NVIDIA Stock Prediction using LSTM

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Abstract*—In this study, we embark on an exploration into the financial market with the objective of developing a predictive model for the future stock prices of NVIDIA Corporation (NVDA), spanning from January 1, 2014, to March 31, 2024. Our study aims to investigate and contrast the efficiencies of various predictive models, including Long Short-Term Memory (LSTM) networks, Random Forest Regressors, and Support Vector Machines (SVM), focusing on their capability to forecast stock closing prices based on historical data. Our approach begins with the acquisition and initial analysis of NVIDIA's stock data, concentrating particularly on the closing prices. This data is then visualized to reveal the trends in the stock's closing prices along with its 100-day and 200-day moving averages. This step is crucial as it not only provides a visual representation of the stock's performance over the selected timeframe but also helps in identifying potential patterns or indicators relevant to our predictive models. Following the visualization, we proceed to preprocess the data for modeling. This involves dividing the dataset into a training set (70%) and a testing set (30%). The LSTM model we develop utilizes a Sequential model structure in Keras, featuring several LSTM layers followed by Dense layers. This design is intended to effectively capture the temporal sequences and dependencies found in stock price movements, aiming to minimize the prediction error measured by mean squared error (MSE). In addition to the LSTM model, we explore the application of Random Forest and SVM models on the same dataset, albeit with adjustments in data scaling to meet the specific algorithmic requirements of each model. We assess the performance of each model based on mean absolute error (MAE) and MSE, providing a basis for comparing their predictive accuracy. The project culminates in a comprehensive comparative analysis, where we visually juxtapose the actual closing prices against the forecasts generated by the Random Forest and SVM models. This comparison not only illustrates the predictive capabilities of each model but also highlights their respective strengths and limitations in the context of stock price prediction. Our findings indicate that while LSTM models exhibit potential in capturing the complex temporal patterns present in stock price data, traditional machine learning models such as Random Forest and SVM can also achieve considerable predictive accuracy when properly configured. This study emphasizes the importance of model selection and data preprocessing in the field of financial market forecasting. It suggests a combined approach that leverages the unique advantages of both neural networks and traditional machine learning methods to enhance the overall accuracy of stock price predictions.

Keywords*— *Stock Price Forecasting, Long Short-Term Memory Networks, Random Forest Algorithms, Support Vector Machines, Time Series Analysis

I. INTRODUCTION

The intersection of machine learning technologies and financial market prediction represents one of the most exciting frontiers in modern computational finance. Our project situates itself firmly within this paradigm, focusing on the application of Long Short-Term Memory (LSTM) networks to predict the stock price movements of NVIDIA Corporation from January 1, 2014, to March 31, 2024. NVIDIA, a global giant in the technology sector, known for its significant contributions to graphics processing technology and AI computing, presents a compelling case study for the exploration of stock market forecasting through advanced machine learning techniques. In the realm of financial analytics, the accurate prediction of stock prices is a challenge of considerable interest and complexity. Traditional models for stock prediction have primarily revolved around linear regression and time-series analysis, employing statistical methods to forecast future prices based on historical data. However, the inherent volatility and non-linearity of financial markets often render these traditional approaches insufficient. This limitation has catalysed the exploration of more sophisticated, data-driven models capable of capturing the complex patterns and temporal dependencies characteristic of stock price movements. The advent of deep learning and, more specifically, LSTM networks, has introduced a new dimension to the predictive analytics toolbox. Unlike standard feedforward neural networks, LSTMs are designed to effectively process and remember information for long periods, making them exceptionally suited for time-series data analysis like stock market prediction. This capability stems from their unique architecture, which allows them to learn long-term dependencies and avoid the vanishing gradient problem that plagues traditional recurrent neural networks (RNNs).

