STOCK PRICE PREDICTION USING LSTM AND DEEP LEARNING TECHNOLOGY

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Abstract— Forecasting stock market trends involves assessing a company's long-term stock value, analyzing current prices, and employing advanced neural networks. Among these networks, the Long Short-Term Memory (LSTM) network, a type of recurrent neural network (RNN), is preferred for its ability to retain contextual information over time. In this model, each training input (x) encapsulates the previous 60 days' values, enhancing accuracy for the current y data. This approach surpasses traditional algorithms through meticulous training and evaluation across varied dataset sizes, systematically recording results. Stock value prediction is inherently complex due to interconnected market dynamics. The proposed algorithm harnesses market data by employing LSTM-based recurrent neural networks. Utilizing Stochastic Gradient Descent adjusts weights for each data point, refining the model for precise predictions. Benchmarked against existing algorithms, the system demonstrates superior accuracy, undergoing comprehensive training and evaluation with diverse datasets and presenting insightful graphical representations. By integrating innovative approaches, this method enhances prediction accuracy and outperforms contemporary algorithms. Such a methodology holds promise in the dynamic landscape of stock market forecasting, providing a robust solution for investors seeking reliable predictions in an ever-changing market environment.

KEYWORDS: Machine Learning, Share Price Prediction, LSTM Networks, Stock Market Trends, Neural Networks, NSE, Financial News Analysis, AI-Based Forecasting.

Introduction

The daily fluctuation in a company's stock price is intricately linked to its exchanges involving products and raw materials. Shares are offered by a company as a means to bolster its production capacity. However, forecasting the share value is a complex task, given the multitude of factors influencing it. Investors strategically allocate their funds in the hopes of yielding profits. This challenge prompts us to leverage technology for precise predictions. The dynamic landscape of technology offers a myriad of tools for constructing a machine-learning model. Amidst the daily stock market activities, four crucial values—high, low, open, and close— define the market performance. Harnessing historical data becomes imperative to discern patterns for predicting whether the company's share value will ascend or descend by the day's end. Numerous machine learning algorithms exist for this purpose, but in the realm of time series forecasting, Support Vector Machines (SVM) and Recurrent Neural Networks (RNN) emerge as promising contenders. SVM and LSTM (a specific type of RNN) exhibit unique functionalities tailored to the nuances of time series forecasting. The pursuit is to implement these algorithms and refine their accuracy.

Employing LSTM involves creating a model that is trained on past data to predict the future performance of seven distinct companies. Subsequently, a thorough analysis of the outcomes obtained from these predictions is conducted. However, it is crucial to acknowledge that predicting stock values encounters challenges, particularly when external factors, often referred to as new features, come into play. Instances where predictions deviate from actual outcomes typically occur when companies introduce new initiatives or political events exert unforeseen influences. The model, in its current form, incorporates solely historical stock datasets. Through this approach, we focus on discerning and understanding the intricate patterns embedded within the sequences of stock market data.

Related Work

In the realm of stock market prediction systems, researchers have conducted an exploration of existing literature spanning the past two decades. Initially, the emphasis lay on identifying linear relationships between macroeconomic factors and stock returns. However, as nonlinear trends in stock market returns gained recognition, there has been a notable shift towards nonlinear prediction models. Many studies in this area have required specifying the nonlinear model before estimation, given the noisy, uncertain, and nonlinear nature of stock returns. Various functions, including binary threshold, linear threshold, hyperbolic sigmoid, and Brownian models, have been employed for predicting parameters.

The integration of machine learning techniques into stock market trend prediction has attracted significant attention. While specific approaches do not consistently produce accurate results, efforts persist in developing strategies for more precise forecasts. Regression techniques like linear regression offer both advantages and limitations, with efficacy depending on the fitting method, whether through least squares or alternative standards. Additionally, there is a growing trend in utilizing AI and awareness frameworks to predict stock prices, aiming to enhance accuracy through diverse methodologies. For instance, one study explores the impact of financial ratios and technical analysis on stock price forecasting using random forests.

