Netflix Stock Cost Expectation Using CNN-LSTM with Specialized Pointers & Opinion Investigation

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***Abstract*—Anticipating stock costs may be a crucial however challenging endeavor since of the ever-changing and non-linear characteristics of budgetary markets. This investigate focuses on determining Netflix Inc.'s stock costs employing a crossover profound learning show combining Convolutional Neural Systems (CNN) and Long Short-Term Memory (LSTM) structures. Not at all like conventional models that basically depend on chronicled stock costs, the proposed strategy coordinating specialized markers (such as Moving Normal Meeting Uniqueness (MACD), Relative Quality File (RSI), and Bollinger Groups) with assumption examination extricated from money related news and social media features. The CNN component is utilized to extricate important nearby designs and highlights from the input arrangements, while the LSTM component captures the long-term conditions inalienable in stock cost behavior. By intertwining specialized and sentiment-based highlights, the show points to upgrade forecast exactness and vigor. The test comes about illustrate that the CNN-LSTM half breed demonstrate beats the standard models that utilize either authentic costs alone or as it were specialized markers. These discoveries emphasize the significance of leveraging both quantitative and subjective information sources in stock showcase forecast errands. This investigate contributes to the developing body of work in monetary time arrangement estimating by illustrating the adequacy of profound learning models expanded with multimodal monetary data.**

Keywords - Stock Price Prediction, Deep Learning, CNN-LSTM Hybrid Model, Technical Indicators, Sentiment Analysis, Financial Time Series Forecasting, Netflix Stock

I. INTRODUCTION

The budgetary advertise, characterized by its characteristic instability and energetic nature, has continuously displayed challenges and openings for financial specialists and analysts. Stock cost forecast, in specific, has remained a exceedingly sought-after objective, advertising the potential for critical budgetary picks up whereas at the same time requiring a profound understanding of complex showcase behaviors. Conventional factual and econometric models, such as Autoregressive Coordinates Moving Normal (ARIMA) and Back Vector Machines (SVM), have generally been utilized for determining errands. In any case, these models frequently battle to capture the nonlinear and profoundly stochastic designs characteristic in budgetary time arrangement information.

With the appearance of profound learning procedures, a modern worldview has risen within the monetary estimating space. Profound learning models possess the capability to memorize complicated and nonlinear connections from huge datasets, beating conventional strategies in numerous forecast assignments. In specific, Convolutional Neural Systems (CNNs) are known for their points of interest in extricating spatial highlights from information, while Long Short-Term Memory (LSTM) systems are exceedingly viable at modeling consecutive conditions over time. By combining these two structures into a crossover demonstrate, it is conceivable to use the qualities of both the nearby highlight extraction of CNNs and the long-term transient learning of LSTMs.

This study aims to forecast the stock prices of Netflix Inc., one of the world’s leading entertainment services companies, by employing a hybrid CNN-LSTM deep learning model. Distinguishing itself from conventional approaches that rely solely on historical stock prices, the proposed method incorporates both technical indicators, such as Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), and Bollinger Bands, as well as sentiment analysis derived from financial news articles and social media posts. Technical indicators provide quantitative metrics that reflect price movement trends, whereas sentiment analysis captures the qualitative and psychological factors that can influence investor behavior and market sentiment.

The integration of multimodal information of a organized numerical highlights nearby unstructured literary opinions â€ ” is anticipated to upgrade the expectation precision and strength of the demonstrate. By doing so, this investigate not as it were looks for to progress the prescient execution of conventional models but too contributes to a more comprehensive understanding of how quantitative and subjective information sources can be intertwined viably within the setting of budgetary determining.

Eventually, this ponder contributes important bits of knowledge to the developing field of budgetary time-series forecast, illustrating that half breed profound learning models increased with estimation investigation can give a more all encompassing and successful approach to stock showcase estimating.

