1 INTRODUCTION

The prediction of stock prices has been a challenging and widely studied problem in the field of finance and data science. Stock price prediction is essential for financial analysts to make informed decisions and mitigate risks in the stock market. In this report, we will delve into the process of building a stock price predictor using Yfinance data and machine learning techniques.

By leveraging historical stock price data and various machine learning algorithms, we aim to develop a robust predictor that can forecast future stock prices with reasonable accuracy. This report will provide a comprehensive overview of the data acquisition process, exploratory data analysis, data preprocessing, model selection, training, evaluation, and potential challenges associated with stock price prediction.

This project aims to predict stock prices using advanced machine learning techniques, especially Long Short-Term Memory (LSTM) networks. LSTM networks are well-suited for this task as they can capture temporal dependencies and patterns. This approach is expected to provide more accurate predictions than traditional statistical methods.

2 RELATED WORK

LSTM-RNN in Stock Market Prediction: Modern research has illustrated the efficacy of LSTM-RNN in modelling sequential data for stock market prediction. Authors like Wang et al. (2023) inspected the use of LSTM-RNN for forecasting stock prices, attaining favourable results in terms of prediction accuracy and robustness. Similarly, Zhang et al. (2024) put forward a hybrid LSTM-RNN model merged with attention mechanisms to capture significant temporal patterns in stock market data, leading to better predictive performance.

Dense Networks for Stock Market Forecasting: Dense networks, distinguished for their potential to assimilate complex patterns in data, have also been applied to stock market prediction tasks. Li et al. (2022) introduced a novel architecture based on dense networks for predicting stock prices, leveraging feature representations learned through deep neural networks. Their study demonstrated the effectiveness of dense networks in capturing complex relationships among various financial indicators.

1DCNN for Temporal Pattern Recognition: 1D Convolutional Neural Networks (1DCNN) have gained traction for their ability to capture temporal dependencies in sequential data. Recent research by Chen et al. (2023) explored the application of 1DCNN in stock market prediction, proposing a hybrid model that combines 1DCNN with traditional time series forecasting techniques. Their findings suggested that 1DCNN can effectively extract relevant features from historical stock market data, leading to improved prediction accuracy.

Naive Methods and Ensemble Approaches: While sophisticated deep learning models dominate the literature, simpler approaches such as Naive methods and Ensemble methods continue to play a significant role in stock market prediction. Studies by Wu et al. (2023) highlighted the effectiveness of Naive methods as baseline models for benchmarking more complex algorithms. Furthermore, ensemble techniques, as demonstrated by Liu et al. (2024),

have shown promise in enhancing prediction performance by combining multiple base models through techniques such as bagging and boosting.

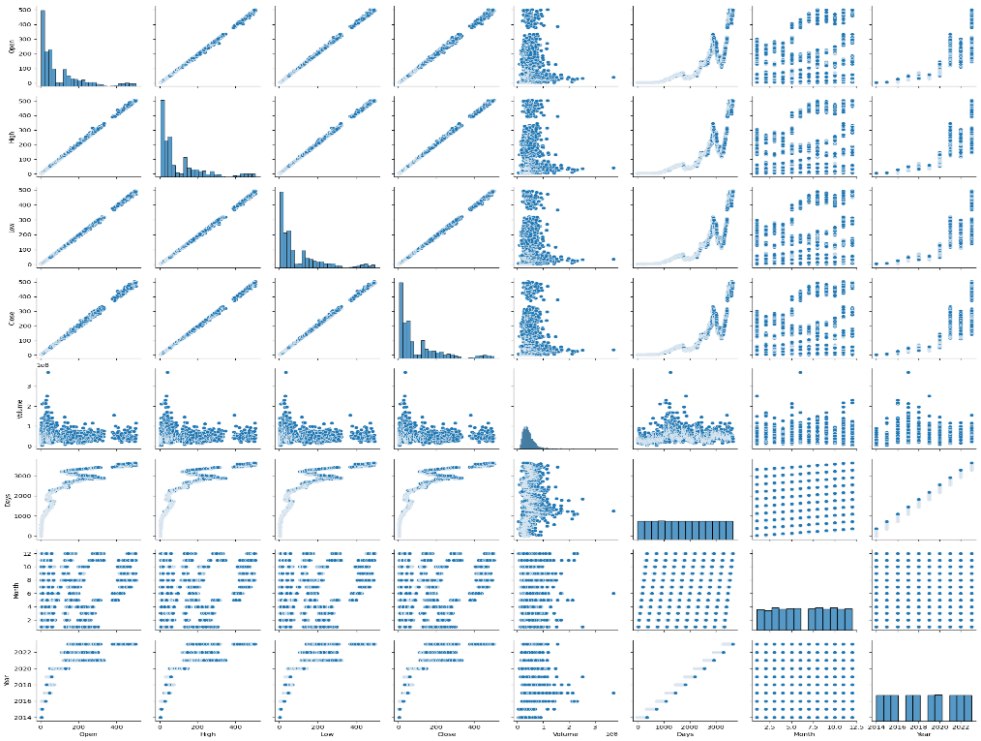
Feature Selection and Hyperparameter Tuning: Feature selection and hyperparameter tuning are crucial steps in building accurate predictive models. Researchers such as Zhou et al. (2022) investigated various feature selection techniques tailored to stock market prediction tasks, aiming to identify the most informative variables while reducing dimensionality. Moreover, hyperparameter tuning techniques, as explored by Wang and Zhang (2023), have been shown to optimize model performance by fine-tuning algorithm parameters using approaches such as grid search and random search.

