Stock Market Prediction using Time Series Analysis and Neural Networks

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Abstract

Stock market prediction has captivated the interest of investors, financial analysts, and researchers for decades. The rapid development of machine learning and advanced statistical techniques has introduced new methods for forecasting stock prices. This study investigates the efficacy of two prominent predictive models: the Autoregressive Integrated Moving Average (ARIMA) and Feedforward Neural Networks (FNNs), in forecasting stock prices for 20 different companies.

ARIMA models, which combine Autoregression (AR), Integration (I), and Moving Average (MA) components, are well-regarded for their ability to analyze and forecast time series data. The AR component leverages past values to predict future trends, while the I component ensures stationarity through differencing, and the MA component addresses the dependency between observations and residual errors (Box et al., 2015).

In contrast, Feedforward Neural Networks (FNNs) are a class of artificial neural networks inspired by the human brain's structure and function. These networks process information unidirectionally, from the input layer through hidden layers to the output layer, without any feedback loops (Goodfellow et al., 2016).

This paper employs both ARIMA and FNN models to predict stock prices, comparing their performance using key metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The analysis reveals insights into the strengths and limitations of each model in capturing the complexities of stock price movements, ultimately providing recommendations for their practical application in financial forecasting.

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Introduction

Stock market prediction has long been a topic of interest for investors, financial analysts, and researchers. With the advent of machine learning and advanced statistical techniques, new approaches to forecasting stock prices have emerged. This study explores the application of Autoregressive Integrated Moving Average (ARIMA) and Feedforward Neural Network models for predicting stock prices of 20 different companies.

ARIMA models are a class of statistical models used for analyzing and forecasting time series data. They combine three components: Autoregression (AR), which uses past values to predict future ones; Integration (I), which makes the time series stationary by differencing; and Moving Average (MA), which incorporates the dependency between an observation and a residual error from a moving average model applied to lagged observations (Box et al., 2015).

Feedforward Neural Networks (FNNs) are a type of artificial neural network, which is a machine learning model inspired by the structure and function of the human brain. FNNs are called "feedforward" because information flows in one direction, from the input layer, through any hidden layers, to the output layer, without any feedback loops or connections (Goodfellow et al., 2016)

Key terms:

- **Time Series:** A sequence of data points indexed in time order.
- **ARIMA:** Autoregressive Integrated Moving Average, a statistical analysis model that uses time series data to predict future trends.
- **MSE:** Mean Squared Error, a measure of the average squared difference between the estimated values and the actual value.

- **MAE:** Mean Absolute Error, a measure of the average magnitude of the errors in a set of predictions.
- **MAPE:** Mean Absolute Percentage Error, a measure of prediction accuracy in statistics.
- **AR (AutoRegressive) Value:** Represents the number of lagged observations included in the model. It indicates how the current value of the time series is influenced by its past values. The AR parameter is usually denoted by p in the ARIMA(p, d, q) model, where p is the order of the autoregressive part. For example, an AR(1) model uses only one lagged term.
- **MA (Moving Average) Value:** Represents the number of lagged forecast errors included in the model. It captures the influence of past forecast errors on the current value of the time series. The MA parameter is usually denoted by q in the ARIMA(p, d, q) model, where q is the order of the moving average part. For example, an MA(1) model uses only one lagged forecast error term.
- **Input Layer:** The layer that receives the input data
- **Hidden Layer:** The intermediate layers between the input and output layers, where the data is transformed and weighted
- **Output Layer:** The final layer that produces the predicted output
- **Neuron:** An interconnected node in the neural network that performs a simple computation
- **Weight:** A value that determines the strength of the connection between neurons
- **Bias:** An additional parameter that shifts the activation function of a neuron
- **Activation Function:** A function that determines the output of a neuron based on its input

- **Loss Function:** A function that measures the difference between the predicted output and the true output, which is minimized during training
- **Gradient Descent:** An optimization algorithm that adjusts the weights and biases of the network to minimize the loss function
- **Backpropagation:** An algorithm used to compute the gradient of the loss function with respect to the weights and biases of the network, which is used in gradient descent

Methodology

Data Acquisition

Data was obtained from Yahoo Finance. The data spans from 1st July 2014 to 28th June 2024.

The data is in the general form:

Date,Open,High,Low,Close,Adj Close,Volume

2014-07-01,23.3799991607666,23.517499923706055,23.282499313354492,23.3799991607666,20.680427551 26953,152892000

2014-07-02,23.467500686645508,23.514999389648438,23.272499084472656,23.3700008392334,20.671592712402344,113860000

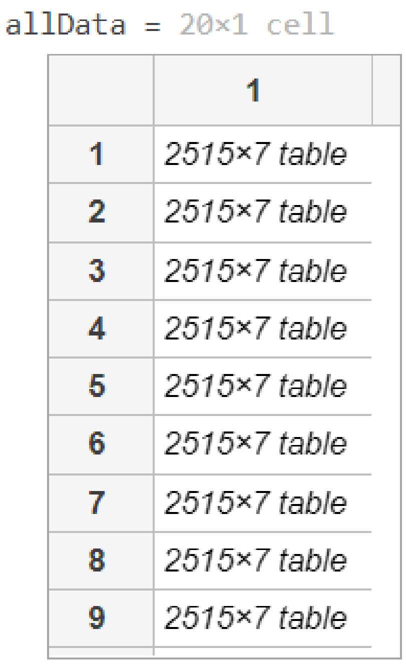
2014-07-03,23.417499542236328,23.524999618530273,23.299999237060547,23.50749969482422,20.793209075927734,91567200

The data was obtained using the Yahoo finance package in Python. By use of a dictionary the 20 companies selected were iterated through and their data written to CSV files. Yahoo Finance was preferred since it offers data for each company separately.

To import data the following code was used:

```
%Loading data from csv files
warning('off', 'all');
folderPath = 'C:\Users\Admin\Documents\GitHub\stock-market-prediction\data'; % Update folder path
filePattern = fullfile(folderPath, '*.csv');
csvFiles = dir(filePattern);

allData = cell(length(csvFiles), 1);

for k = 1:length(csvFiles)
    baseFileName = csvFiles(k).name;
    fullFileName = fullfile(folderPath, baseFileName);
    allData{k} = readtable(fullFileName);
end
allData
```

This code imports all CSV files from the specified folder into a cell array allData. Each element of allData contains a table with the stock data for one company.



```
allData = 20×1 cell
```

	1
1	2515×7 table
2	2515×7 table
3	2515×7 table
4	2515×7 table
5	2515×7 table
6	2515×7 table
7	2515×7 table
8	2515×7 table
9	2515×7 table

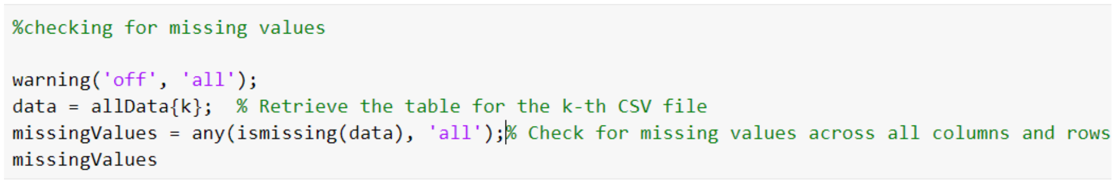
Data Preprocessing

Data was imported into MATLAB in bulk and stored in an array. This enables the use of iteration and control structures to access the data. Warnings are suppressed for cleaner output and if there are any missing values they are pointed out.

