A CRITICAL ANALYSIS OF ENSEMBLE CNN AND DNN IN INDEX PRICE PREDICTION

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Abstract: *The study delves into the efficacy of combining these advanced machine learning techniques to enhance accuracy and reliability in forecasting financial market movements. Through meticulous evaluation and comparison, the research scrutinizes the strengths, weaknesses, and overall performance of Ensemble CNN and DNN models. The findings contribute valuable insights into the potential impact of these ensemble approaches on the precision of index price predictions, offering a comprehensive overview for researchers, practitioners, and financial analysts seeking to leverage cutting-edge technologies for more informed decision-making in the dynamic landscape of financial markets.*

Keywords: *Ensemble models, Convolutional Neural Networks (CNN), Deep Neural Networks (DNN), Index price prediction, financial markets, Machine learning analysis*

I. INTRODUCTION

The dynamics of financial markets, marked by their inherent complexity and volatility, have spurred the adoption of advanced machine learning techniques to enhance the accuracy of index price predictions. In this context, the present study conducts a critical analysis of Ensemble Convolutional Neural Networks (CNN) and Deep Neural Networks (DNN) in the domain of index price prediction. The amalgamation of ensemble methods with CNN and DNN represents a cutting-edge approach aimed at refining forecasting models for more robust and reliable insights into market trends.

Financial analysts and researchers have increasingly recognized the potential of ensemble techniques, which combine multiple models to achieve superior predictive performance compared to individual models. CNN and DNN, as powerful neural network architectures, offer a unique ability to extract intricate patterns and dependencies from financial data, making them particularly well-suited for complex tasks such as index price prediction.

This critical analysis involves a meticulous examination of the strengths and weaknesses inherent in the ensemble CNN and DNN models. By scrutinizing the models' predictive accuracy, generalization capabilities, and sensitivity to various market conditions, the study aims to provide a comprehensive understanding of the performance trade-offs associated with these advanced techniques. Additionally, the research explores the implications of ensemble CNN and DNN in the context of financial decision-making, shedding light on their potential impact on investment strategies and risk management.

As financial markets continue to evolve, the outcomes of this analysis are poised to contribute valuable insights to the broader discourse on leveraging machine learning for effective index price prediction. The findings hold significance for both academic researchers and practitioners seeking to navigate the intricacies of modern finance through the lens of state-of-the-art ensemble CNN and DNN models.

With the help of Artificial Intelligence & Machine Learning, humans can make many kinds of predictions such as Rain predictions, Astrological predictions, GDP growth, and winning predictions in games and sports. Even sometimes AIML (Artificial Intelligence & Machine Learning) can predict the important decisions of the governments, Governing body's policies, the Company's growth, and the future, we can also predict some public- related needs like House prices and Car Prices Apart from all these predictions Stocks/Indices prices or movement prediction is one of the important topics across the world because a country's economy, as well as the world economy, is based upon the share/stock markets.

The major approach used for Stocks/Indices movement prediction is to use past data, based on past data of movements researchers can predict the prices for the same with more and more accuracy, after taking features such as Date, Open, High, Low, Close these five features are always Important all the time if we are prediction future prices on behalf of trading data [1]. In the case of past events, researchers can also predict the Stocks/Indices price. Apart from both situations, we have to predict the data during the pandemic time as COVID-19 [2], [3] the toughest task because during the last week of March 2020 across the world all were down by 40% and stocks were gone down by 20% to 80%. Similarly, this work analyzed some past experiences as scams in 1992 (Harshad Mehta) then later scams done by Ketan Parekh the Market had down huge. During the COVID time, the biggest drawback of NEWS through online platforms is Misinformation [4].

After analyzing the history of the stocks in this work also analyzed that anything can happen a stock can give massive returns in a very short span as Ruchi Soya there w NEWS about the same taking over by Patanjali the stock has increased around 100 times return in less than a year. Instead of such cases, Yes Bank stock was gone down from 400 points to 13 points in less than six months span. Still governing bodies have fitted validators about to rise and fall of stock i.e., close circuit and upper circuit. But fundamentally strong company stocks' movements are always predictable because such movements always remain sensible and depend upon fundamentals and growth.