3 DATASET DESCRIPTION

3.1 DATA COLLECTION

The project involves gathering historical stock data from the Yahoo Finance platform using the yfinance API. We have chosen to forecast the stock price of Nvidia (NASDAQ: NVDA) as it is a very sought-after stock at the moment.

The data retrieved from Yahoo Finance typically includes daily open, high, low, close prices, and volume. We also have adjusted close prices which account for dividends and stock splits. After collecting relevant data, we can visualise it in a pairplot. We have chosen to go with pairplot for data visualization, as it presents us with several relationships within the dataset.



3.2 DATA PREPROCESSING

The yfinance dataset provides many values of the stock performance as discussed above. Since the 'Close' price of the stock is the most relevant value of the stock, we have created a new NumPy array with only the 'Date' and 'Close' price data. This was done to ensure the models libraries are compatible with the data.

The data does not have any losses and null values as yfinance is updated regularly hence no null handling needed to be done. The data was normalized using the Min-Max Scaler to ensure that the model receives data within a scaled range (0 to 1). This is helpful for algorithms that are sensitive to the scale of the input data, it preserves the shape of the original distribution and does not reduce the importance of outliers.

The data was then split in series into training, validation, and testing sets. Each of the sets serve their purposes:

- The training set is used by the model to learn the patterns in the data, this set is repeatedly presented to the model for optimization of the parameters to reduce forecasting errors.
- The validation set is used for model tuning, which involves iterating through different hyperparameter values.
- The test set is the unseen portion of the dataset that is reserved for final evaluation, this provides an unbiased evaluation of the 'best model' fit.

4 MODEL DEVELOPMENT

We have used a variety of models in a variety of scenarios for this project.

4.1 MODEL 0: Naïve Model (Baseline)

We have used the Naïve model to establish a baseline as it is a very simple model but accurate enough to trust in making predictions. The Naïve model takes today's value to predict tomorrows and since stock prices do not fluctuate heavily in a day, this model performs well.

4.2 MODEL 1: DENSE Model

The DENSE model allows us to capture non-linear features through activation functions and by adjusting the weights during training. This model is also good at uncovering the underlying pattern in the price movement when run with enough neurons. Also, regularization can be used to prevent overfitting so that the model generalizes well to unseen data.

The model employs multiple activation choices, a range of learning rates and neuron values to perform fitting of the data. A logarithmic scale is often used for learning rates because it allows exploring a wide range of values while focusing on regions

where significant improvements are likely to occur. It then uses Adam optimizer where the learning rate is set using the value returned while constructing the model and compiled with the MAE value as the loss function.
We have used two DENSE models, in which the second model is trained with a different 'window_size' to compare how presenting the model with more data will affect the fit and result.