This allows for missing values to be dropped to ensure that operations are not skewed or curtailed by this data.

Furthermore, data is normalized between the range of 0 and 1 for our Time Series Analysis and Neural Network models to be able to work with our data. Only numerical columns are normalized. The column *date* is not affected in any way.

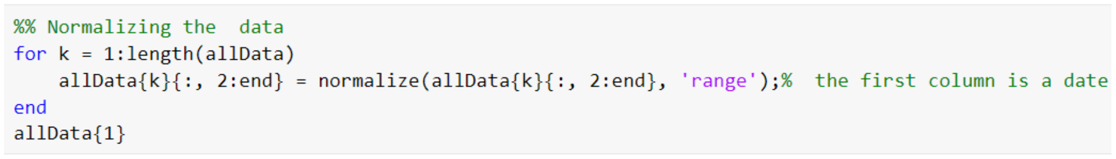
Data integrity was checked using:



```
%checking for missing values

warning('off', 'all');
data = allData{k};  % Retrieve the table for the k-th CSV file
missingValues = any(ismissing(data), 'all');% Check for missing values across all columns and rows
missingValues
```

This code checks for missing values across all columns and rows in each dataset. No missing values were found in the data sets.

Data normalization was performed using:



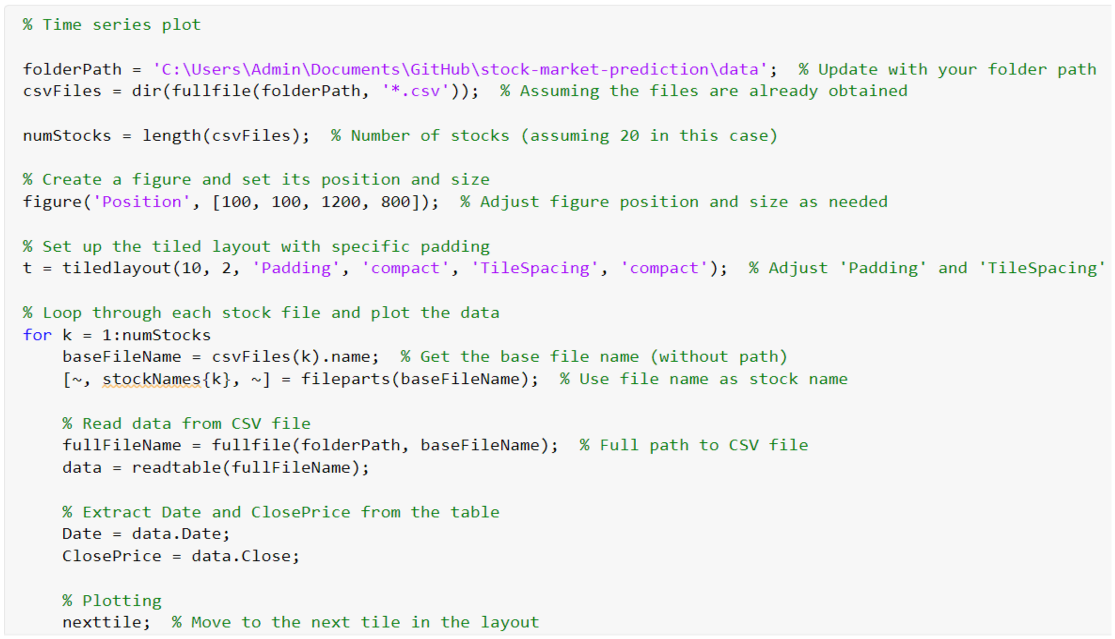
```
%% Normalizing the  data
for k = 1:length(allData)
    allData{k}{:, 2:end} = normalize(allData{k}{:, 2:end}, 'range');%  the first column is a date
end
allData{1}
```

This normalizes all numerical columns to the range [0, 1], facilitating comparison between stocks with different price ranges.

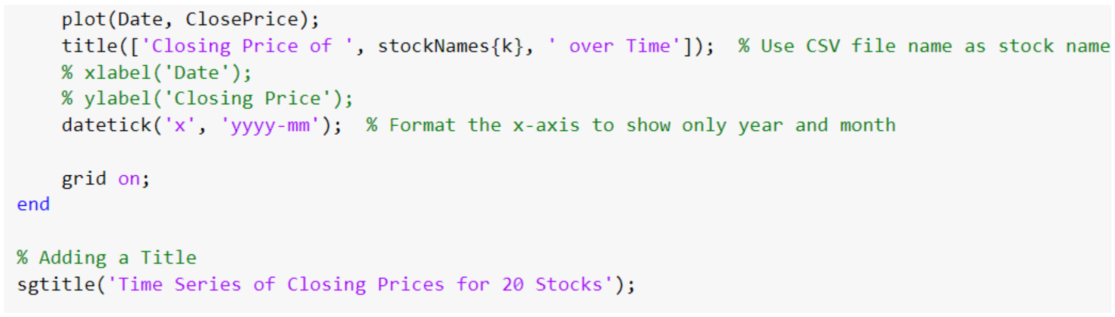
Machine Learning Models

Times Series Analysis

The following code was used to create time series plots for all 20 stocks:



```
% Time series plot

folderPath = 'C:\Users\Admin\Documents\GitHub\stock-market-prediction\data';  % Update with your folder path
csvFiles = dir(fullfile(folderPath, '*.csv'));  % Assuming the files are already obtained

numStocks = length(csvFiles);  % Number of stocks (assuming 20 in this case)

% Create a figure and set its position and size
figure('Position', [100, 100, 1200, 800]);  % Adjust figure position and size as needed

% Set up the tiled layout with specific padding
t = tiledlayout(10, 2, 'Padding', 'compact', 'TileSpacing', 'compact');  % Adjust 'Padding' and 'TileSpacing'

% Loop through each stock file and plot the data
for k = 1:numStocks
    baseFileName = csvFiles(k).name;  % Get the base file name (without path)
    [~, stockNames{k}, ~] = fileparts(baseFileName);  % Use file name as stock name

    % Read data from CSV file
    fullFileName = fullfile(folderPath, baseFileName);  % Full path to CSV file
    data = readtable(fullFileName);

    % Extract Date and ClosePrice from the table
    Date = data.Date;
    ClosePrice = data.Close;

    % Plotting
    nexttile;  % Move to the next tile in the layout
```



```
    plot(Date, ClosePrice);
    title(['Closing Price of ', stockNames{k}, ' over Time']);  % Use CSV file name as stock name
    % xlabel('Date');
    % ylabel('Closing Price');
    datetick('x', 'yyyy-mm');  % Format the x-axis to show only year and month

    grid on;
end

% Adding a Title
sgtitle('Time Series of Closing Prices for 20 Stocks');
```

This code creates a 10x2 grid of subplots, each showing the closing price over time for one stock.