Literature Survey:

Previous works have explored stock price prediction using advanced models. Notable studies include the application of LSTM and Bi-Directional LSTM models, Regression and LSTM for forecasting, and the combination of LSTM and ARIMA for trend prediction.

These works emphasize the significance of leveraging sophisticated algorithms for precise predictions.

Objective:

Forecasting stock market movements involves the endeavor to predict the future valuation of a company's stocks or other financial assets traded within the stock exchange. Successfully anticipating the upcoming stock prices through accurate estimation is referred to as achieving a significant yield in profits. This strategic foresight aids in making prudent investment decisions, leading to substantial financial gains.

a) Proposed Approach

In the realm of forecasting stock market trends, our approach focuses on utilizing machine learning, particularly Long Short-Term Memory (LSTM), to predict future stock values accurately. The main goal of this machine learning algorithm is to offer precise predictions for upcoming stock prices. LSTM, known for its sophistication, excels at capturing subtle shifts in stock price behaviors over a defined period. Our proposal introduces a machine learning-based normalization technique tailored specifically for stock price prediction. The dataset selected for this analysis is obtained from Yahoo Finance, comprising approximately 900,000 records encompassing stock prices and pertinent data. Parameters such as date, symbol, open price, close price, low price, high price, and volume are crucial factors to consider. It's important to note that we focused on data from a single company for this analysis. Initially stored in CSV format, the data underwent preprocessing using the Pandas library in Python. Normalization, a critical step in our methodology, was conducted using the sklearn library in Python. Subsequently, the dataset was split into distinct segments: training and testing sets, with the experiment set constituting 20% of the available dataset. Our investigation revolves around two distinct architectures: the Regression-based Model and LSTM. The Regression-based Model is employed for predicting continuous values based on given independent variables, utilizing a specified linear function for predictions. In contrast, the LSTM architecture demonstrates its proficiency in identifying trends and behavioral shifts in our dataset, as evidenced by the results. Following a rigorous evaluation, LSTM emerged as the most effective model for our proposed methodology, highlighting its ability to discern interrelations within the data.In the dynamic landscape of the stock market, consistent cycles or regular patterns may not always prevail. The duration of these trends varies, depending on factors such as specific companies and sectors. For investors aiming for optimal returns, meticulous analysis of trends and cycles becomes imperative. Leveraging networks like LSTM, which heavily rely on current information for comprehensive data analysis, proves to be a strategic choice in this context.

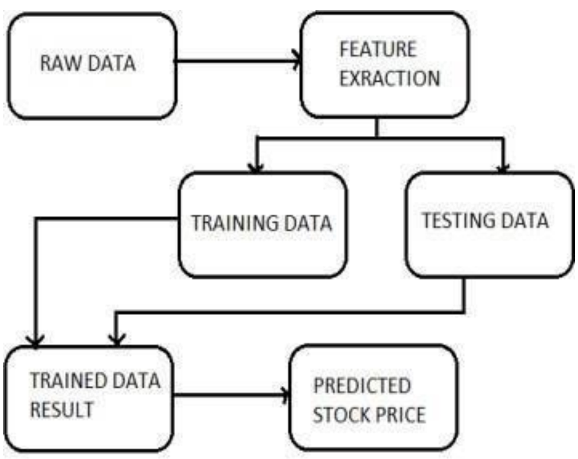


Figure 1: System Architecture

1. Dataset Input Module
The system outlined here comprises five integral modules, with the first being the Dataset Input. Massive datasets, encompassing attributes such as open, high, low, close, and adjusted close prices, serve as the initial input for our predictive models.

2. Preprocessing Module
Moving to the second module, the Preprocessing phase plays a pivotal role. Techniques like normalization and one-hot encoding are skillfully applied to refine and enhance the quality of the dataset, ensuring optimal performance in subsequent stages.

3. Data Splitting Module
The third module involves Data Splitting, where the meticulously preprocessed dataset is divided into two sets—training and testing. This division follows an 80:20 ratio, strategically chosen to train and evaluate the models effectively.