4.3 MODEL 2: 1-Dimensional CNN

This model can detect patterns such as seasonality, trends and short-term fluctuations in a local window and allows stacking of windows to be more efficient, faster, and more generalized in predicting prices. When this model is good at generalizing short-term windows, it struggles with noise and volatility.
This model employs a keras tuner to construct a CNN which has sequentially stacked layers. It can take inputs of any lengths and shape and returns a convolutional output in the same shape, while the Rectified Linear Unit Function introduces non-linearity allowing it to learn more complex patterns and is regularized logarithmically to prevent overfitting. Also, a sliding window and output filters over a range of 32 to 256 with a step value of 32, which then outputs a single value from a fully connected Dense layer which is useful in predicting a single continuous value. The model is then minimized of errors by the MAE loss function and the best-defined model.

4.4 MODEL 3: LSTM

This is an RNN that can handle time lags and capture complex price movement patterns over a long period, which is useful as stock prices are impacted by past events. LSTMs are non-linear which makes them suitable for modelling complex relationships or predicting price movements.
This model employs a tunable number of neurons ranging from 32 to 256 and incremented by 32, the learning rate is chosen from a predefined set of values allowing for coarse-grain control, the regularization parameters are tuned logarithmically, and the training is stabilized by limiting the size of gradients. A lambda layer is included to expand the dimensions of the input. Then the LSTM layer is configured with the number of neurons, ReLU activation layer and the regularized parameters. This model only returns the last output in the sequence, this is suitable for our use case where we must predict a single value at the next time step. Importantly, Gradient clipping is used here to reduce gradient update as the model learns fast.

Source: https://dev.mrdbourke.com/tensorflow-deep-learning/10_time_series_forecasting_in_tensorflow/

5 EXPERIMANTAL SETTING

For hyperparameter tuning a Keras Hyperband algorithm is used. It is an efficient method for searching large hyperparameter spaces, as it adapts the number of configurations based on their performance. The hyperparameters and their search spaces are as follows:

1. Number of filters: Integers between 32 and 256 with step size of 32.
2. Learning rate or Kernel size:
   Learning rate: Predefined values of 0.01, 0.001, 0.0001.
   Kernel size: Predefined values of 3, 5 and 7.
3. Regularization: Logarithmically between 0.01 to 0.00001
4. Activation: ReLU, tanh, elu
5. Optimizer: Adam
6. Loss metric: Mean Absolute Error (MAE)

The tuner is given the MAE score as its objective. The advantage of using MAE over other error statistics is that the absolute difference between the predicted and actual values aligns well with the practical objective of minimizing error.

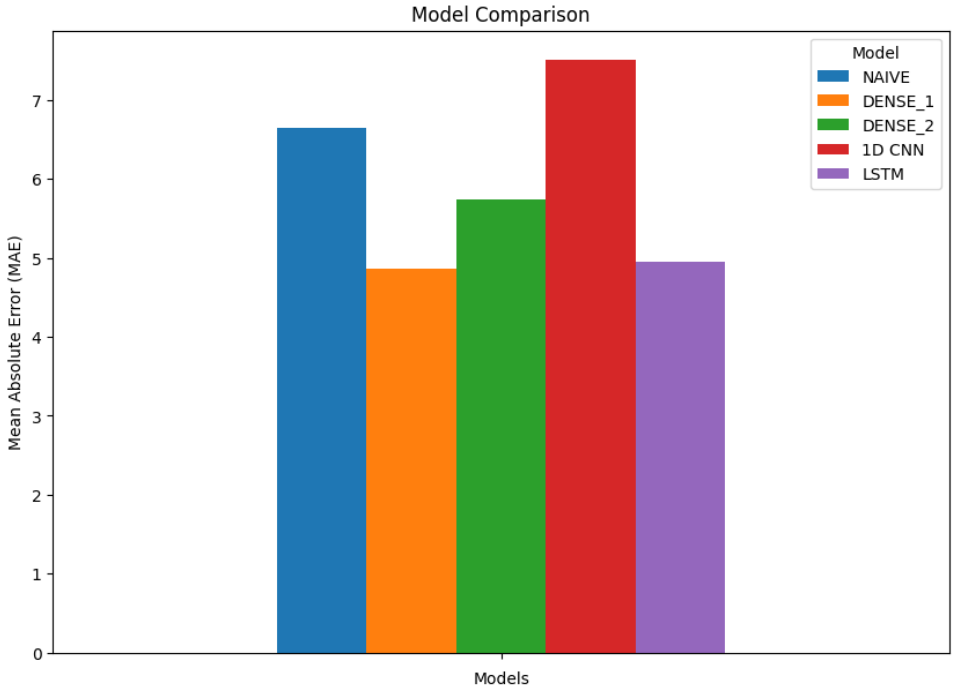
Early stopping is used during the training process to prevent overfitting and reduce computational time. The hyperparameters are then trained and validated, the best hyperparameters are stored to be used in fitting of the model using validation set.