The ARIMA(1,1,1) model was implemented for each stock using:

```
% Fit ARIMA model
Mdl = arima(1,1,1);
EstMdl = estimate(Mdl, trainData);

% Forecast future values using the custom ARIMA forecast function
numForecastSteps = length(testData);
forecast = customARIMAForecast(EstMdl, trainData, numForecastSteps);
```

Here, arima(1,1,1) specifies the ARIMA model order. The estimate function fits the model to the training data, and customARIMAForecast (a custom function) generates predictions for the test period.

Neural Networks

The neural network uses different functions to compute the values. In simplified terms a neural network is a polynomial function whose parameters we do not know. That is, we do not know the degree, variables or coefficients. Nonetheless, what we do know are the weights and biases. These weights and biases are updated using polynomial functions that differentiated and integrated as needed. Furthermore, an activation function and delta variable are employed to control the rate at which the weights and biases are updated. This modification of weights and biases is how the model ‘learns’.

Forward Propagation

For forward propagation the functions employed are:

$$h = f(W_1 x + b_1)$$

The function above computes a linear combination of the weights and biases then this linear combination is transformed using a non-linear function. This enables complex relationships to be learnt.

$$\hat{y} = g(W_2 h + b_2)$$

The function receives the output from the entry node and then computes the linear combination of weights and biases which are then transformed by the Sigmoid function (defined below).

$$f(z) = \ max(0, z)$$

This function is the Rectified Linear Unit (ReLU) activation function which outputs a value directly if it is positive. Otherwise, it outputs zero.

$$g(z) = \frac{1}{1 + e^{-z}}$$

This function is the Sigmoid function which maps any real-valued number into the range (0, 1).

Back Propagation

The function below is the loss function which calculates the Mean Squared Error (MSE) between the actual values and the predicted values. The aim is to minimize the value obtained from the loss function to get a more accurate neural network.

$$L = \frac{1}{2}\sum(y - \hat{y})^2$$

The function below is the derivative of the loss which indicates how much the loss changes with a small change in the predicted output. If $\hat{y}$ is greater than y, the derivative will be positive, suggesting that decreasing $\hat{y}$ will reduce the loss. Conversely, if $\hat{y}$ is less than *y*, the derivative will be negative, indicating that increasing $\hat{y}$ will help reduce the loss. This will inform the network on the way weights and biases should be updated.

$$\frac{\partial L}{\partial \hat{y}} = \hat{y} - y$$

This function is the derivative with respect to weights. This term $g'(W_2 h + b_2)$ assesses the sensitivity of the output with respect to the input of the activation function. The product with *h* reflects how changes in the weights affect the output based on the current output from the first layer. This derivative is then employed in backpropagation to adjust the weights in the direction that reduces the loss.

$$\frac{\partial \hat{y}}{\partial W_2} = h \cdot g'(W_2 h + b_2)$$

The last function is the derivative with respect to bias. Like the derivative with respect to weights function this one is used to adjust the bias in the direction that minimizes the loss.

$$\frac{\partial \hat{y}}{\partial b_2} = g'(W_2 h + b_2)$$

Gradients

The functions are the derivatives with respect to the hidden layer output, weights and bias. These derivatives are then used to update their respective variables. This backpropagation aims to reduce the error between the predicted and the actual values.

$$\frac{\partial L}{\partial h} = \left(\frac{\partial L}{\partial \hat{y}}\right) \cdot W_2$$

$$\frac{\partial h}{\partial W_1} = x \cdot f'(W_1 x + b_1)$$

$$\frac{\partial h}{\partial b_1} = f'(W_1 x + b_1)$$

Weight Update Rules

The weights are then updated using the following functions to minimize the value obtained from the loss function.

$$W_2 = W_2 - \eta \frac{\partial L}{\partial W_2}$$

$$W_1 = W_1 - \eta \frac{\partial L}{\partial W_1}$$

Bias Update Rules

Lastly, the biases are updated.

$$b_2 = b_2 - \eta \frac{\partial L}{\partial b_2}$$

$$b_2 = b_2 - \eta \frac{\partial L}{\partial b_2}$$

Results and Discussion

Time Series Analysis

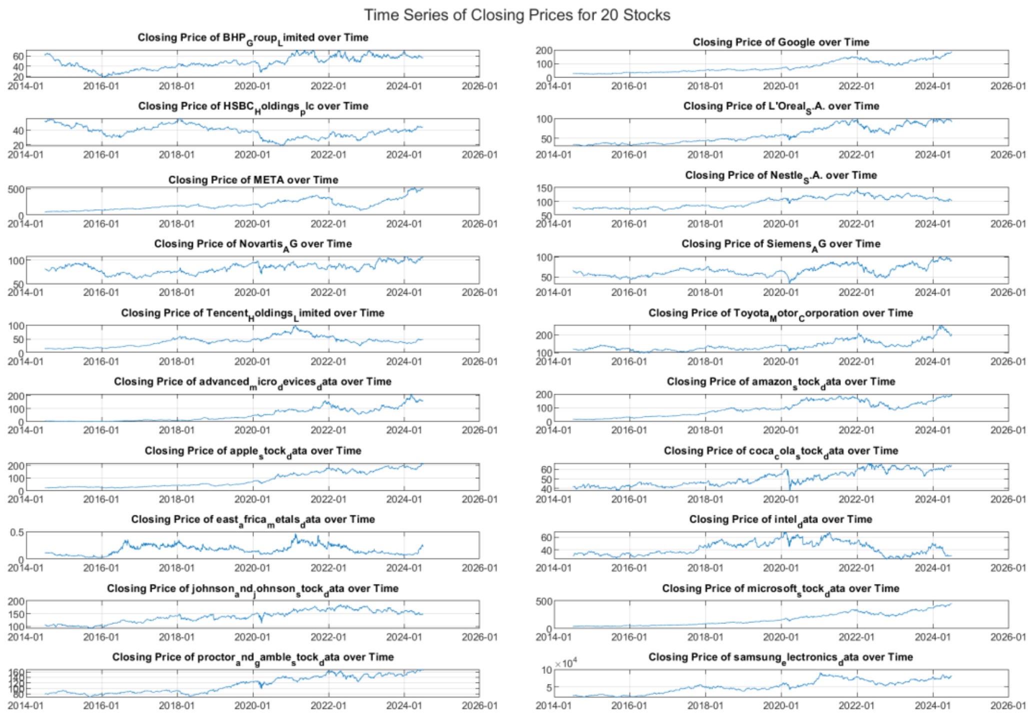
Results

Performance metrics were calculated using:

```
% Calculate error metrics
mse = mean((testData - forecast).^2);
mae = mean(abs(testData - forecast));
mape = mean(abs((testData - forecast) ./ testData)) * 100;
```

These metrics provide different perspectives on the model's prediction accuracy.

