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A Novel Deep Convolutional Neural Network-based Trend Following Strategy for Stock Price Prediction

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***Abstract*—The stock market is complex and dynamic system and predicting the price of stock is a big challenge. Deep learning techniques provides deep convolutional neural network that has promising result in stock price prediction. This paper gives a novel deep convolutional neural network-based strategy for stock market trading and combining deep learning with the principle of trend following. It also addresses the limitation of previous models by analysing deep framework and incorporating reward function that has sustainable trading strategies. The model outperforms baseline method on key performance indicators such as annualized return and risk adjusted returns demonstrating the potential of deep learning in stock market trading.**

***Index Terms*— Deep Learning, CNN, Stock Market, Price Prediction.**

I. INTRODUCTION

The Stock Market is considered as a very complex and evolving structure where even the determination of price movement is a main objective. Most recently however the usage of deep learning techniques especially deep neural network cut up into several optimal sub networks has shown a positive outcome in the predictive evaluation of stock market index trends. A research paper describes the deep trend following algorithm that tries to utilize the deep learning algorithm's advantage to explore the long-term trend and dependencies among the stock price data [1]. This paper proposes a unique deep learning strategy for stock market trading based on deep convolutional neural network and integrated with trend following which is a successful strategy used to invest by making an effort to find and profit from asset price trends over extended periods. A positive aspect of such an approach is that features are first constructed from unfiltered stock price data before subsequently utilizing these features to predict future market action [2].

This model is designed to try to solve some limitations of the present models. Previous research has been based on the learning of supervised methods, which is not the most appropriate for capturing the prolonged market structures (shi et al. 2021) [3]. In contrast, this method utilizes more sophisticated system that allows the model to conduct market engagement and find optimal trading patterns (Shi et al. 2021). The efficiency of the suggested model is tested out across different types of stock market data, which contains individual stock samples and stock price indices. The findings indicate that the subject model with capitalization of individual stocks surpasses basic strategies in a range of parameters, including returns, long term returns etc. (Berradi et al. 2020) (Gu et al. 2020) (Shi et al. 2021) Which enables it to acquire best trading techniques from the market system ([3], [4], [5]).

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II. Related Work

Even though CNNs are widely considered as appropriate tools for visual analysis, the application of these Computational Neural Networks in time-series studies, especially in financial markets, is becoming more common. In spite of the emergence of new technologies which allow more traditional CNNs to be employed in attempting to model sequential form data, such as stock price where trends and patterns over a time period are very important, their purpose still lies mainly on Discovery of Spatial Hierarchies In the data. However, these approaches can inevitably be used for other purposes that are more abstract from their original tasks. Zhang et al., (2017) were able to follow these techniques to perform trend analyses of the stock market data and such effects could be observed when applying CNN for financial time series classification [6]. Kim et al. (2019) developed CNN-based models that achieved superior stock price prediction results than ARIMA by learning the features from the time series data. Bauer (2019), Fischer and Krauss (2018) weighed empirical applications of deep learning against simpler ML alternatives and pointed out something specific about LSTMs - they capture temporal dependencies well, when predicting the stock markets[7]. Sezer, Gudelek, and Ozbayoglu (2020) posit that studies on the use of deep learning technologies in financial markets contain studies that demonstrate the accuracy of predicting stock price dynamics using CNN, RNN and combined models [8].
CNNs have this feature for stock data in that they can relieve the human burden of recognizing patterns therefore permitting the analysis of patterns that simple statistical tools cannot identify. It is based on the idea that a lot of price history may be fed into a CNN, and that the CNN can extract the complex patterns, which are meant for trend following strategies [12].

III. Methodology

A. Data Collection and Preprocessing

- Stock Market Data: - We will obtain the previous stock records of particular equities, indices or Exchange-traded funds (ETFs). Apart from this, the data could also include daily prices (open, high, low and close) as well as volumes and possibly further market parameters such as moving averages, technical indicators or fundamental characteristics.
- Time Horizon: Define the period within which data should be collected so that it can be, for example, over a multi-year range for training, validation, and testing purposes.