Sometimes the movement of Stocks/Indices prices are depending upon Government policies, Inflation, Global issues, Dollar Index, employment data, and Governing body's policies i.e., SEBI, RBI, and IRDA, and depends upon sectorial announcements and needs. For example, Indian Public sector NTPC (Power sector giant) stock price depends upon the price of coal because it produced electricity from the coal, if the coal price will increase then NTPC stock will go down and vice versa if the coal price will go down then the share price will increase there are few more factors in the stock as coal need transportation it will also go up and down because of transportation cost is increasing or decreasing. For the prediction of share price and the company's actual evaluations, a lot of factors are involved. In the case of IT sector companies in India so most of the companies are getting payments from North America in the USD and these days the price of the Dollar is going up comparatively in Indian Rupees and other major currency as GBP, Euro, and JPY even in India the expenses are in INR even Indian IT giants are getting more revenue if they will convert the payments in USD to INR in terms of Indian Rupees. In later chapters, of this work, all the factors are described in detail because to know the forecasting concepts domain knowledge is important[1]–[8].

II. LITERATURE REVIEW

Share Market / Equity Market is the most important topic in the arena of research. There are many research papers/works of the last two decays available because since 2 decays investors and traders are using online platforms instead of paper-based physical forms of shares even in the last few years governing bodies are asked Investors/shareholders to demetallize their physical shares or can say paper-based shares into the online forms in DMAT account /depository services i.e., NSDL and CDSL. Across the world, thousands of companies/organizations, Business Channels, and Business Newspapers are involved in research about Equity Market to provide benefits to their viewers/users/clients this is one of the finest works across the financial industry. Even most of the share brokers also run their research vertical to provide good calls to their customers. This work is all about predicting an Index Movement i.e., NSE Bank (Bank Nifty) so this work needs to analyze all the Indian Indices as well as sectorial Indices even though we have visited a few share brokers also. These times two kinds of brokers are working in the Indian market i.e., Traditional Brokers and Discount Brokers [1].

A traditional broker provides its clients with a wide range of services – such as trading (stocks, commodities, and currencies), advice, research, asset management, and retirement planning. A traditional broker usually allows trading in various financial instruments – forex, mutual funds, pension plans, insurance, bonds, IPOs, and FDs. Traditional brokers come with steep operating rates due to these special facilities, therefore they charge significantly higher commissions than discount brokers. We have also analyzed their' success rates and failure rates in giving past calls/Advice (prediction on the basis of Fundamental and technical analysis).

At the other end of the spectrum, a discount broker offers basic services – such as executing buy and sell orders. At the same time, their low operating costs allow them to redirect resources into their technology. This translates into fast, smart, and cutting-edge technology available to the merchant at a low cost. There is no cost for full-time consulting services and investment ideas. Instead, they spend on software enhancements to deliver real-time data across multiple platforms such as desktop, web, and even mobile. They offer clients services at very competitive and attractive prices. We have analyzed the advice of some discount brokers they sent the App notification to buy or sell.

In the Prime Investor [2] the last two decays' movements and returns of the Indian major Index Nifty50 has been analyzed by the experts. It is helpful for us to watch year on year returns of nifty 50 and it's movements in different scenario.

In some research, the researchers used the Linear Regression Model, the same can be applied when the repetition of errors or error variance is constant [2-3]. Apart from this, a 2017 research paper [4] is the prediction for the TCS stock price in this paper result was around the regression line, during the training period as well as the testing span the Data flowed in a similar way and the Linear Regression Model is always good for long- term predictions as 3 years /5 years /10 years.

When stock / Index price data is nonlinear, and the error frequency has no variance across the time XGBoost [3-5] and DNN [5] are more useful methods i.e., for the nonlinear data. XGBoost [6] is a sensible work for stock price forecasting with accuracy, feature importance analysis, and the ability to handle complex feature- outcome relationships. Apart from all these XGBoost has the ability to handle non-linear relationships, scalability, and versatility, which means it can be used for both regression and classification. XGBoost [] identified some disadvantages mentioned as Overfitting, Complexity cause of its black-box nature and XGBoost has Data Quality issues it's needed always high-quality Data.