The time series plots (Image 1) provide valuable insights into the price movements of the 20 stocks over the period from 2014 to 2024:



Discussion

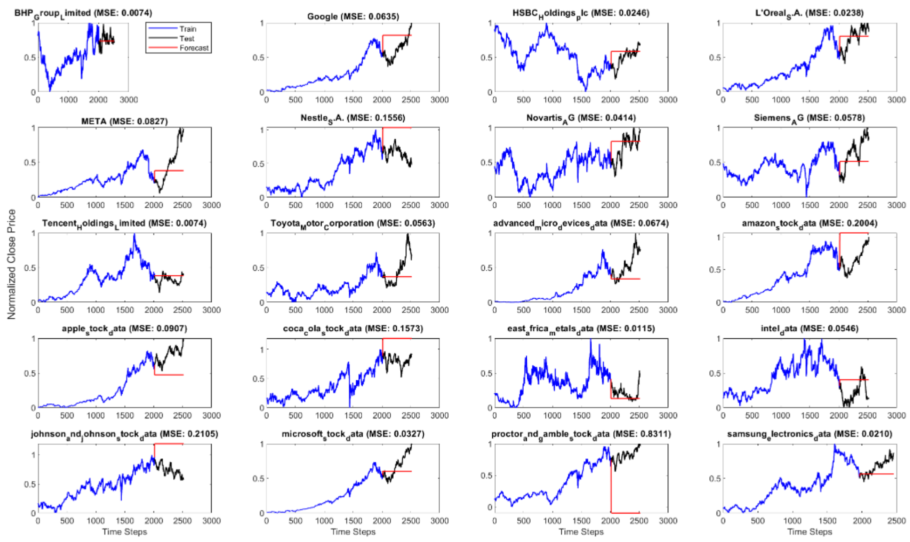
Key Observations

1. Overall Market Trend: Most stocks show a general upward trend from 2014 to 2024, indicating broad market growth over this decade. This aligns with the overall bullish trend in global markets during this period.

2. Tech Stock Performance: Technology stocks like Google, Amazon, Microsoft, and Apple demonstrate particularly strong and consistent growth. This reflects the increasing dominance of the tech sector in global markets.
3. Volatility Differences: Some stocks, such as Intel and Johnson & Johnson, show more pronounced fluctuations, indicating higher volatility. In contrast, stocks like Nestlé and Procter & Gamble display more stable price movements, typical of consumer staples companies.
4. COVID-19 Impact: A sharp decline is visible across most stocks around early 2020, corresponding to the onset of the COVID-19 pandemic. However, the recovery patterns vary:
   - Tech stocks like Amazon and Microsoft show rapid recovery and accelerated growth post-dip.
   - Traditional industries like Toyota and Johnson & Johnson show a slower, more gradual recovery.
5. Sector-Specific Trends:
   - Financial stocks (e.g., HSBC) show more cyclical patterns.
   - Consumer goods companies (e.g., Coca-Cola, Procter & Gamble) display relatively stable growth with less pronounced peaks and troughs.
   - Pharmaceutical companies (e.g., Novartis) show steady growth, likely influenced by healthcare sector dynamics.
6. Regional Variations: Stocks from different regions (e.g., Tencent from China, Samsung from South Korea) show some unique patterns, possibly reflecting local economic conditions and regulations.

Model Performance

The ARIMA(1,1,1) model performance varied significantly across the 20 stocks analysed:



1. Best Performing Stocks:
   - BHP Group Limited (MSE: 0.0074)
   - Tencent Holdings Limited (MSE: 0.0074)
   - L'Oreal S.A. (MSE: 0.0238)

For these stocks, the ARIMA model's predictions closely align with actual price movements. The low MSE values indicate that the model captured the underlying trends and patterns effectively. These stocks likely have more predictable price movements or stronger adherence to historical patterns.

2. Worst Performing Stocks:
   - Proctor & Gamble (MSE: 0.8311)
   - Coca-Cola (MSE: 0.1573)
   - Johnson & Johnson (MSE: 0.2105)

The high MSE values for these stocks suggest that the ARIMA model struggled to accurately predict their price movements. This could be due to higher volatility, more frequent external shocks, or complex underlying patterns that a simple ARIMA(1,1,1) model cannot capture adequately.

The performance distribution exhibited the following characteristics:

- The wide range of MSE values (from 0.0074 to 0.8311) indicates that the ARIMA model's performance is highly stock-specific.
- Stocks with MSE values below 0.05 (e.g., BHP, Tencent, L'Oreal, HSBC) show good model fit.
- Stocks with MSE values above 0.1 (e.g., Proctor & Gamble, Coca-Cola, Johnson & Johnson) indicate poor model fit.

In terms of sector-based performance it is evident that:

- The model seems to perform better for some technology and financial stocks.
- Consumer goods companies (Proctor & Gamble, Coca-Cola) show poorer performance, possibly due to their more stable price movements which might not benefit from the ARIMA model's strength in capturing trends and seasonality.

By visual analysis:

- For well-performing stocks, the forecast line (red) closely follows the actual price line (black) in the test period.

- Poorly performing stocks show significant divergence between forecast and actual prices, often with the model failing to capture rapid price changes or reversals.

Model Parameters and Statistical Significance

Examining the ARIMA model outputs for each stock reveals interesting patterns. The following is a sample of the outputs of the ARIMA model.

```
ARIMA(1,1,1) Model (Gaussian Distribution):

                 Value       StandardError    TStatistic    PValue
              ___________    _____________    __________    _______

Constant      -3.6643e-05     0.00092815       -0.039479    0.96851
AR{1}               2e-12         22.291      8.9722e-14          1
MA{1}          0.00075248         22.291      3.3757e-05    0.99997
Variance       0.00028467     5.4987e-06          51.771          0
```

The key observations are:

1. AR and MA Coefficients:
   - AR{1} coefficients range from highly negative (e.g., -0.65488 for L'Oreal) to positive (e.g., 0.63026 for Samsung Electronics).
   - MA{1} coefficients show similar variability, with values ranging from -0.71849 (Samsung Electronics) to 0.61574 (L'Oreal).