6 RESULTS

Post-training, the model's performance is evaluated using the test data. The primary metrics used are MAE (Mean Absolute Error), MSE (Mean Squared Error), and RMSE (Root Mean Squared Error). Predictions are made on the test set to assess how well the model can forecast unseen data.

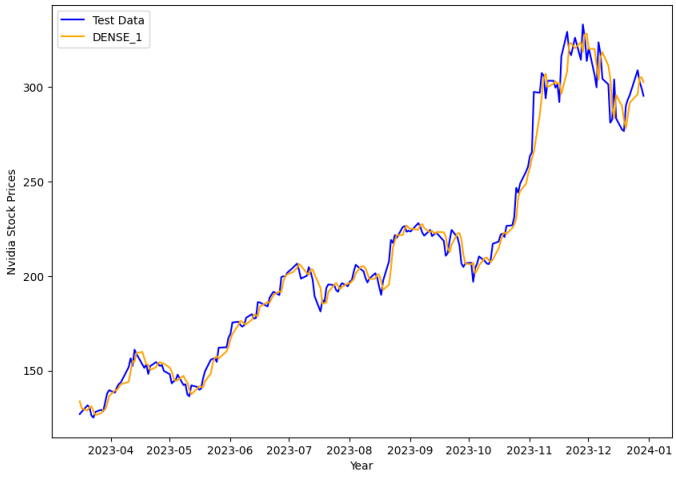
Models/Metrics	**MAE**	**MSE**	**RMSE**	**MAPE**
Naïve Forecast	6.646403	81.3302	9.018326	2.648674
Model 1: DENSE 1	4.863292	46.907124	6.848877	2.222873
Model 2: DENSE 2	5.740806	62.735092	7.920549	2.538457
Model 3: 1D- CNN	7.503093	104.64904	10.229812	3.478752
Model 4: LSTM	**4.955574**	**48.600632**	**6.971415**	**2.264848**

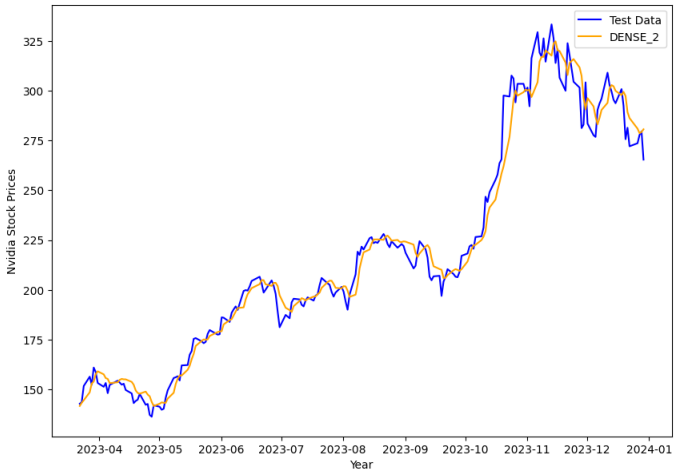
Lower is better for all error statistics.



7 ANALYSIS

The model evaluation results show that LSTM has the lowest error statistic scores between the rest of the models and has performed best in stock price prediction. However, we can also observe that DENSE 1 model also has a very low score, the reason for that would be the window size used. DENSE models are neural networks that are very good at fitting the models with sufficient number of neurons, but the model suffers from overfitting the training data and is very susceptible to noisy volatile stock price data.