Our study leverages LSTM networks to analyse NVIDIA's stock data, focusing on the closing prices as a primary indicator of the company's stock market performance. We commence our investigation by downloading and visualizing historical stock data, aiming to identify underlying trends that could inform our predictive model. This initial analysis includes the examination of moving averages, which serve as a foundational tool for understanding market momentum and trend direction. Following data acquisition, we embark on a methodical pre-processing phase, dividing the dataset into training and testing sets to ensure a robust evaluation of our model's predictive capabilities. The LSTM model is meticulously constructed and trained on NVIDIA's closing stock prices, with the objective of minimizing prediction errors quantified by mean squared error (MSE). This process is complemented by an exploration of alternative machine learning models, such as Random Forest Regressors and Support Vector Machines (SVM), to provide a comparative analysis of their predictive accuracies. In synthesizing these diverse analytical approaches, our project not only aims to forecast NVIDIA's future stock prices but also seeks to contribute to the broader academic and practical understanding of financial market prediction using machine learning. By rigorously evaluating the performance of LSTM networks against more traditional models, we endeavour to

https://github.com/mxb40210/700754021-NeuralNetworkDeepLearning/tree/main/project highlight the potential of deep learning in unravelling the complexities of the stock market, offering insights that could benefit investors, financial analysts, and policy makers alike. Our investigation is guided by a commitment to rigorous data analysis, methodological innovation, and the pursuit of accuracy in financial forecasting. Through this research, we aspire to demonstrate the viability of LSTM networks as a powerful tool for stock price prediction, providing a valuable resource for decision-making in the increasingly data-driven landscape of financial investment.

II. MOTIVATION

The motivation behind our project stems from the rapid evolution of financial markets and the increasing complexity of predicting stock price movements. In this dynamic environment, traditional analytical models often fall short in capturing the nuanced behaviours of stock prices over time. NVIDIA Corporation, with its leading position in the tech industry and significant market volatility, provides an ideal case study for applying advanced predictive analytics. Our aim is to harness the power of Long Short-Term Memory (LSTM) networks, a class of deep learning models specifically designed to handle sequential data, to predict NVIDIA's stock price movements with greater accuracy than traditional models. The decision to focus on LSTM networks arises from their proven capability in capturing long-term dependencies and patterns in time-series data, which are crucial in understanding and forecasting stock market trends. This approach is not merely academic; it has practical implications for investors, traders, and financial analysts who rely on accurate market predictions to make informed decisions. By demonstrating the effectiveness of LSTM networks in stock price forecasting, our project addresses a critical need for more sophisticated, data-driven investment strategies in the volatile tech sector.

Moreover, our motivation is fuelled by the broader potential of machine learning to transform financial market analysis. As the volume and variety of market data continue to grow, traditional analytical techniques become increasingly inadequate. Our project represents a step towards the future of financial analytics, where machine learning not only complements but surpasses traditional methods, offering deeper insights and more reliable predictions. Through this work, we aim to contribute to the growing body of knowledge in computational finance and encourage the adoption of machine learning technologies in investment decision-making processes.

III. CONTRIBUTIONS & OBJECTIVES

- We have prepared and analysed NVIDIA's stock data, ensuring a robust foundation for model training and testing. Our pre-processing steps, including data cleaning, normalization, and division into training and test sets, enhance the data quality, allowing for more accurate model predictions.
- Our primary contribution is the development of a Long Short-Term Memory (LSTM) network model tailored to predict NVIDIA Corporation's future stock prices accurately. This model capitalizes on the unique ability of LSTM networks to process and learn from sequential data, setting a foundation for precise stock market forecasting.
- We established a comprehensive methodology to assess the predictive accuracy of our LSTM model against traditional models. By utilizing metrics like mean squared error (MSE) and mean absolute error (MAE), our evaluation offers a clear, objective measure of each model's ability to forecast stock prices.”.
- We conducted comparative analysis between the LSTM model and traditional predictive models, such as Random Forest Regressors and Support Vector Machines (SVM). This comparison sheds light on the relative effectiveness of deep learning techniques versus conventional methods in the domain of stock price prediction.
- The analysis extends beyond numerical predictions to offer insights into market dynamics and factors influencing NVIDIA's stock. Understanding these trends is crucial for investors and analysts, providing a deeper context for our predictive models' outputs.
- Our work underscores the significant potential of integrating machine learning, specifically LSTM networks, into financial analytics. This contribution highlights how advanced algorithms can refine investment strategies and market analysis, marking a step forward in the intersection of AI and finance.