    - The variability in these coefficients suggests different underlying price dynamics across stocks.

2. Statistical Significance:
    - Many stocks show statistically significant AR{1} and MA{1} coefficients (p-value < 0.05), indicating that these components contribute meaningfully to the model.
    - The constant term is often not statistically significant (p-value > 0.05), suggesting that the differencing component adequately captures the trend in most cases.
3. Variance:
    - The variance term is consistently small and statistically significant across all stocks, indicating that the model captures a significant portion of the price variability.
4. Model Interpretation:
    - Negative AR{1} coefficients suggest a tendency for the series to oscillate, while positive coefficients indicate momentum in price movements.
    - The MA{1} term captures the impact of past forecast errors, with its sign and magnitude indicating how quickly the model adjusts to these errors.

Neural Networks

The code that accomplished this uses a loop to create a neural network for each stock index in the allData array. The code is as below:

```
% Create an empty table to store MSE values
resultsTable = table('Size', [numel(allData), 2], 'VariableTypes', {'string', 'double'}, 'VariableNames', {'FileName', 'MSE'});

% Loop over each table in allData
for k = 1:numel(allData)
    data = allData{k};

    % Extract the Close variable as the target
    target = data.Close;

    % Remove Date and Close columns as they are not needed for prediction
    data(:, {'Date', 'Close', 'AdjClose'}) = [];

    % Convert table to matrix
    data = table2array(data);

    % Normalize data (optional but often recommended for neural networks)
    data_normalized = normalize(data);
    target_normalized = normalize(target);

    % Number of data points
    num_data = size(data, 1);

    % Split ratio (e.g., 75% training, 25% testing)
    train_ratio = 0.75;
    train_size = round(train_ratio * num_data);

    % Training data
    train_data = data_normalized(1:train_size, :);
    train_target = target_normalized(1:train_size, :);

    % Testing data
    test_data = data_normalized(train_size+1:end, :);
    test_target = target_normalized(train_size+1:end, :);
```

```
    % Define the neural network architecture
    hidden_layer_size = 40;
    net = feedforwardnet(hidden_layer_size);

    % Set training options
    train_options = trainingOptions('adam', ...  % Use Adam optimizer (or other optimizer)
        'MaxEpochs', 1000, ...  % Number of epochs to train
        'Verbose', true, ...   % Show training progress
        'Plots', 'training-progress');  % Show training progress plot

    % Train the neural network with specified options
    [net, tr] = train(net, train_data', train_target', [], [], [], [], [], [], train_options);

    % Predict on test data
    predictions = net(test_data');

    % Measure the performance (e.g., Mean Squared Error)
    clear mse;
    neural_mse = mse(predictions - test_target');
    clear mse;
    disp(['Mean Squared Error: ', num2str(neural_mse)]);

    % Denormalize the predicted values
    predicted_close = predictions' * std(target) + mean(target);
    actual_close = target(train_size+1:end);

    % Get the file name (without extension)
    [~, fileName, ~] = fileparts(csvFiles(k).name);

    % Add the MSE to the results table
    resultsTable(k, 1) = {fileName};
    resultsTable(k, 2) = {neural_mse};
    % Plotting with title including file name
    figure;
    plot(actual_close, '-o', 'DisplayName', 'Actual Close');
    hold on;
    plot(predicted_close, '-x', 'DisplayName', 'Predicted Close');
    hold off;
    xlabel('Data Points');
    ylabel('Close');
    title(['Actual vs Predicted Close - ', fileName]);
    legend;
    grid on;

    % Validate on the validation data
    validation_data = validationData{k};
    validation_target = validation_data.Close;
    validation_data(:, {'Date', 'Close', 'AdjClose'}) = [];
    validation_data = table2array(validation_data);

    validation_data_normalized = normalize(validation_data);
    validation_target_normalized = normalize(validation_target);

    validation_predictions = net(validation_data_normalized');
```

```
    % Calculate MSE for validation data
    clear mse;
    validation_mse = mse(validation_predictions' - validation_target_normalized);
    clear mse;
    disp(['Validation Mean Squared Error: ', num2str(validation_mse)]);

    % Add the validation MSE to the results table
    resultsTable{k, 3} = validation_mse;

    % Denormalize validation predicted values
    validation_predicted_close = validation_predictions' * std(validation_target) + mean(validation_target);
    actual_validation_close = validation_target;

    % Plotting validation data
    figure;
    plot(actual_validation_close, '-o', 'DisplayName', 'Actual Validation Close');
    hold on;
    plot(validation_predicted_close, '-x', 'DisplayName', 'Predicted Validation Close');
    hold off;
    xlabel('Data Points');
    ylabel('Close');
    title(['Actual vs Predicted Validation Close - ', fileName]);
    legend;
    grid on;
end

writetable(resultsTable, 'FNN_MSE.csv');
```

Training

We decided to use a Feedforward Neural Network that:

- Has 40 hidden nodes
- Trains for a maximum of 1000 epochs
- Uses the adam optimizer

- Utilizes 75% of the data to train
- Utilizes 25% of the data to test
- Uses the Mean Squared Error to test the error of the results
- Utilizes validation data from 1st July 2024 to 26th July 2024

Testing

In testing the MSE's obtained were as detailed in the table below.

Company	**MSE**
HSBC Holdings	0.000289854
Tencent Holdings Limited	0.000328486
Samsung Electronics	0.000384859
Amazon	0.000831416
Alphabet	0.000862567
Nestle	0.000945337
Intel	0.001157845
Proctor and Gamble	0.001207186
BHP Group Limited	0.001295159
East Africa Metals	0.003050332
AMD	0.005859265
Coca Cola	0.006657724
Apple	0.007479319
Novartis AG	0.007599726
Siemens AG	0.021622344
L'Oreal	0.026000365
Microsoft	0.041602214
Johnson and Johnson	0.077928339
Meta	0.123486883
Toyota Motor Corporation	0.156136595

The smallest MSE is the one from HBSC Holdings at 0.000289854 and the largest is by Toyota Motor Corporation at 0.156136595. An interesting trend that emerges that for companies that:

1. Have a wide range of products for sale.
2. Were not affected by the AI boom.

3. Were not really affected by COVID 19.

The model can use data for the first seven and a half years to predict the remaining two and a half years. This explains why Samsung Electronics or Alphabet despite being technological companies have such low MSEs.