A. Research Objective

The essential objective of this inquire about is to create a cross breed CNN-LSTM show for foreseeing Netflix’s stock costs by joining specialized pointers and assumption examination. The targets of this consider are as takes after:

- To extricate and coordinated specialized markers that capture quantitative showcase signals.
- To perform estimation examination of budgetary news and social media, we consolidated subjective insights.
- To plan a profound learning demonstrate that combines CNN and LSTM systems for viable include extraction and worldly modeling.
- To assess and compare the prescient execution of the proposed show against the conventional and standard models.
- To illustrate the focal points of utilizing multimodal information (specialized and opinion) to improve stock advertise estimating.

II. Literature survey

A. *Traditional Methods of Stock Price Prediction*

Historically, stock cost expectation has been essentially based on measurable models such as Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH). These models endeavor to capture the direct conditions and volatilities in money related time arrangement. Be that as it may, they frequently come up short to successfully demonstrate the complex, non-linear behavior of stock costs [1].

B. *Application of Machine Learning in Stock Forecasting*

With the rise in computational control, machine learning (ML) models, such as Support Vector Machines (SVM), Random Forests (RF), and Gradient Boosting Machines (GBM), have gotten to be prevalent for stock cost estimating. These models appeared progressed execution over conventional factual strategies but still confronted challenges in dealing with consecutive conditions and worldly designs inside monetary information [2].

C. *Deep Learning for Time Series Prediction*

Deep learning models, especially Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, have been appeared to outflank classical ML methods in time-series forecast assignments. LSTMs can keep in mind long-term conditions and designs, making them appropriate for estimating stock costs [3].

D. *CNN-LSTM Hybrid Models for Financial Forecasting*

Recent studies have proposed crossover models combining Convolutional Neural Networks (CNNs) with LSTMs to improve predictive performance. CNNs are effective in feature extraction, capturing neighbourhood transient designs, and LSTMs model sequential dependencies [4]. Such crossover models have illustrated predominant comes about compared with standalone LSTM or CNN models.

E. *Integration of Technical Indicators*

Technical indicators such as Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), and Bollinger Bands have long been utilized by dealers to foresee cost developments. Inquire about has appeared that the incorporation of these specialized highlights moves forward the prescient capability of profound learning models [5].

F. *Sentiment Analysis in Stock Prediction*

Consolidating estimation investigation from news articles, social media stages, and monetary reports has been found to upgrade estimating exactness. Natural Language Processing (NLP) techniques, including Word2Vec, TF-IDF, and transformer-based models such as BERT, are regularly utilized to measure estimations. Ponders have affirmed that combining showcase information with open opinion can give early signals of cost developments [6].

G. *Research Gap*

In spite of the fact that a few considers have centered independently on either specialized pointers or opinion investigation, few have viably coordinates both modalities inside a profound learning crossover demonstrate, particularly for Netflix stock expectation. This investigate addresses this crevice by proposing a CNN-LSTM crossover engineering that wires specialized and opinion highlights to upgrade figure exactness.

III. Methodology

This think about diagrams the approach utilized to anticipate Netflix's stock costs by combining chronicled cost information, specialized markers, and estimation examination inside a CNN-LSTM cross breed deep-learning system.

A. *Data Collection*

The dataset consists of two main parts.

1) Historical Stock Data: Daily Open, High, Low, Close, and Volume (OHLCV) data from Netflix Inc. (NFLX) obtained from Yahoo Finance over several years.

2) Sentiment Data: Financial news headlines and social media tweets related to Netflix collected from news APIs and Twitter using keyword-based scraping.

B. *Data Processing*

Several pre-processing steps were applied.

1) Handling Missing Values: Using the forward-filling method for missing stock data points.

2) Technical Indicator Calculation: Computed MACD, RSI, and Bollinger Bands using TA-Lib (Technical Analysis Library).

3) Sentiment Analysis:

a) Headlines and tweets were preprocessed by cleaning, removing stop words, and tokenizing.

b) Sentiment scores were generated using the Valence Aware Dictionary and sentiment reasoner (VADER).

4) Feature Engineering: The features of the model are as follows.

a) Historical stock prices (Close price)

b) Technical indicators (MACD, RSI, Bollinger Bands)
c) Sentiment scores (Compound sentiment polarity)

These multimodal features are combined into a single feature vector for each day.