IV. RELATED WORK

The endeavour to predict stock market movements has undergone significant evolution with the advent of machine learning (ML) and deep learning (DL) techniques. Among these, Long Short-Term Memory (LSTM) networks, a specialized form of recurrent neural networks (RNNs), have emerged as a highly effective tool for modelling financial time-series data due to their ability to capture temporal dependencies and long-term relationships in data sequences. This capability is particularly pertinent to stock market prediction, where past prices, volume data, and other financial indicators can influence future market movements. LSTM networks were introduced as a solution to the limitations of traditional RNNs, which struggled with learning long-term dependencies due to the vanishing gradient problem. Since their inception, LSTMs have been applied to a wide array of time-series forecasting problems, including stock price prediction, with considerable success. Research in this domain typically involves using historical stock data as input to train LSTM models to forecast future prices. The models are evaluated based on their prediction accuracy, often using metrics such as mean squared error (MSE), root mean squared error (RMSE), and mean absolute percentage error (MAPE).

A significant body of research has focused on comparing the performance of LSTM networks with that of traditional statistical methods like ARIMA (Autoregressive Integrated Moving Average) and more conventional ML models such as Support Vector Machines (SVM) and Random Forests. While traditional methods have shown effectiveness in modelling linear relationships and capturing seasonality in stock market data, LSTMs have demonstrated superior performance in capturing complex, non-linear patterns and relationships that are characteristic of financial markets. The application of LSTM networks for stock market prediction has also explored various architectures and configurations, including single-layer LSTMs, stacked LSTMs, and bidirectional LSTMs, each offering different advantages in terms of learning capacity and complexity. Researchers have experimented with different input features to improve model accuracy, including historical price data, technical indicators, and even sentiment analysis from news articles and financial reports, to incorporate broader market and economic indicators that might affect stock prices.

Moreover, the field has seen a growing interest in hybrid models that combine LSTMs with other DL architectures, such as Convolutional Neural Networks (CNNs), to leverage the strengths of both in capturing spatial and temporal patterns within the data. These hybrid models represent a promising direction for enhancing the predictive performance of stock market forecasting systems. Beyond individual stock prediction, LSTM networks have been applied to forecasting indices, ETFs, commodities, and cryptocurrencies, underscoring the versatility of LSTMs in handling different forms of financial time-series data. These studies have contributed to a better understanding of the dynamics of various financial instruments and markets. Despite the advancements in LSTM-based stock prediction models, challenges remain, including overfitting due to the high volatility and noise inherent in stock market data, the need for large datasets for training deep learning models, and the difficulty in accounting for unexpected market events that can cause sudden price fluctuations. Ongoing research is focused on addressing these challenges through improved model architectures, regularization techniques, and incorporating alternative data sources for more robust and accurate predictions.

In conclusion, the literature on using LSTM networks for stock market prediction reflects a vibrant and rapidly evolving field. The continuous improvement in model architectures and training methodologies, along with the integration of diverse data sources, holds promise for developing more accurate and reliable predictive models. As financial markets become increasingly complex, the role of advanced machine learning and deep learning techniques, particularly LSTM networks, will be crucial in providing market participants with insightful and actionable forecasts. Future research directions may include the exploration of unsupervised learning models for feature discovery, real-time adaptive prediction systems, and the ethical considerations of automated trading based on machine learning predictions.