Validation

On the other hand, when it comes to validation HBSC Holdings maintains its position as the one with the most accurate FNN, yet Intel moves from somewhere in the middle to being the one with the least accurate FNN. Toyota Motor Corporation curiously has a smaller MSE over the brief validation time frame. This means that its stock must be volatile and best assessed over shorter periods. This same trend occurs for Meta, Johnson and Johnson, and Microsoft also.

Company	**Validation MSE**
HSBC Holdings	0.011285854
Meta	0.014930324
Alphabet	0.015347291
Toyota Motor Corporation	0.017593062
Microsoft	0.020737847
Apple	0.024885528
Siemens AG	0.028157622
Coca Cola	0.028276792
Tencent Holdings Limited	0.03699829
Samsung Electronics	0.041988428
Amazon	0.044326173
East Africa Metals	0.049413927
Novartis AG	0.049855178
Nestle	0.051387616
BHP Group Limited	0.072831488
Proctor and Gamble	0.102384032
L'Oreal	0.126287847
Johnson and Johnson	0.154387357
AMD	0.174740765
Intel	0.483313323

Conclusion and Recommendations

Time Series Analysis

1. Model Simplicity: The ARIMA(1,1,1) model, while effective for some stocks, may be too simplistic for others. More complex ARIMA models (with different p, d, q parameters) might yield better results for some stocks.
2. Stationarity Assumptions: The ARIMA model assumes that the differenced series is stationary. This assumption may not hold for all stocks, particularly those with changing volatility over time.
3. External Factors: The model does not account for external factors (e.g., market sentiment, economic indicators, company-specific news) that can significantly impact stock prices.
4. Short-term vs. Long-term Predictions: The model's performance in short-term predictions may differ from its long-term forecasting ability. This aspect needs further investigation.
5. Data Normalization Impact: While normalization allows for easier comparison across stocks, it may obscure some stock-specific characteristics that could be relevant for prediction.

In conclusion, the ARIMA(1,1,1) model shows varied performance across different stocks, highlighting the complexity of stock price prediction. While it performs exceptionally well for some stocks, it struggles with others, underscoring the need for stock-specific modelling approaches and the potential inclusion of additional predictive factors.

Neural Networks

The FNN:

1. Has low values for every stock index. The value is either 0.x or 0.0x or even 0.00x and in cases it goes down to 0.000x. This illustrates that when used in a real-world context the model will be precise in predicting the values hence will be generally profitable.
2. Brings to the light the effect of confounding factors on the stock market trends. This makes evident that for certain volatile stock- that is stock with a wide variety of confounding factors in comparison to the diversity of goods sold- when the contextual data is briefer it is much more accurate. For such stock if the data spans a large time frame it underfits.
3. Illustrates that for less volatile stock the neural network does extremely well when the data spans long periods of time.
4. Displays that there exist outliers that have very stable stocks like HBSC Holdings. When trained over long periods of time it performs just as well in short term prediction.

In conclusion the methodology used to train the model is extremely useful in identifying stable stock indices that would be invaluable in growing one’s money predictably. It also identifies stock indices that are riskier yet will return a higher Return on Investment (ROI). And our model could be an invaluable key to this process of investing.

References

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Appendices

Company	**Testing MSE**	**Validation MSE**	**Difference**
HSBC Holdings	0.000289854	0.011285854	0.010996
Tencent Holdings Limited	0.000328486	0.03699829	0.036669804
Samsung Electronics	0.000384859	0.041988428	0.041603569
Amazon	0.000831416	0.044326173	0.043494757
Alphabet	0.000862567	0.015347291	0.014484724
Nestle	0.000945337	0.051387616	0.050442279
Intel	0.001157845	0.483313323	0.482155478
Proctor and Gamble	0.001207186	0.102384032	0.101176846
BHP Group Limited	0.001295159	0.072831488	0.071536329
East Africa Metals	0.003050332	0.049413927	0.046363595
AMD	0.005859265	0.174740765	0.1688815
Coca Cola	0.006657724	0.028276792	0.021619068
Apple	0.007479319	0.024885528	0.017406209
Novartis AG	0.007599726	0.049855178	0.042255452
Siemens AG	0.021622344	0.028157622	0.006535278
L'Oreal	0.026000365	0.126287847	0.100287482
Microsoft	0.041602214	0.020737847	-0.020864367
Johnson and Johnson	0.077928339	0.154387357	0.076459018
Meta	0.123486883	0.014930324	-0.108556559
Toyota Motor Corporation	0.156136595	0.017593062	-0.138543533

Fig 1: Testing and Validation MSE's with the Difference

ARIMA(1,1,1) Model (Gaussian Distribution):

```
                 Value       StandardError    TStatistic    PValue
              ___________    _____________    __________    _______

  Constant    -3.6643e-05     0.00092815       -0.039479    0.96851
  AR{1}             2e-12         22.291      8.9722e-14          1
  MA{1}        0.00075248         22.291      3.3757e-05    0.99997
  Variance     0.00028467     5.4987e-06          51.771          0
```

```
ARIMA(1,1,1) Model (Gaussian Distribution):

                Value       StandardError    TStatistic      PValue
              __________    _____________    __________    __________

Constant      0.00039164     0.00024744        1.5828        0.11348
AR{1}           -0.46309        0.12945       -3.5772      0.00034726
MA{1}            0.39382        0.13335        2.9533       0.0031441
Variance      6.0012e-05     8.4202e-07        71.272               0


ARIMA(1,1,1) Model (Gaussian Distribution):

                Value       StandardError    TStatistic    PValue
              __________    _____________    __________    _______

Constant      -0.0003605     0.00047079      -0.76573      0.44384
AR{1}           -0.44141        0.45479      -0.97057      0.33176
MA{1}            0.41146         0.4621       0.89041      0.37324
Variance      0.00020679     4.2404e-06        48.767            0


ARIMA(1,1,1) Model (Gaussian Distribution):

                Value       StandardError    TStatistic     PValue
              __________    _____________    __________    ________
```

```
Constant    0.00036578    0.00036635      0.99845      0.31806

AR{1}         -0.41885       0.16408      -2.5527     0.010689

MA{1}          0.35417       0.16881        2.098     0.035902

Variance    0.00014274    2.3214e-06        61.49            0
```

ARIMA(1,1,1) Model (Gaussian Distribution):

```
               Value       StandardError    TStatistic      PValue
            __________    ______________    __________    __________

Constant    0.00017365    0.00036545      0.47517        0.63467

AR{1}         -0.56642       0.15401      -3.6779     0.00023517

MA{1}           0.5128       0.16144       3.1765      0.0014907

Variance    9.5612e-05    5.7214e-07       167.11              0
```

ARIMA(1,1,1) Model (Gaussian Distribution):

```
               Value       StandardError    TStatistic     PValue
            __________    ______________    __________    ________

Constant    0.00038733    0.00045561      0.85015      0.39524

AR{1}         -0.46608       0.24275        -1.92     0.054859

MA{1}          0.42689        0.2488       1.7158     0.086193

Variance    0.00019259    3.2377e-06       59.483            0
```