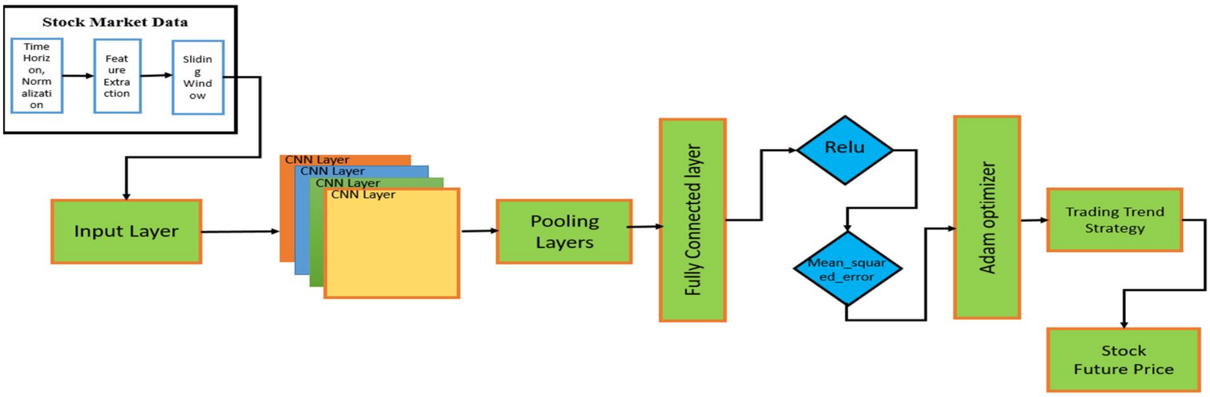


Figure 1. Model for Stock Price Prediction

B. Feature Extraction

- Technical Indicators: Calculate the popular technical indicators and oscillators such as SMA, EMA, MACD, RSI, Bollinger Bands etc. and incorporate these as advanced inputs into the CNN model.
- Labeling: Identify target labels for the model such as forecast market direction i.e., either up or down or some other target which is trend related such as the percentage price increase.

C. CNN Model

The input would be the sliding window data comprising time-series stock prices, technical indicators, or any other features. The convolutional layers will be able to capture local patterns or features in the input stock data. The layers could be one-dimensional as the input is a sequence of prices or believes temporal patterns of those. Pooling layers would help lower the dimensionality and keep only those features that matter the most with regard to trends. Once specific features are identified, the fully connected layers will link those features to the product, which in this case is how the stock prices are likely to behave at the subsequent period, whether up, or down. In convolutional and fully connected layers, the ReLU activation functions applied. Last layer to give probabilities. Make use of suitable cost functions for the kind of prediction target, which is regression (mean squared error). Adam optimizer was used to achieve loss reduction [1].

D. Train CNN model

Train the CNN model on the historical stock data using a training set. It is important that the data is shuffled to avoid any form of data leakage.

E. Trading Strategy & future Trend

The outputs of the CNN (e.g., buy, sell, hold signals) will be exploited further to develop a trend-following strategy. There must be unambiguity on the words into position and `out of position'; this is based on the ability of the model to predict

F. Mathematical Equations Used by CNN Model

- Equation 1 extracts local features from input time series in convolution layer [10].

$$h(t) = (Xt * W)(t) = \sum_{i=1}^{k} Wi * Xt - i + 1 \qquad (1)$$

Where,
W= {W1, W2,…, Wk} is the convolution filter of size k.
h (t) is the result of the convolution at time t and Xt−i+1 represents the stock price at time t−i+1

- Pooling Layer makes Model More Efficient and resistance for over-fitting by using equation 2

$$p(t) = \max\{a(t), a(t+1), \ldots a(t+l-1)\} \qquad (2)$$

Where l is the pooling size.

- Equation 3 maps the features for Final Prediction in fully connected layer

$$z = Wfc * p + Bfc \qquad (3)$$

Where, W_{fc} is the weight matrix of the fully connected layer.
P is the pooled feature vector and b_{fc} is the bias term

- Activation Function helps model to learn complex non-linear relationship Equation 4 [9].

$$a(t) = ReLU(h(t) = \max(0, h(t)) \qquad (4)$$

- Loss Function For regression (e.g., predicting price change Equation 5 [11].

