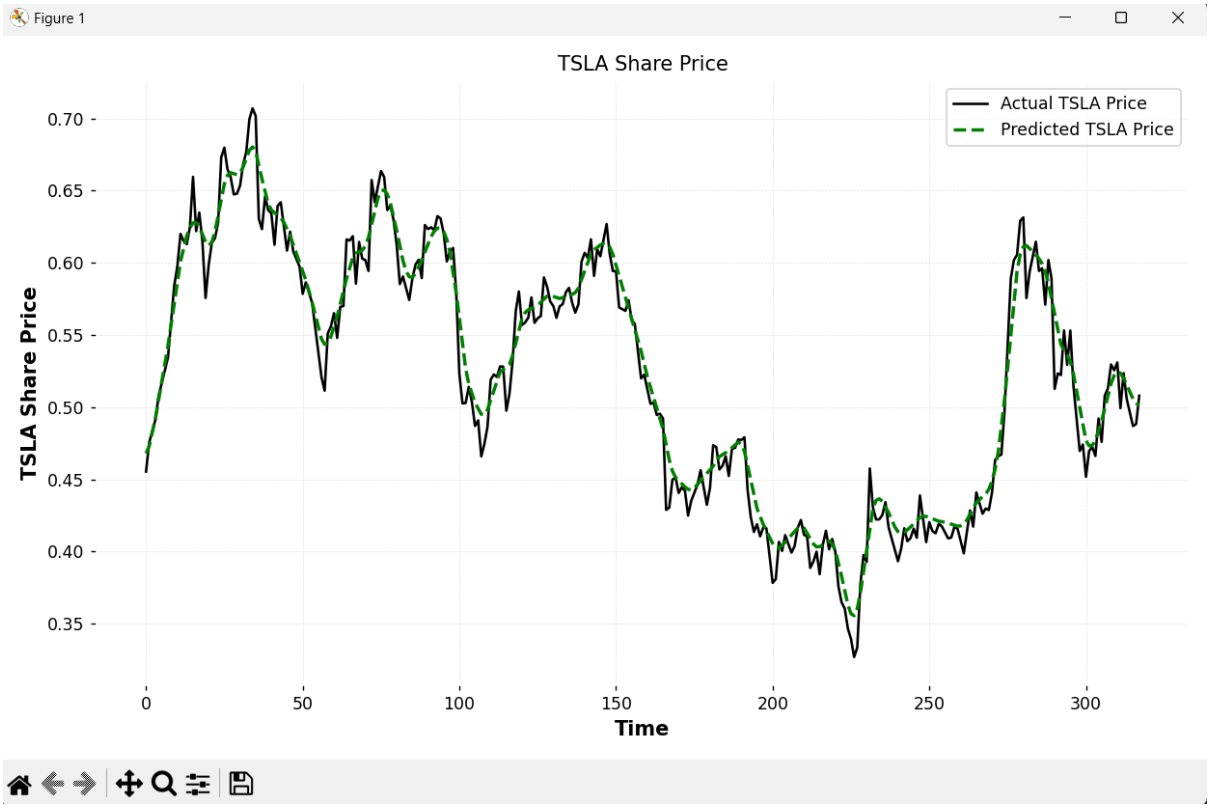
Compiling the model involves selecting suitable loss functions (e.g., 'Huber' for robustness to outliers) and optimizers ('Adam' for adaptive learning rates), both essential to the model's learning behaviour.

Summaries of Experiments with Different Configurations:

Configuration 1 –

Combined LSTM, GRU, and Dense Architecture

- **Setup**: Added an LSTM layer with 150 units, followed by a GRU layer with 100 units, and a Dense layer with 50 units. Increased dropout rates to 0.3 and 0.2, using 'Huber' as the loss function. Used 100 as the value of epochs and 16 for the batch size, I used 100 epochs since the model utilises ‘early stopping’ to stop training the model when validation loss stops improving so to provide the model enough epochs I used 100.
- **Results**: Noticeable improvement in validation loss, better training stability, and reduced overfitting. Mean Absolute Error being an impressive score of 0.0091908728271149 which suggests that the average error is about 0.92% of the scaled range.