ARIMA(1,1,1) Model (Gaussian Distribution):

```
             Value       StandardError    TStatistic     PValue  
           __________    _____________    __________    _________

Constant    5.2094e-05     0.00068235      0.076344       0.93915
AR{1}         -0.50743        0.15567       -3.2595     0.0011159
MA{1}          0.45553         0.1608        2.8329     0.0046128
Variance    0.00042192     7.0103e-06        60.185             0
```

ARIMA(1,1,1) Model (Gaussian Distribution):

```
              Value       StandardError    TStatistic    PValue 
           ___________    _____________    __________    _______

Constant   -0.00011657     0.00050719      -0.22984     0.81821
AR{1}         -0.51496        0.32328       -1.5929     0.11118
MA{1}          0.48085        0.33158        1.4502       0.147
Variance    0.00022999     4.1866e-06        54.935           0
```

ARIMA(1,1,1) Model (Gaussian Distribution):

```
             Value       StandardError    TStatistic    PValue 
           __________    _____________    __________    _______
```

```
Constant    0.00020324     0.00030648       0.66315     0.50723
AR{1}        -0.090296       0.11666      -0.77398     0.43895
MA{1}        -0.024245       0.11727      -0.20675      0.8362
Variance     0.0001877     2.3863e-06        78.657           0
```

ARIMA(1,1,1) Model (Gaussian Distribution):

```
                Value      StandardError    TStatistic    PValue
             ___________    _____________    __________    ________

Constant    0.00010889     0.00029901        0.36417    0.71573
AR{1}            2e-12         1.1126     1.7976e-12          1
MA{1}        -0.012728         1.1126       -0.01144    0.99087
Variance    0.00013663     2.3304e-06         58.632          0
```

ARIMA(1,1,1) Model (Gaussian Distribution):

```
                Value      StandardError    TStatistic    PValue
             ___________    _____________    __________    ________

Constant    0.00017431     0.00015871       1.0982       0.2721
AR{1}          0.10152        0.12371      0.82065      0.41185
MA{1}         -0.17279        0.12285      -1.4065      0.15957
Variance    7.3553e-05     9.2561e-07       79.464            0
```

```
ARIMA(1,1,1) Model (Gaussian Distribution):

              Value       StandardError    TStatistic      PValue
            __________    _____________    __________    __________

Constant    0.00043083      0.0004029        1.0693        0.28492
AR{1}         -0.65488        0.14145       -4.6297     3.6621e-06
MA{1}          0.61574        0.14677        4.1954     2.7235e-05
Variance    0.00012152     1.5574e-06        78.028              0


ARIMA(1,1,1) Model (Gaussian Distribution):

              Value       StandardError    TStatistic    PValue
            __________    _____________    __________    _______

Constant    0.00025011     0.00016378        1.5271      0.12673
AR{1}          0.17469        0.18059       0.96736      0.33336
MA{1}          -0.2336        0.17941        -1.302      0.19291
Variance      6.55e-05     9.0201e-07        72.616            0


ARIMA(1,1,1) Model (Gaussian Distribution):

              Value       StandardError    TStatistic    PValue
            __________    _____________    __________    _______

Constant    0.00047757     0.00063923        0.7471        0.455
```

```
AR{1}        -0.33949       0.31312      -1.0842     0.27827
MA{1}         0.31457       0.31799      0.98923     0.32255
Variance   0.00040733    5.2256e-06       77.949           0
```

```
ARIMA(1,1,1) Model (Gaussian Distribution):

              Value       StandardError    TStatistic      PValue
            __________    _____________    __________    __________

Constant    5.9394e-05     0.00026263       0.22615        0.82108
AR{1}          0.43385       0.051651        8.3996     4.4788e-17
MA{1}         -0.62812       0.043805       -14.339      1.249e-46
Variance    0.00094052     1.6617e-05        56.602              0
```

```
ARIMA(1,1,1) Model (Gaussian Distribution):

              Value       StandardError    TStatistic      PValue
            __________    _____________    __________    __________

Constant    0.00012732      0.0006632       0.19198        0.84776
AR{1}         -0.45949       0.055396       -8.2945       1.09e-16
MA{1}          0.28742       0.058768        4.8908     1.0045e-06
Variance    0.00049473     5.9266e-06        83.477              0
```

```
ARIMA(1,1,1) Model (Gaussian Distribution):
```

```
              Value       StandardError    TStatistic      PValue   
            __________    _____________    __________    __________

Constant    0.00052917     0.00048107           1.1         0.27134
AR{1}         -0.33405       0.095636       -3.4929      0.00047782
MA{1}          0.24417       0.098429        2.4807        0.013112
Variance    0.00026932     3.6333e-06        74.124               0
```

ARIMA(1,1,1) Model (Gaussian Distribution):

```
              Value       StandardError    TStatistic      PValue   
            __________    _____________    __________    __________

Constant    0.00034476     0.00017418        1.9794        0.047777
AR{1}          -0.2838       0.060033       -4.7274      2.2736e-06
MA{1}          0.11398       0.063001        1.8091         0.07043
Variance    4.4992e-05     6.4988e-07        69.231               0
```

ARIMA(1,1,1) Model (Gaussian Distribution):

```
              Value       StandardError    TStatistic      PValue   
            __________    _____________    __________    __________

Constant     0.0001146     9.7907e-05        1.1705         0.24181
AR{1}          0.63026       0.060467        10.423       1.941e-25
```

MA{1}	-0.71849	0.056925	-12.622	1.6023e-36
Variance	0.00016926	2.0906e-06	80.961	0

ARIMA(1,1,1) Model (Gaussian Distribution):

	Value	StandardError	TStatistic	PValue
Constant	0.00023972	0.00029747	0.80584	0.42033
AR{1}	-0.036543	0.5292	-0.069053	0.94495
MA{1}	0.07098	0.52546	0.13508	0.89255
Variance	0.0001304	2.4457e-06	53.32	0