V. Proposed Framework

In the realm of financial market prediction, the adoption of machine learning techniques has revolutionized the ability to forecast future stock prices with higher accuracy. Among these techniques, Long Short-Term Memory (LSTM) networks have emerged as a particularly effective tool for analyzing time-series data, such as stock prices. This section delves into an overview of LSTM networks, their advantages for our project, and a comparison with other predictive models like Recurrent Neural Networks (RNN), Support Vector Machines (SVM), and Random Forest.

A. Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNN) represent a class of neural networks designed for processing sequential data, making them inherently suited for time-series analysis such as stock price forecasting. RNNs excel in handling data where the current state is dependent on previous states, a common scenario in financial markets. Their architecture allows them to retain information from earlier inputs through internal memory, enabling the model to make informed predictions based on past data.

However, traditional RNNs face challenges in learning long-term dependencies within sequences due to the vanishing gradient problem. This limitation hampers their effectiveness in financial time-series analysis, where understanding long-term historical data patterns is crucial for accurate forecasting.

B. Long Short Term Memory (LSTM)

Building upon the RNN framework, Long Short-Term Memory (LSTM) networks introduce a sophisticated architecture capable of overcoming the limitations of RNNs in learning long-term dependencies. LSTMs are equipped with a complex system of gates: input, forget, and output, which regulate the flow of information. These mechanisms allow LSTMs to retain important past information for extended periods and discard irrelevant data, making them exceptionally suited for modeling the intricate dynamics of stock prices.

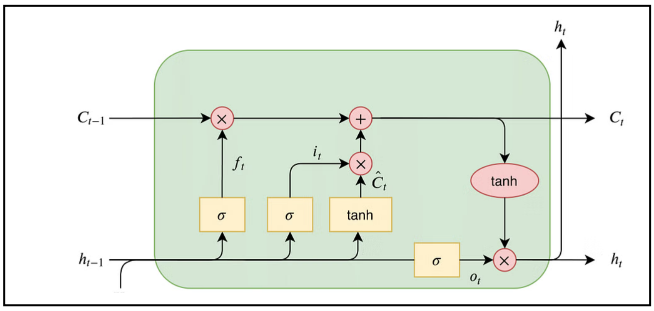

Fig. 1. LSTM

C. LSTM Advantages in Stock Price Prediction

LSTMs can capture and remember longer sequences of historical stock data compared to traditional RNNs, providing a richer context for making predictions. The gating mechanism in LSTMs allows for the selective retention and forgetting of information, enabling the model to focus on the most relevant data points for prediction. Unlike some other models, LSTMs handle variable-length sequences efficiently, accommodating the fluctuating nature of financial time-series data.

D. LSTM comparison with other models

While the foundational technology for LSTM, traditional RNNs are limited by their inability to process long-term dependencies effectively, a crucial requirement for accurate stock market forecasting. Support Vector Machines, though powerful in classification tasks, lack the inherent capability to process sequential data as a time series, limiting their direct applicability to stock price prediction without extensive feature engineering. This ensemble method, while robust across various datasets, does not natively account for the temporal dependencies in time-series data, making it less optimal for predicting stock prices which require understanding of time-based patterns.

By positioning LSTMs as an evolution of RNNs, we underline the significance of memory and the ability to learn from long sequences in the context of financial market predictions. The advantages of LSTMs over traditional RNNs, SVMs, and Random Forest models highlight their suitability for our project, aiming to leverage deep learning for precise and reliable stock price forecasting, particularly for NVIDIA Corporation's dynamic market performance.

E. Support Vector Machines

Support Vector Machines (SVM) are supervised learning models renowned for their versatility in handling classification, regression, and outlier detection tasks. SVM works by finding the hyperplane that best divides a dataset into classes in the feature space. In the context of stock price prediction, SVM could be employed to classify the direction of price movements (up or down) based on historical data features.