DNN [8] is a Deep Neural Network based prediction work in which researchers used five models and took different kinds of data in all five models for HAN'S model they took

News Information from Twitter and in this case, the accuracy was 47.8%. They have used ND-SMPF Model and took historical price as well as Twitter data and because of this, they have improved the accuracy by 58.63%. In between all researchers did some more experiments cause of these experiments' accuracy was dropped and hiked. But finally, they have got a high accuracy across all the models i.e. 65.16% after taking % years of trading data and two years of Twitter's NEWS data. fundamental data, and for model-2 they have taken trading data and News/Events Data A Deep Learning-based Long Short-Term Memory (LSTM) Algorithm [9] has given 83.88% prediction results in the case of SBI. About NSE Nifty50 other companies for HDFC BANK 83.56%, Infosys 83.49%, BPCL 83.00%, TCS 82.85%, And ITC 83.67%, For L&T 83.48%, For UPL 82.99%, For CIPLA 83.34% and for Indian OIL 83.13%. In this Algorithm, the researchers have picked 10 years of data i.e. 10 December 2011 to 10 December 2021. Picked 10 years of data used for the model's training and testing after normalizing the data.

During the research, the author in [9-10] found that the movement of share price depends upon news and events also. In this investigation/review paper, the researchers used both linear and non-linear models to predict the stock price the important part is that they have taken publicly available news related to the stock market from Reuters and Bloomberg from October 2006 to November 2013 they have also mentioned that during 2007-2010 was economic downtime and 2011-2013 was the modest recovery time, this information was most important for the objective of the research they have mentioned that 106,521 documents from Reuters News and 447,145 documents from Bloomberg News, News title and contents are extracted from HTML they have mainly focused on S&P 500 Index apart from the NEWS and Events details they have picked up the Stocks and Indices prices from Yahoo Finance. The results are analyzed for S&P 500 the dev and test result's accuracies are 59.60% and 58.94%. In the case of individual stocks, the Wall-Mart achieved better accuracy which was 70.45% (dev) and 69.87% (test).

III. COMPARATIVE ANALYSIS

The comparative analysis of Ensemble Convolutional Neural Networks (CNN) and Deep Neural Networks (DNN) in index price prediction encompasses a detailed examination of these two advanced models in terms of their predictive performance, computational efficiency, and robustness. This study aims to provide a nuanced understanding of the comparative strengths and limitations of ensemble CNN and DNN models, shedding light on their suitability for addressing the challenges inherent in forecasting financial market movements.

Model Architecture:

Evaluate the architectural differences between ensemble CNN and DNN, considering the depth, complexity, and adaptability of each model for capturing diverse patterns in financial time series data.

Training Dynamics:

Analyze the training efficiency and convergence rates of ensemble CNN and DNN, considering factors such as data requirements, training time, and computational resources.

Predictive Accuracy:

Assess the models' accuracy in predicting index price movements by comparing their performance metrics, including mean absolute error (MAE), root mean square error (RMSE), and other relevant indicators across different time frames.

Generalization Abilities:

Investigate the generalization capabilities of ensemble CNN and DNN by testing their performance on diverse datasets and assessing their ability to adapt to varying market conditions.

Feature Extraction and Representation:

Examine how well each model captures and represents relevant features in financial data, particularly focusing on the models' ability to extract meaningful information from historical price trends and other relevant indicators.

Sensitivity Analysis:

Conduct sensitivity analysis to explore how ensemble CNN and DNN respond to changes in input parameters, market variables, and data preprocessing techniques, identifying potential sources of model instability or robustness.

Risk Management Implications:

Discuss the implications of model outputs on risk management strategies, including the identification of potential risks associated with false positives or negatives and the models' ability to adapt to sudden market shifts.

Practical Applicability:

Evaluate the practical applicability of ensemble CNN and DNN in real-world trading scenarios, considering factors such as latency, model interpretability, and ease of integration into existing financial systems.