Fig 2: ARIMA(1,1,1) Model Gaussian Distribution

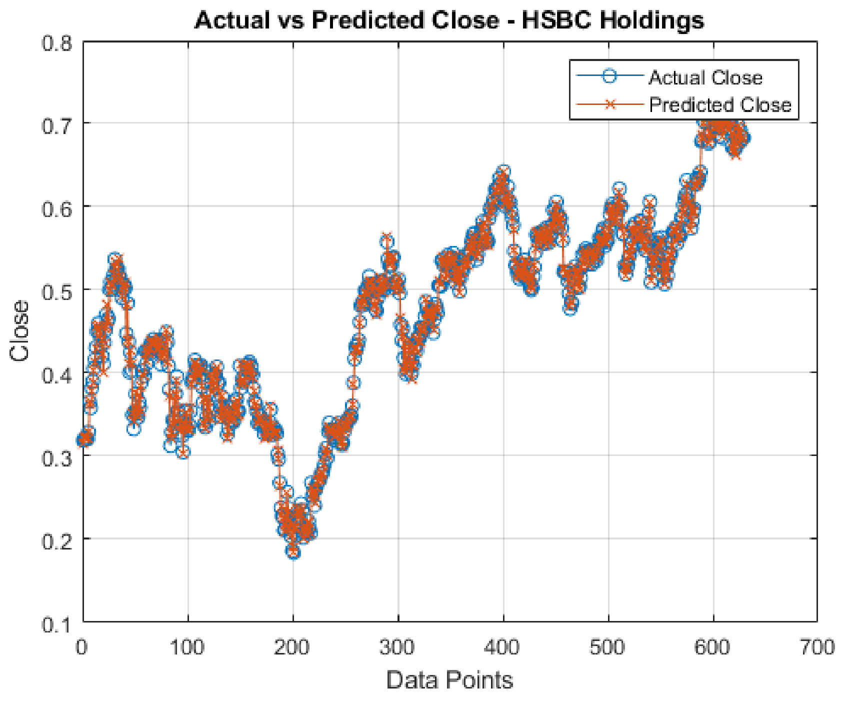

Fig 3: HBSC Holdings Testing Data

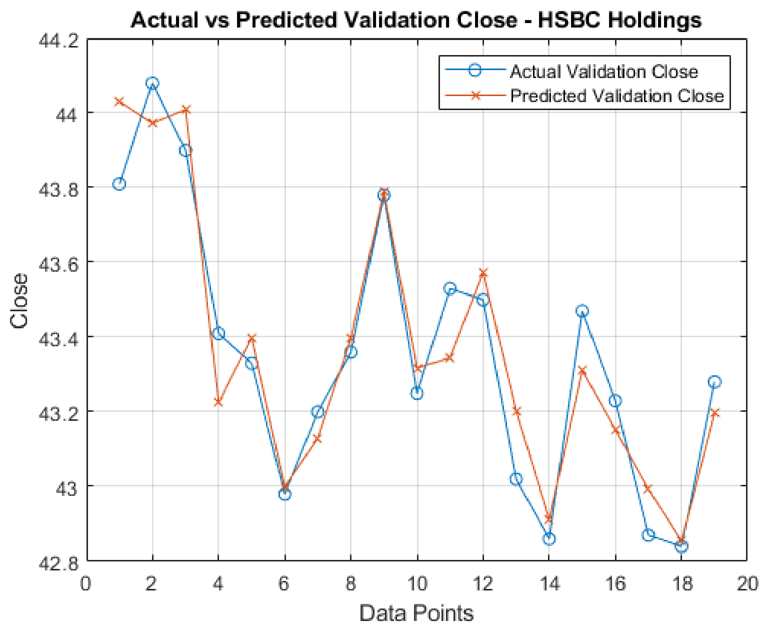

Fig 4: HBSC Holdings Validation Data

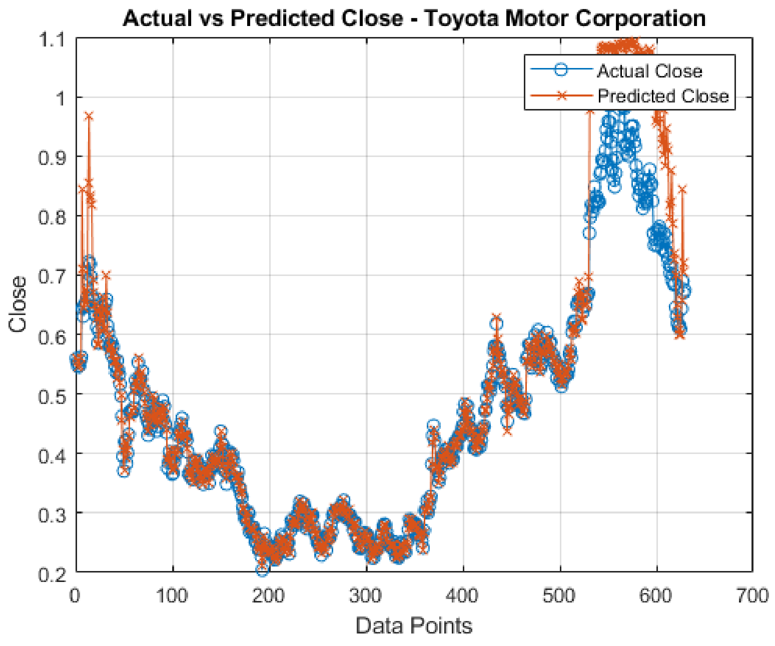

Fig 5: Toyota Motor Corporation Testing Data

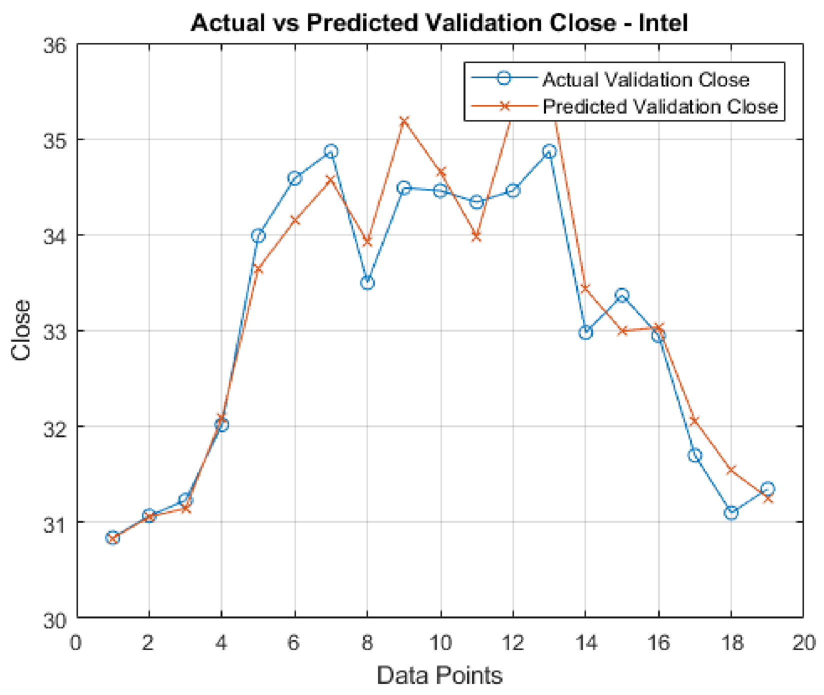

Fig 6: Intel Validation Data