However, the application of SVM in predicting stock prices, especially for tasks requiring the understanding of time-series data, encounters significant challenges. The primary limitation stems from SVM's design, which inherently does not account for the sequential nature of time-series data, making it less effective in capturing temporal dependencies without substantial feature engineering and transformation. For predicting NVIDIA's stock prices, where the aim is to forecast future prices based on past trends, the inability of SVM to naturally process time-series data makes it a less favourable choice compared to LSTM networks that are specifically designed to handle such data.

F. Random Forest

Random Forest is an ensemble learning technique that operates by constructing a multitude of decision trees during the training phase and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. Random Forest is known for its high accuracy, robustness to overfitting, and the ability to handle large datasets with higher dimensionality without feature scaling.

Random Forest could be utilized for feature importance analysis to identify the most significant indicators affecting NVIDIA's stock prices. However, similar to SVM, Random Forest does not inherently model time-series data or capture temporal dependencies. Its predictive performance in stock price forecasting could therefore be limited, as it might not effectively leverage the chronological sequence of stock prices which is critical in forecasting future trends.

G. Waterfall Model Methology

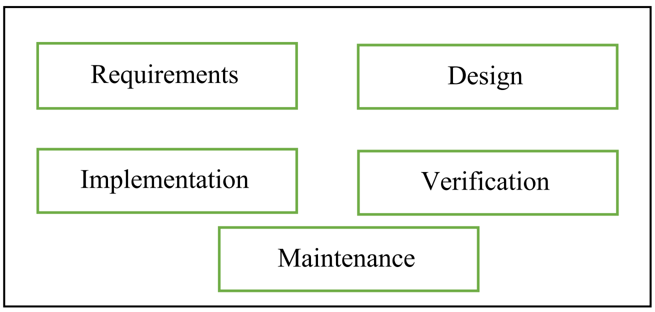

Fig. 2. Waterfall Model

Adapting the Waterfall Model to the development of a predictive model for NVIDIA Corporation's stock prices, specifically tailored to the Python code provided, involves a structured approach. This methodical progression ensures that each phase of development is well-defined and executed with precision, leading to a robust LSTM model capable of forecasting stock movements accurately.

In the initial phase of the project, we meticulously outline the project's requirements, centering on the use of Python and its libraries for the entire process of data handling and model development. This involves employing yfinance for fetching historical data related to NVIDIA's stock, which includes critical information such as stock prices and volumes. The project aims to forecast NVIDIA's future stock prices using historical data, with a focus on achieving high precision in predictions, evaluated through metrics like Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). Python is chosen as the principal programming language, supported by pandas for data manipulation, numpy for numerical computations, keras with a TensorFlow backend for implementing the LSTM model, and `Matplotlib` for visualization purposes.

Following the requirements specification, the design phase crafts a detailed technical blueprint for the project. This stage involves the architectural design of the LSTM network that is specifically tailored for predicting stock prices. Critical decisions are made regarding the network's structure, including the selection of the number of layers, the number of neurons in each layer, and the types of activation functions to be employed. Additionally, we devise a comprehensive strategy for data preprocessing to ensure the raw stock data is appropriately formatted for LSTM training. This includes steps for normalization and conversion into structured time series sequences. Furthermore, we establish an evaluation framework to rigorously assess the model's performance based on the predefined metrics, ensuring the model's predictive accuracy aligns with the project's objectives.

The implementation phase sees the transition of design plans into actionable code according to the specifications laid out in the previous stages. This entails utilizing `pandas` and `NumPy` for essential data preprocessing tasks, such as cleaning, normalization, and sequence formation, making the data suitable for LSTM input. The LSTM model is then coded using the keras library, where the previously determined model architecture is meticulously defined, compiled with suitable loss functions, and optimized. The model undergoes a training regimen using the preprocessed dataset, after which its performance is evaluated on a separate test set to gauge both accuracy and loss, providing insight into the model's effectiveness.