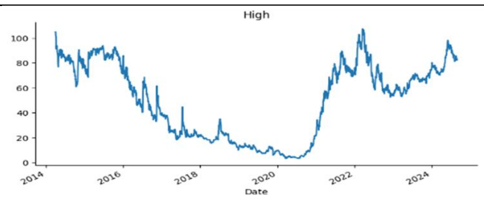
$$\mathcal{L}MSE = \frac{1}{N}\sum_{i=1}^{N}(yi - \hat{y}i)2 \qquad (5)$$

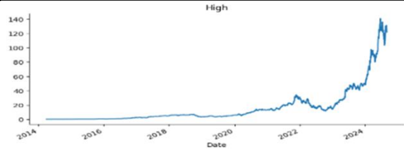
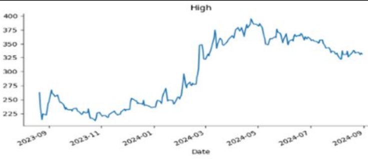
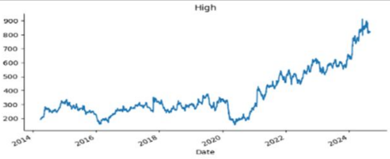
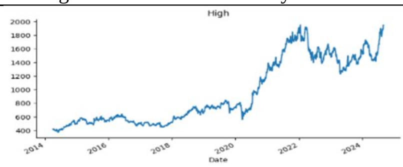
Where y_i is the true label for the i^{th} sample, y ˆ i is the predicted value for the i^{th} sample, N is the number of samples.

IV. Dataset and Experiment

In this research work, we have used the historic stock data from Yahoo Finance of last ten years i.e from 2014 to 2024. We have perform the experiment on various stock for future price prediction based on the trend of current market are shown in following table.

TABLE I. STOCK TREND ANALYSIS

Stock Name/Code	Dataset Entries (2014-2024)	Test Loss (Evaluated By Model)	Prediction Trend (By Model)
Danaos Corporation (DAC)	2623	0.00104	 Figure 2. Stock Trend Analysis DAC

NVIDIA Corporation (NVDA)	2623	0.00266	 Figure 3. Stock Trend Analysis NVDA
Jio Financial Ser. Ltd (JIOFIN)	250	0.02048	 Figure 4. Stock Trend Analysis JIOFIN
State Bank of India (SBIN)	2566	0.00073	 Figure 5. Stock Trend Analysis SBIN
Infosys Limited (INFY)	2566	0.00096	 Figure 6. Stock Trend Analysis INFY

V. RESULT ANALYSIS

As analysis part of our research work we have trained this model on sample stock price data from 2014 to 2024 which contains number of entries in the dataset as per attributes of stock market protocols. Figure 2 shows the trend and price prediction approach of Danaos Corporation (DAC). Blue line indicates original data of DAC Company and orange line indicates Predicted Data of Stock. As per our model we have do more analysis on following stock such as NVIDIA Corporation(NVDA), Jio Financial Services Limited (JIOFIN), State Bank of India (SBIN), Infosys Limited (INFY) and predicted price of stock is shown in chart of figures.