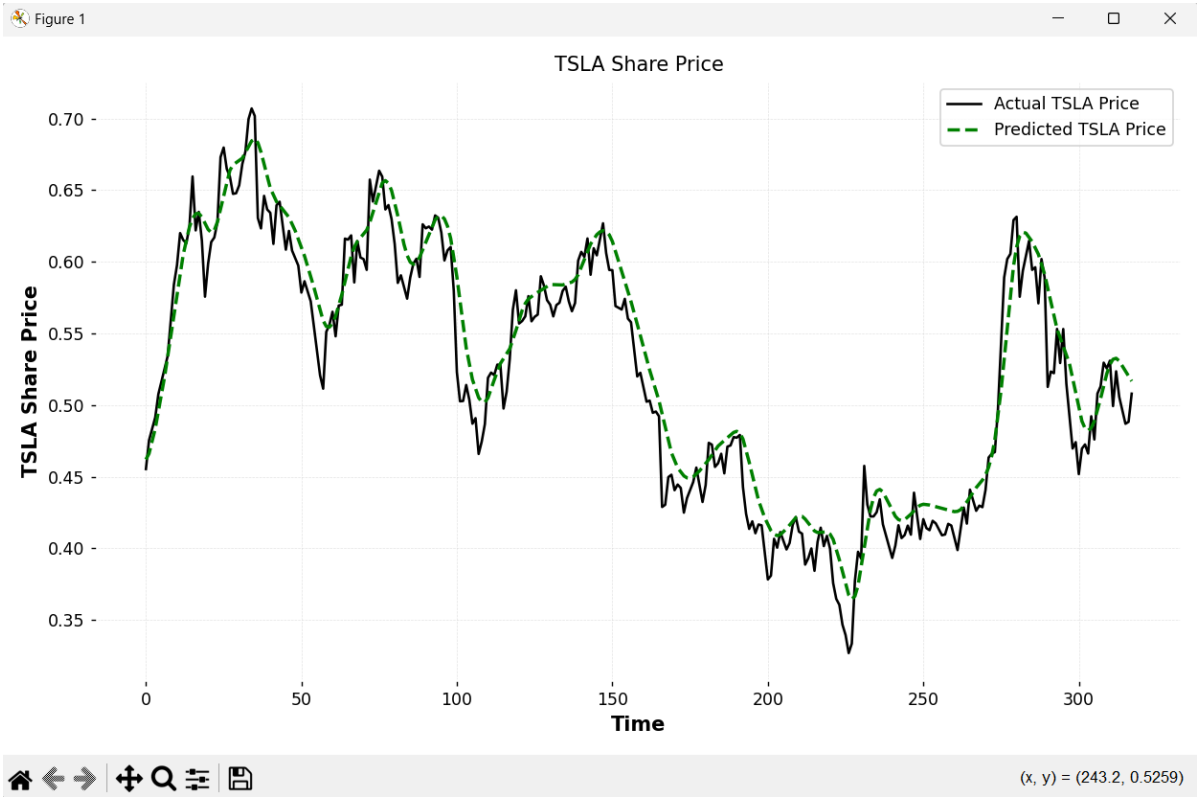
- **Insight**: The combined architecture of LSTM and GRU layers captures sequential dependencies more effectively, with dropout providing essential regularization.

Configuration 2 –

An LSTM only configuration –

- **Setup**: Added 3 LSTM layers with 100 units each, with steady dropout rates of 0.2 for each layer. Using 'Huber' loss as the loss function and 'Adam' as the optimiser. Used 100 for the epochs and 32 for the total batch sizes.
- **Results**: Degraded quality in validation loss, training stability.

Increased batch size provided more overfitted results, decreased model robustness. Compared to the first configuration, the LSTM only configuration with changed hyperparameters such as layer units, dropout rates, provided worse results with an average mean absolute error (MAE) of: 0.01886164370696024, this MAE indicates that the average error is about 1.89% of the scaled range which is quite worse when compared to the first configuration.