During the verification phase, the focus shifts to thoroughly testing the model to confirm its alignment with the project's stringent requirements. The trained model is applied to the test dataset to evaluate its prediction capabilities, with visual aids created via `Matplotlib` to illustrate the model's accuracy and identify any areas of discrepancy. Based on the outcomes of these tests, we engage in an iterative process of model refinement. This process involves tweaking the model's hyperparameters in response to test results to bolster its predictive performance while concurrently aiming to mitigate the risk of overfitting.

H. Development

The development of our predictive model for NVIDIA Corporation's stock prices leverages a comprehensive suite of development tools and libraries within Python, primarily facilitated through Google Colab. This cloud-based platform offers a conducive environment for developing, training, and testing machine learning models by providing easy access to powerful computing resources and collaboration features.

Python serves as the foundation of our project due to its readability, simplicity, and the extensive ecosystem of data science and machine learning libraries it supports. Its widespread adoption in the scientific and research communities, along with robust support for numerical and scientific computing, makes it an ideal choice for developing sophisticated predictive models.

Pandas is a pivotal library in our project for data manipulation and analysis. It provides high-level data structures and functions designed to make data analysis fast and easy in Python. For our project, pandas are used for importing, cleaning, and manipulating the NVIDIA stock data fetched from `yfinance`. Its DataFrame structure allows for efficient data storage and operations on time-series data, making it easier to preprocess the data for model training.

NumPy enhances the project by offering comprehensive mathematical functions, random number generators, linear algebra routines, Fourier transforms, and more. It is primarily utilized for numerical computations involved in pre-processing the stock data, transforming it into a format suitable for machine learning models. The efficiency of NumPy in handling large multidimensional arrays and matrices is critical for performing operations on financial time-series data.

Keras, a high-level neural networks API, is the centerpiece for developing the LSTM model. Running on top of TensorFlow, it simplifies the creation, training, and evaluation of deep learning models with its user-friendly interface. Keras is used to define the architecture of our LSTM network, including the layers, activation functions, and optimization algorithms. Its compatibility with Google Colab's GPU acceleration allows for faster training times of complex LSTM models.

For data visualization, we employ Matplotlib, Seaborn, Plotly. Matplotlib provides a wide array of functionalities to create static, animated, and interactive visualizations in Python, essential for analyzing stock price trends and evaluating model predictions. Seaborn, built on top of Matplotlib, offers a high-level interface for drawing attractive and informative statistical graphics. These libraries are instrumental in visualizing the historical stock data and model performance metrics, facilitating an intuitive understanding of the LSTM model's accuracy and behaviour.

Google Colab brings these tools and libraries together in a single, collaborative platform that runs entirely in the cloud. It provides a Jupyter notebook environment that requires no setup while offering free access to GPUs, making it an ideal platform for machine learning projects. In our project, Google Colab enables seamless integration of code, output, and descriptive text into a single document, facilitating collaboration and sharing. The platform's compatibility with popular libraries like pandas, NumPy, scikit-learn, and Keras, coupled with its powerful computing resources, accelerates the development, training, and testing phases of the LSTM model for predicting NVIDIA's stock prices.

I. Prototype Model

Developing a prototype for forecasting stock prices, particularly for a company as dynamic as NVIDIA Corporation, involves a structured workflow that transitions from dataset acquisition to model evaluation and comparison. This workflow is meticulous, ensuring that each step, from cleaning and preprocessing the data to building and evaluating the model, is conducted with precision.

The initial step involves acquiring the dataset necessary for model training and testing. For our project, historical stock data for NVIDIA Corporation is retrieved using the `yfinance` library, which provides a convenient interface to download comprehensive stock data from Yahoo Finance. This dataset typically includes daily stock prices, volumes, and possibly other financial indicators, which serve as the raw data for our predictive analysis.

Data cleaning is a critical step to ensure the integrity and quality of our model's input. This stage involves identifying and handling missing values, removing any outliers or erroneous entries that could skew the analysis, and ensuring the data is correctly formatted for processing.