4. Build & Model Training Module (LSTM, CNN, Hybrid LSTM+CNN)
The fourth module is dedicated to constructing and training models. Three distinct approaches—LSTM, CNN, and a hybrid fusion of LSTM and CNN—are employed. Each model is trained on the preprocessed dataset, adapting to the unique characteristics of the input attributes.

5. Output Prediction Module
The final module, Output Prediction, focuses on forecasting attributes such as open, high, low, close, and adjusted close prices. The models, now enriched with insights from the training phase, are utilized to generate predictions for the specified attributes.

LSTM Model Architecture
The figure depicts the architecture of the LSTM model. Long Short- Term Memory, a specialized type of recurrent neural network, excels in addressing the challenge of long-term dependencies. In traditional RNNs, performance diminishes as the temporal gap increases. LSTM, by default, retains information over extended periods, making it particularly suitable for processing, predicting, and classifying time-series data.

Structure of LSTM:
LSTM boasts a chain organization comprising four neural networks and distinct memory blocks known as cells. The critical component is the memory cell, responsible for decision-making regarding information storage, reading, writing, and forgetting. Within the memory cell, three primary gates—Input gate, Forget gate, and Output gate—regulate the flow and utilization of information, ensuring the LSTM's efficiency in capturing temporal dependencies and providing accurate forecasts based on recent data.

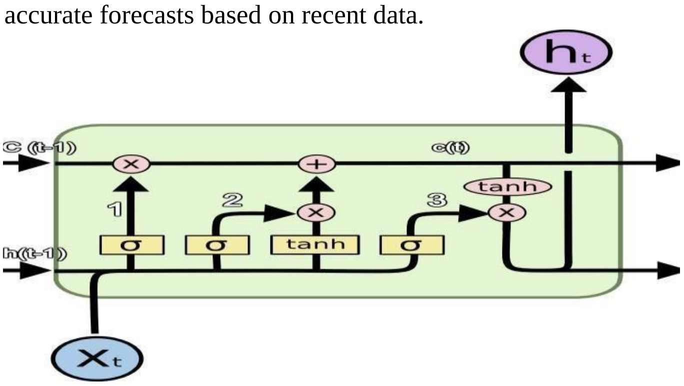


Fig- LSTM model

METHODOLOGY:

In this segment, we'll outline the key stages involved in the research project, covering data procurement, data preparation, specifics regarding the neural network (NN) models utilized, and the assessment criteria.

(i) Data Acquisition:

The information employed for this inquiry. will be sourced from two primary platforms: multpl.com and finance.yahoo.com

(ii) Data Preprocessing:

Data normalization will be conducted using the Python library, sklearn. Feature scaling, a method employed to standardize the range of independent feature variables, will be applied. Subsequently, the data will be partitioned into training and testing sets.

(iii) Details about NN-Based Models:

The data will be utilized to train single-time scale feature models through multiple iterations to predict each variable independently. Traditional models, such as predicting closing prices, will be used as a feature to train a control model. Another model will be trained using prices from multpl.com as a feature. Following evaluation, multiple time scale feature models will be created and trained. The initial step involves training a control model using the optimal features from the standard dataset. These features will be selected through tests for various combinations, comparing their losses. The label for this model will be set to the closing price, and stock prices will be calculated using a specific equation involving earnings per share (EPS) and the price-to-earnings ratio (PE). Subsequently, additional feature models will be trained using EPS, PE, and calculated price as features, with the price as the label. These models will be compared against the control model.

(iv) Evaluation Metrics:

A comparison will be made between traditional models and the proposed multiple feature models. To optimize a standard dropout LSTM model, experimentation with hyperparameters will be conducted. The optimized model will be compared with various LSTM variants.

By detailing each of these steps, the research project aims to provide a comprehensive understanding of the data processing, model training, and evaluation processes involved in predicting stock prices.