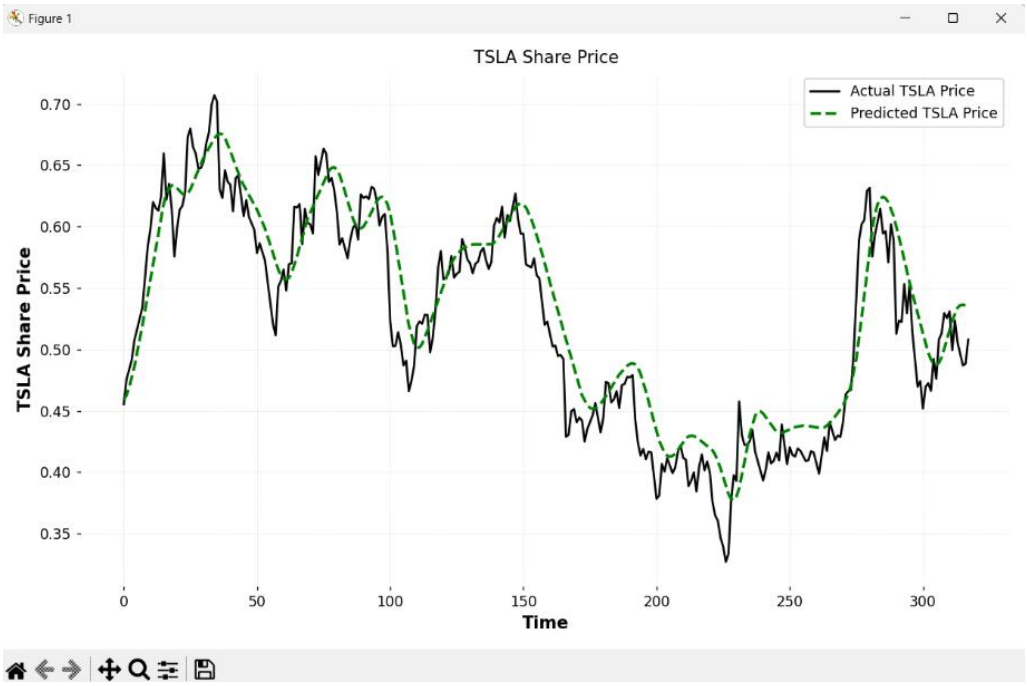


- **Insight**: The LSTM only configuration combined with the dropout regularization and using the 'Huber' loss function provides good results but is prone to overfitting data.

Configuration 3 –

Combined LSTM, Dense, GRU, RNN layers –

- **Setup:** This approach will leverage the strengths of different types of layers—LSTMs and GRUs for sequential memory, Dense layers for final aggregation, and RNNs for simpler recurrent patterns.



- **Results:** This model provides the worse results with the worse accuracy and overall mean absolute error of about 2.70% of the scaled range.
- **Insight:** The decreased performance in prediction could suggest that the increased complexity of the model could be leading to data overfitting. The model requires further configuration with these layers and hyperparameters to improve its efficiency in predicting.

Further insight –

- **Setup**: Compared tanh activation for recurrent layers versus Relu for Dense layers.
- **Results**: Models using tanh demonstrated smoother learning curves, particularly beneficial for LSTM and GRU layers, while Relu was effective for Dense layers in final predictions.
- **Insight**: Matching activation functions to the specific characteristics of layer types enhances performance and convergence.

Testing Loss Functions and Optimizers

- **Setup**: Compared 'Adam' and 'sgd' optimizers, tested 'mse' against 'Huber' loss.
- **Results**: The 'Adam' optimizer consistently led to faster convergence and better performance metrics compared to 'sgd', and 'Huber' loss proved robust against price outliers.
- **Insight**: Using 'Adam' with 'Huber' loss is advantageous for financial data due to its volatility and noise.

Next Steps to Improve Performance:

1. Refine Model Architecture:
    - Simplify the model by removing unnecessary layers or focusing on a consistent architecture like multiple LSTM or LSTM + GRU only.
2. Use Additional Features:
    - Incorporate more relevant features, such as technical indicators, to enhance the model's ability to make accurate predictions.
3. Cross-Validation:
    - Use cross-validation to ensure that the MAE observed is consistent across different data splits and not due to specific quirks of the test set.
4. Evaluate Other Metrics:
    - Consider using other metrics like RMSE, MAPE, or R-squared to get a fuller picture of model performance beyond MAE.