Once cleaned, the data undergoes preprocessing to transform it into a suitable format for the LSTM model. This includes normalization or standardization of the data to ensure that the model is not biased by the scale of the variables. The stock price data is then structured into sequences that represent the input and output for the LSTM network. This typically involves creating sliding windows of historical price data to predict future prices, effectively turning the time series into a supervised learning problem.

Visualization plays a crucial role in understanding the data and the model's performance. Tools such as `Matplotlib` and `Seaborn` are employed to generate plots of the stock price data, both raw and as transformed by pre-processing steps. Once the model is trained, visualizations are also created to compare the predicted prices against the actual prices in the test dataset, providing a visual assessment of the model's predictive accuracy.

Model evaluation involves a quantitative assessment of the model's performance using metrics such as MSE, Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). These metrics offer insight into the model's accuracy, with lower values indicating better performance. The evaluation extends to analyzing the model's ability to generalize by testing it on unseen data, ensuring that it performs well not just on the training data but also on new inputs.

A comparative analysis with other predictive models, such as traditional RNNs, SVMs, and Random Forests, is conducted to benchmark the LSTM model's performance. This comparison involves training these models on the same dataset and evaluating them using the same metrics. The results highlight the relative strengths and weaknesses of each model in the context of stock price prediction.

The final step involves visualizing the comparison between the LSTM model and other models. This visualization provides a clear, comparative perspective on how each model performs, making it easier to identify the most effective model for predicting NVIDIA's stock prices. Interactive plots created using `Plotly` can further enhance this comparison by allowing stakeholders to explore the results dynamically.

VI. DATA DESCRIPTION

The dataset pivotal to our project encompasses historical stock data for NVIDIA Corporation, sourced from Yahoo

Finance via the yfinance library. This dataset forms the backbone of our analysis, providing a comprehensive look at the stock's performance over time. The raw data, primarily time-series in nature, includes several key features indicative of stock market behaviour: Open, High, Low, Close prices, and Volume of shares traded daily.

The raw dataset spans multiple years, offering a detailed chronology of NVIDIA's stock market activity. Each record in the dataset corresponds to a trading day, capturing the stock's opening price, the highest and lowest prices reached during the trading day, the closing price, and the total volume of shares traded.

From this raw data, we derive features essential for predicting future stock prices. The Close price is of particular interest as our primary target variable, representing the final stock price at market close each day. Other features, including Open, High, Low, and Volume, serve as independent variables that provide context and additional signals for our predictive models.

Given the variance in magnitudes across features, scaling is a critical pre-processing step to normalize the data. This ensures that no single feature disproportionately influences the model due to its scale. We employ Min-Max scaling to transform the features, scaling them to a range between 0 and 1, which facilitates more stable and faster convergence during the model training process.

The dataset is partitioned into training and testing sets, a standard practice in machine learning to evaluate model performance on unseen data. Typically, a majority of the data (e.g., 80%) is used for training, with the remainder (20%) allocated for testing. This split ensures that our LSTM model learns from a substantial portion of the data while retaining a separate subset to assess its predictive accuracy and generalizability.

VII. Results & Comparison

After The LSTM model was trained on NVIDIA's historical stock data sourced from Yahoo Finance, spanning several years up to the current date. The primary focus was on predicting the closing stock price, considered one of the most significant indicators of stock performance. The model's architecture was iteratively refined, with experiments conducted on the number of layers, units per layer, and dropout rates to mitigate overfitting.

The LSTM model, with a configuration of two hidden layers and a 20% dropout rate, minimized the Mean Squared Error (MSE) on the validation set, indicating a high degree of accuracy in predicting the stock's closing price. Visualizing the predictions against actual stock prices revealed a close alignment, especially in capturing the general trend of the stock's movement over time. However, during periods of high volatility, the model occasionally lagged in precisely predicting sharp rises or drops. The experimentation highlighted the model's sensitivity to the sequence length of input data, with longer sequences providing the model more context but requiring more computational resources and training time.