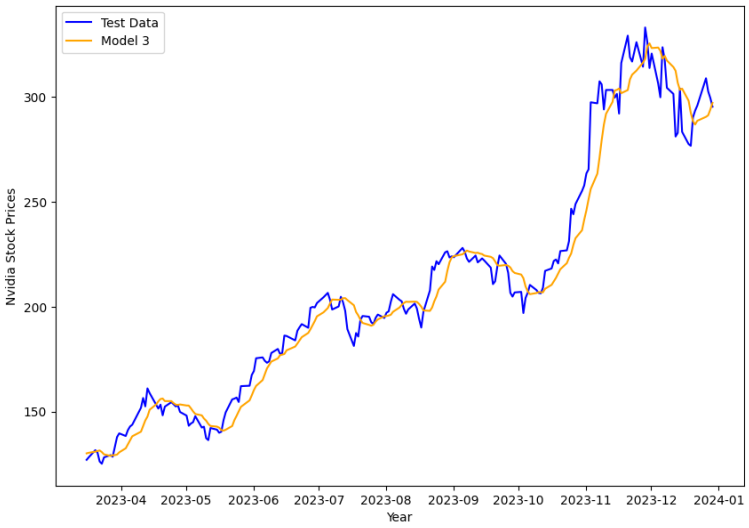


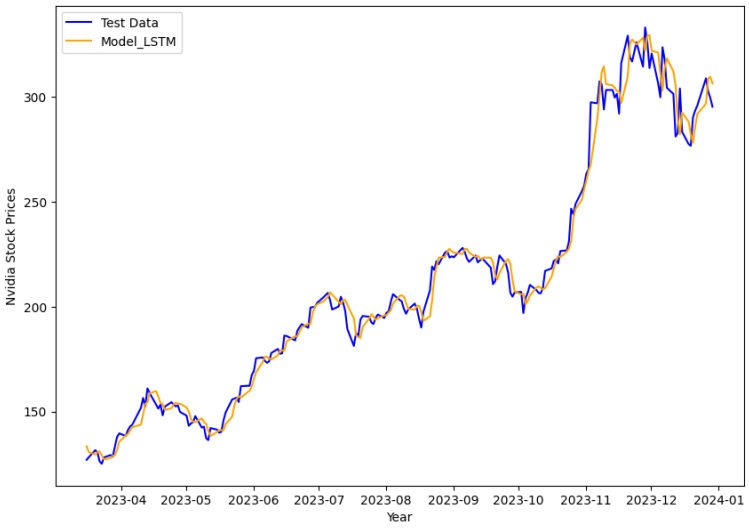
We should also note when DENSE 1 performed on par with LSTM, DENSE 2 performs worse, this can be explained by the window size used in the models for prediction. While DENSE 1 had a window size of 7 with a horizon value of 1, DENSE 2 had window size 60 with horizon = 1. When training neural network models, beginning the training

window too far back in time can make the outcomes more vulnerable to noise, as the testing data increased in size, the result was exposed to more volatility in the data. This is a problem with forecasting with neural networks.

1D-CNN, another neural network, performed worse than DENSE model due to backpropagation and the vanishing gradient problem, due to which the information from the previous layer is lost. 1D-CNN also suffers from sliding window problem, it can only use a fixed predetermined subset of data to make a prediction at each step. Stock prices are non-stationary, meaning their statistical properties change over time, as a sliding window is being trained in a fixed window, that data might not be representative of trends outside the window, thus performing worse.

LSTM's have the ability to filter out noise and are specifically designed to handle sequential data. They can also adjust to new patterns and utilize past information over long sequences, which is critical in stock price prediction.





8 CONCLUSION AND FUTURE WORK

In conclusion, we have explored various machine learning models with the objective of predicting stock prices. The models used include Naïve as a baseline, DENSE models with different window sizes, 1D-CNN, and LSTM, each presenting their own challenges in time series forecasting.

The LSTM model performed best with the least error statistic values, this can be attributed to its ability to adapt to sequential data and remembering past patterns for an extended period. DENSE networks showed varying results based on window sizes, that is predominantly due to the volatile and noisy nature of the dataset.

The findings from this report present us with the importance of choice of machine learning models in forecasting stock prices. In the future we may build more robust networks that can combine strengths of multiple neural networks and implement recognition of external factors in stock price fluctuation.

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