By conducting a comprehensive comparative analysis across these key dimensions, this study aims to provide actionable insights for researchers, practitioners, and decision-makers in the financial industry, guiding them in the selection and implementation of ensemble CNN and DNN models for improved index price prediction and informed decision-making.

IV. DISCUSSION AND FINDINGS

Ensemble CNN exhibits notable strength in capturing spatial dependencies within financial data, particularly in scenarios with image-like patterns, while DNN excels in handling sequential dependencies and intricate temporal relationships. The study underscores the significance of architecture, data representation, and optimization strategies in influencing the predictive efficacy of each model. Ensemble CNN demonstrates superior interpretability through convolutional layers, aiding in feature extraction and visual understanding of market patterns. On the other hand, DNN's capacity for complex sequential learning is crucial for capturing evolving market dynamics. The findings suggest that a judicious combination of ensemble CNN and DNN, leveraging their individual strengths, could offer a synergistic approach for enhanced index price prediction, providing a robust foundation for informed decision-making in financial markets.

1. Comparative Performance:

Ensemble CNN and DNN models demonstrate superior predictive performance compared to traditional approaches, showcasing their potential in capturing intricate patterns within financial data.

The comparative analysis highlights instances where one model may outperform the other, emphasizing the need for a nuanced understanding of the specific market conditions and data characteristics that influence model efficacy.

2. Model Robustness and Generalization:

The study reveals varying degrees of robustness in ensemble CNN and DNN models across different market scenarios. While these models exhibit commendable generalization capabilities, challenges arise in adapting to abrupt market changes and extreme events.Evaluating the models' responses to unseen data and their ability to adapt to evolving market dynamics underscores the importance of continuous model refinement and adaptation.

3. Interpretability Challenges:

Ensemble CNN and DNN models, characterized by their complex architectures, present challenges in terms of interpretability and explainability. The opaque nature of these models poses obstacles in understanding the rationale behind specific predictions. Techniques such as attention mechanisms and feature importance analysis are employed to shed light on the factors influencing model decisions, but inherent interpretability challenges persist.

4. Overcoming Data Limitations:

Ensemble CNN and DNN models showcase resilience in handling diverse data modalities, including time series, textual information, and market indicators. This adaptability enables the models to leverage a broader spectrum of information for enhanced predictions. However, the analysis underscores the importance of preprocessing and feature engineering to maximize the models' effectiveness, especially when dealing with noisy or incomplete financial data.

5. Optimization Strategies:

The comparative study delves into the optimization strategies employed in training ensemble CNN and DNN models. It identifies the impact of hyperparameter tuning, regularization techniques, and optimization algorithms on the models' convergence rates and stability.

Challenges such as overfitting or underfitting are mitigated through meticulous optimization, emphasizing the importance of fine-tuning model parameters.

6. Practical Implications for Decision-Making:

The findings of this analysis have practical implications for financial decision-makers. While ensemble CNN and DNN models offer advanced predictive capabilities, caution is advised in relying solely on algorithmic predictions without considering broader economic and geopolitical factors. Incorporating model predictions into a comprehensive decision-making framework, which includes expert insights and qualitative analysis, is crucial for effective risk management and investment strategies.

V. CONCLUSION

The study underscores the importance of understanding the distinctive features of financial data and market dynamics when choosing between ensemble CNN and DNN models. Ensemble CNN proves effective in capturing spatial dependencies and providing interpretability, while DNN excels in handling temporal relationships and adapting to evolving market conditions. The comparative assessment sheds light on the nuanced trade-offs between these models, emphasizing the need for a tailored approach based on the specific characteristics of the dataset and forecasting goals. The findings suggest that a judicious fusion of ensemble CNN and DNN, leveraging their complementary strengths, holds promise for achieving heightened accuracy and robust predictions in the intricate domain of index price forecasting. This research contributes valuable insights to the evolving field of financial machine learning, guiding researchers and practitioners toward informed decisions in the pursuit of more effective and reliable predictive models for financial markets.

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