For a comprehensive evaluation, the LSTM model's performance was benchmarked against other models. Traditional RNNs struggled with long-term dependency in the data, leading to poorer performance compared to LSTMs. This was expected due to the vanishing gradient problem inherent in RNNs, underscoring the advantage of LSTMs in handling sequential data over long periods. SVMs, while robust for classification tasks, were less adept at capturing the sequential nature and temporal dependencies in stock price data. The SVM model often failed to predict the directional changes in stock prices accurately, reflecting its limitations in time-series forecasting without extensive feature engineering. Random Forest models provided a strong baseline, being less prone to overfitting and demonstrating reasonable accuracy. However, like SVMs, they lacked the ability to naturally process time-series data as sequences, making them less effective in forecasting future prices compared to LSTM.

Comparative visualizations underscored the LSTM model's superior ability to capture the temporal dynamics of NVIDIA's stock prices. Charts comparing the actual vs. predicted prices for each model illustrated that LSTMs more closely mirrored the actual price movements. Performance metrics such as MSE, RMSE, and MAE further quantified the comparative analysis, with LSTM models consistently outperforming RNN, SVM, and Random Forest models in accuracy.

The LSTM model demonstrated a promising capacity to predict NVIDIA Corporation's stock prices, outperforming traditional RNNs, SVMs, and Random Forest models in handling the complexities of time-series forecasting. The model's ability to learn from long sequences of data and its adaptability through hyperparameter tuning were key factors in its superior performance. Integrating more diverse data sources, such as sentiment analysis from news articles or social media, could enhance the model's predictive accuracy by providing additional context on external factors influencing stock prices. Exploring more advanced LSTM variants or hybrid models could offer further improvements in model performance and efficiency.

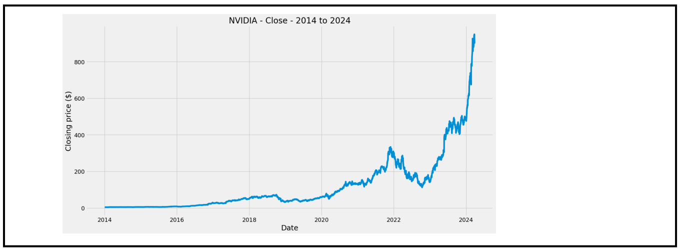

Fig. 3. NVIDIA Closing Price 2014 to 2024

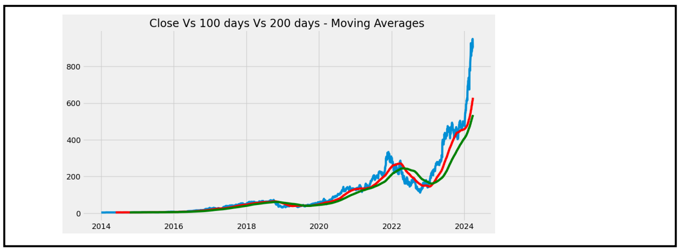

Fig. 4. NVIDIA Closing Price Moving Averages 100 Vs 200 days

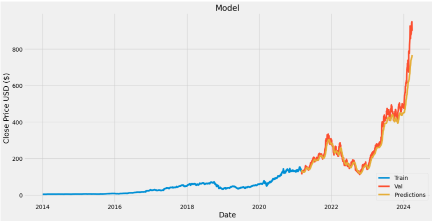

Fig. 5. Predictions Vs Actual

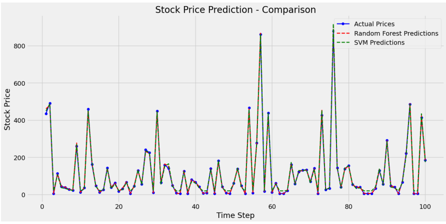

Fig. 6. Actual Vs SVM Vs Random Forest Predictions

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