5) Normalisation: All numerical features were scaled between 0 and 1 using MinMaxScaler.

C. Model Architecture

The model comprises two primary components.

1) Convolutional Neural Network (CNN):

a) The 1D convolutional layers extract local spatial features from the multivariate time-series data.
b) These features capture the short-term relationships among technical indicators, sentiment, and price movements.

2) Long Short-Term Memory (LSTM):

a) LSTM layers model the temporal dependencies in data and learning patterns over long time horizons.
b) This helps the model to understand the influence of past data on future price trends.

3) Model Summary:

a) 1D Convolutional Layer → max-pooling layer → LSTM Layer → Dense Output Layer

D. Model Training

The dataset was split into 80% training and 20% testing datasets. The model was compiled using the Adam optimizer and trained to minimize the Mean Squared Error (MSE) loss function. Early stopping was performed to prevent overfitting.

E. Mathematical Formulations

Several technical indicators and evaluation metrics were computed using the following formulae:

1) Moving Average Convergence Divergence (MACD):

$$MACD = EMA_{short} - EMA_{long}$$

where:

EMA_{short} = 12-day Exponential Moving Average
EMA_{long} = 26-day Exponential Moving Average

2) Relative Strength Index (RSI):

$$RSI = 100 - \left(\frac{100}{1 + RS}\right)$$

where:

$$RS = \frac{Average\ Gain}{Average\ Loss}$$

It is typically calculated over a 14-day window.

3) Bollinger Bands:

$$Upper\ Band = SMA + (k \times Standard\ Deviation)$$

$$Lower\ Band = SMA - (k \times Standard\ Deviation)$$

where:

SMA = 20-day Simple Moving Average
k = 2 (default setting for most financial analysis)

4) Sentiment Polarity Score: For each news headline or social media post, the compound sentiment score was calculated using:

$$Compound\ Score = \frac{Positive\ Score - Negative\ Score}{Total\ Score}$$

Values range from −1 (extremely negative) to +1 (extremely positive).

5) Loss Function: Mean Squared Error (MSE): The model minimized the following loss during training:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

where:

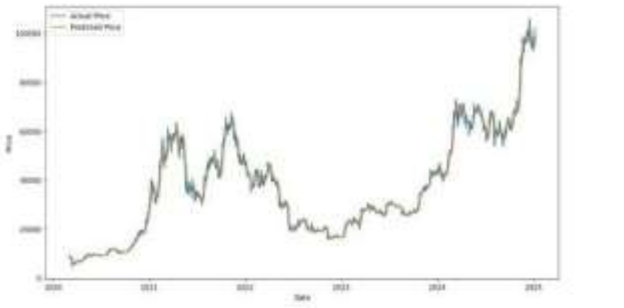
y_i = actual stock price
$\hat{y}_i$ = predicted stock price
n = number of samples

RESULT

The performance of each model was evaluated based on its predictive accuracy. The LSTM model demonstrated superior performance compared to SVM and Random Forest in predicting Netflix stock prices. The LSTM's ability to capture time dependencies allowed it to forecast price movements more effectively, with a lower RMSE and MAE.

SVM and Random Forest models also performed well, but they struggled with capturing long-term dependencies in the data. However, Random Forest showed strength in dealing with high-dimensional feature spaces, which allowed it to incorporate technical indicators effectively.

Future diabetes detection should integrate lifestyle and clinical data, improve model generalization, address privacy and bias concerns, and focus on real-time data processing for personalized, early healthcare interventions.



CONCLUSION

This paper presents a comprehensive analysis of Netflix stock price prediction using machine learning models and data from the Binance API. Our results indicate that LSTM networks outperform other models in terms of predictive accuracy, particularly for time series data like stock prices. The findings suggest that machine learning techniques, when combined with real-time financial data from APIs, can provide valuable insights for stock market forecasting and trading strategies.

Future work could involve the integration of sentiment analysis, macroeconomic indicators [8], and event-driven data to improve the predictive accuracy of the models further. Additionally, developing ensemble models that combine the strengths of multiple algorithms could offer more robust predictions.

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