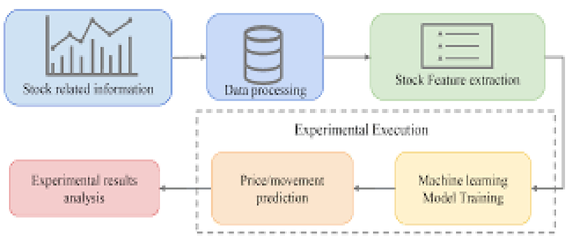
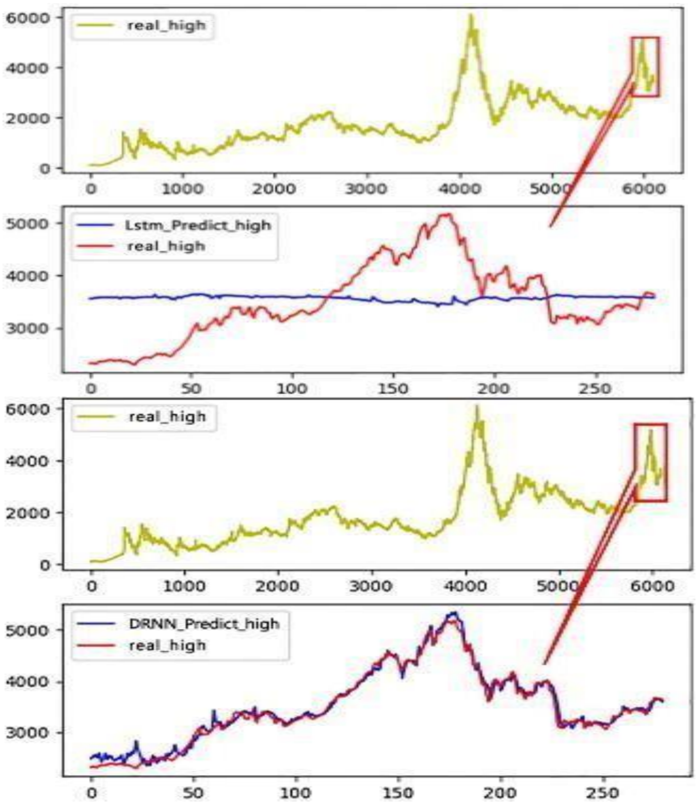


Fig- System Architecture.

Result:



In an investigation using the Shanghai Stock Index training dataset, a comparative analysis was conducted to discern the disparities among the Associated Net, LSTM network, and a Deep Recurrent Neural Network (DRNN). The training phase entailed predicting the highest stock price for the subsequent day separately using LSTM and Associated Net. Notably, as training iterations increased, there was a gradual decrease in the mean square error for all three models. However, both the LSTM network and DRNN exhibited minor fluctuations during this process.

Upon dimensional analysis at identical training intervals, it became apparent that as training iterations progressed, the average mean square error of LSTM consistently outperformed the other two models. However, during the testing phase, LSTM demonstrated the poorest predictive performance and the lowest average accuracy. This discrepancy was attributed to LSTM experiencing overfitting as the number of training iterations increased.

Interestingly, the average mean square error of the Associated Net surpassed that of LSTM. This divergence was rationalized by the inherent complexity of our model, necessitating a greater number of iterations for optimal performance.

Figure: Company Data on Women Employees by Department

Conclusion

The project introduces an innovative approach — an Associated Net, a multi-value associated network model based on LSTM deep-recurrent neural networks. This model aims to predict multiple stock prices simultaneously. The documentation encompasses the model's structure, algorithmic framework, and experimental design. To validate its feasibility and accuracy, the Associated Net is compared with both a traditional LSTM network model and an LSTM deep-recurrent neural network model.

Various datasets were employed to ascertain the applicability of the Associated Net model. Experimental results reveal that the average accuracy of the Associated Net model surpasses that of the other two models. Furthermore, the Associated Net can predict multiple values concurrently, with an average accuracy exceeding 95% for each predicted value. While the model has demonstrated commendable effectiveness, there remains room for improvement.

In conclusion, this research showcases the potential of the Associated Net model in stock price prediction, outperforming traditional LSTM models in terms of accuracy and the ability to forecast multiple values simultaneously. Despite its achievements, certain challenges persist. It's crucial to acknowledge the areas where enhancements can be implemented for even better performance.

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