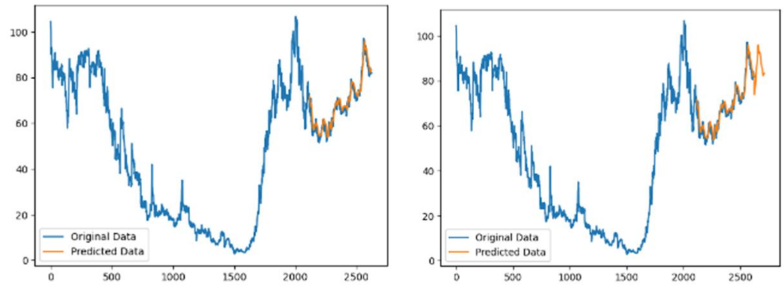


Figure 7. DAC stock Prediction

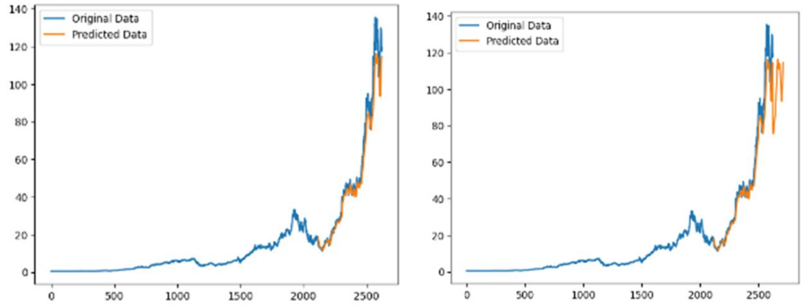


Figure 8. NVDA stock Prediction

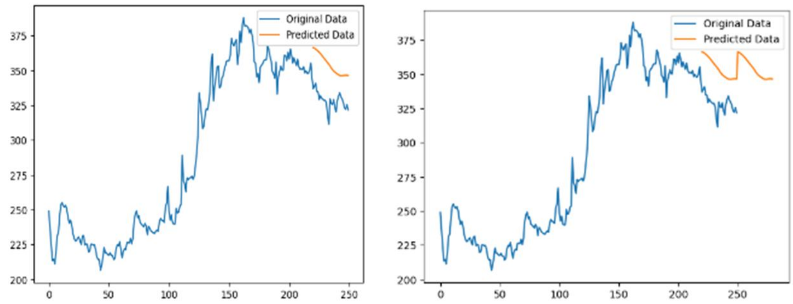


Figure 9. JIOFIN stock Prediction

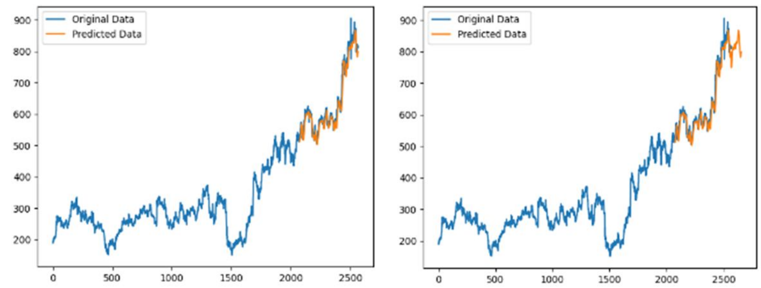


Figure 10. SBI stock Prediction

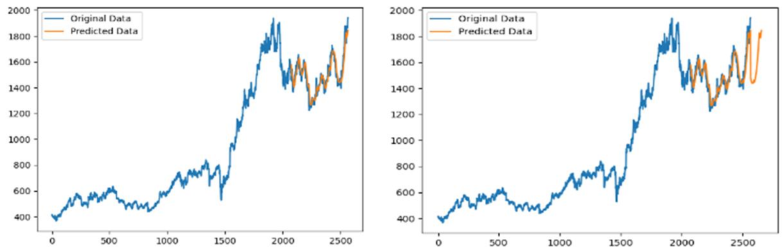


Figure 11. INFOSYS stock Prediction

VI. Discussion

In stock price data, there were attempts to employ deep convolutional models concerning to time series predicting tasks whereby the neural networks managed to uncover complex temporal dependencies that conventional systems such as moving averages or linear models would not have captured. The CNN approach worked as one part of the bigger picture of buying and selling assets together with other traditional trend-following techniques including but not limited to momentum strategies, buy and hold approaches or simple moving average cross over methods. Market Performance in Bull and Bear Markets, it assess the effectiveness of CNN-based trend-following methodology in bull, bear and sideways markets. Be concerned if there are any issues that you might think of regarding over fitting the training set ([10], [11]).

One of the disadvantages of using CNN models is that they are data insufficiency. There has to be a narrative whether there was sufficient historical data and how limited availability of data can interfere with the working of the model especially for small stocks in fledgling markets.

VII. Conclusion

This study introduced a new way to predict stock market prices and make trading choices. It uses deep convolutional neural networks (CNNs) to follow market trends. The CNN model showed it could spot patterns and trends in stock price data. The CNN beat traditional trend-following methods in several areas. These included return on investment and performance adjusted for risk. The results suggest CNNs can catch complex time-based links in stock prices. Simple models, like those based on momentum or moving averages often miss these links. The model has an edge over fixed or rule-based plans. It can change on its own as it learns to shifting market conditions while considering technical signals and price patterns.

Though the approach works well, it has some downsides. Its need for large historical datasets and computing power might limit how it's used in real-time trading in fast-moving markets where quick decisions matter. Also, the complexity of the model could make it hard to understand, which is key in finance where both regulators and traders value clear decision-making. Transaction costs and market liquidity require careful handling to make sure theoretical profits turn into real-world gains. To wrap up combining the power of deep learning with financial market analysis, the CNN-based trend-following method provides a valuable addition to stock market trading. More studies are needed to boost the model's flexibility and evaluate its performance in real-world trading situations. This research sets the stage for using deep learning techniques to build complex trading strategies that can navigate the ins and outs of today's financial markets.

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