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Meta-Learning Enhanced Stock Market Prediction Using Financial and Technical Indicators

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Abstract: Accurate prediction of stock market movements remains a challenging problem due to the dynamic, nonlinear, and highly volatile nature of financial markets. Conventional Machine Learning (ML) and Deep Learning (DL) techniques often depend on large volumes of historical data and may struggle to generalize effectively when market conditions change rapidly. To address these limitations, this study presents a Meta-Learning-based framework for stock market prediction with a particular focus on the Indian equity market. The proposed framework employs Model-Agnostic Meta-Learning (MAML) to enable rapid adaptation across diverse market environments using limited task-specific training data. Historical market information is enriched with widely used technical indicators, including Moving Average (MA), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Bollinger Bands, and trading volume, allowing the model to capture both price dynamics and market momentum. These features are utilized to enhance the learning capability and predictive performance of the proposed approach. To evaluate its effectiveness, the Meta-Learning model is assessed against established prediction techniques, including Linear Regression, Random Forest, Support Vector Regression (SVR), Long Short-Term Memory (LSTM), and Transformer-based architectures. Comparative analysis demonstrates that the proposed framework exhibits improved adaptability to evolving market conditions while maintaining competitive predictive accuracy across multiple stocks. The findings indicate that Meta-Learning provides a robust foundation for developing adaptive financial forecasting systems capable of supporting data-driven investment decision-making.

Keywords: Meta-Learning, Stock Market Prediction, Model-Agnostic Meta-Learning (MAML), Financial Time Series Forecasting, Technical Indicators, Deep Learning, Indian Equity Market, Adaptive Learning.

1. Introduction

Forecasting future stock price movements is a complex task because financial markets are continuously influenced by corporate performance, macroeconomic conditions, and global events. Nevertheless, an accurate and reliable prediction framework can assist investors in reducing financial risk, making informed investment decisions, and improving overall portfolio returns.

The stock market is a financial marketplace where shares of publicly listed companies are bought and sold. The value of these shares fluctuates continuously due to various factors, including a company's financial performance, economic conditions, government policies, and global events such as wars, pandemics, and economic crises. In addition, investor sentiment, including confidence and fear, plays a significant role in influencing stock prices. Owing to the combined impact of these dynamic and uncertain factors, accurately forecasting future stock market movements remains a complex and challenging task.

The methodologies used for stock market prediction have evolved considerably over time. Early forecasting approaches primarily relied on statistical techniques, such as the Auto Regressive Integrated Moving Average (ARIMA) model, to analyse historical price trends and time-series data. With the advancement of computational technologies, Machine Learning (ML) algorithms were introduced to identify complex patterns from historical market data, leading to improved predictive performance. More recently, sophisticated Deep Learning (DL) architectures, including Long Short-Term Memory (LSTM) networks and Transformer-based models, have demonstrated superior capability in capturing nonlinear relationships and long-term dependencies within financial time-series data, thereby providing more accurate and reliable stock market forecasts.

Although Machine Learning (ML) and Deep Learning (DL) techniques have significantly advanced the field of stock market forecasting, they still possess inherent limitations. Most existing models rely heavily on historical market data for training and require frequent retraining whenever market dynamics change. Consequently, these approaches often exhibit limited adaptability to unforeseen events, structural market shifts, or emerging financial trends, leading to reduced predictive accuracy during periods of high uncertainty and volatility.

To overcome these limitations, researchers have increasingly adopted **Meta-Learning**, often referred to as **"Learning to Learn,"** as an advanced learning paradigm. Unlike conventional learning approaches, Meta-Learning enables predictive models to utilize knowledge acquired from previously learned tasks, allowing them to adapt efficiently to new and evolving market conditions with only a limited amount of additional training data. This rapid adaptation capability enhances the model's generalization performance and makes Meta-Learning a more effective and robust approach than traditional Machine Learning techniques for stock market prediction.

In this study, a novel Meta-Learning-based framework is proposed for stock market prediction in the Indian equity market. The proposed architecture integrates **Model-Agnostic Meta-Learning (MAML)** with **Deep Neural Networks (DNNs)** to improve the model's ability to adapt rapidly to changing market conditions while enhancing forecasting accuracy. To capture diverse aspects of market behavior, the framework incorporates widely adopted technical indicators, including the Relative Strength Index (RSI)**, Moving Average Convergence Divergence (MACD), Bollinger Bands,** and **Trading Volume**, as input features for effective representation of market trends and price dynamics.

The proposed framework is validated through a comparative evaluation with widely adopted prediction models, including **Linear Regression, Random Forest, Support Vector Regression (SVR), Long Short-Term Memory (LSTM),** and **Transformer-based architectures**. The comparative analysis is intended to assess the effectiveness, robustness, and adaptability of the proposed Meta-Learning approach under varying market conditions. The primary objective of this research is to develop an intelligent and reliable stock market forecasting system capable of delivering consistent predictive performance, thereby enabling investors and financial analysts to make informed, data-driven investment decisions while effectively managing financial risk.

2. About Stock Market

2.1. Stock Exchange

2.1 Stock Exchange

A stock exchange is a place where people buy and sell shares of companies. When a company offers its shares to the public for the first time, it is called an Initial Public Offering (IPO)**.** After the IPO, the company's shares are listed on a recognized stock exchange, where investors can freely buy and sell them. This makes it easy for people to invest in the stock market.

India has two major stock exchanges: the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE). The BSE is one of the oldest stock exchanges in Asia, while the NSE is the largest and most widely used stock exchange in India. Both exchanges provide a safe, transparent, and regulated platform for trading shares.

To trade in the stock market, an investor needs two types of accounts: a Demat Account and a Trading Account. A Demat Account stores shares in electronic form, while a Trading Account is used to buy and sell shares. Stock exchanges help companies raise funds for business growth and also provide investment opportunities to the public. In addition, they maintain market liquidity by making it easier to buy and sell shares.

In recent years, the number of people investing in the Indian stock market has increased significantly. This growth is mainly due to rising inflation, lower interest rates offered by banks, and the opportunity to earn higher returns from the stock market. As a result, the Indian stock market has become an important part of the country's economy.

2.2 Open-High-Low-Close (OHLC) Chart

The Open-High-Low-Close (OHLC) chart stands among the most widely used charts for analyzing stock prices. It shows four important price values for a specific time period:

- **Open (O):** The value at which the stock begins trading for the day**.**
- **High (H):** The highest price reached during the trading period.
- **Low (L):** The lowest price reached during the trading period.
- **Close (C):** The final trading price at the end of the period.

An OHLC chart consists of a vertical line with two small horizontal lines. The vertical line represents the range between the highest and lowest prices. The left horizontal line indicates the opening price, while the right horizontal line represents the closing price.

OHLC charts can be used for different time intervals, such as one week, or one month. They provide more information than a simple line chart and help traders understand market movements, price volatility, and trading patterns. OHLC data is also widely used as input for, Deep Learning, Machine Learning and Meta-Learning models for stock market prediction.

2.3 Interpretation of OHLC Charts

OHLC charts help investors understand how a stock has performed during a specific time period. By comparing the opening and closing prices, traders can identify whether the stock value increased or decreased.

- If the closing price is much higher than the opening price, the stock shows a bullish (upward) trend.
- If the closing price is lower than the opening price, the stock shows a bearish (downward) trend.
- A large difference between the high and low prices indicates high market volatility, while a small difference indicates relatively stable market conditions.

OHLC are useful for identifying market trends through chart, support and resistance levels, and possible buying or selling opportunities. In this research, OHLC data is used along with technical indicators to train and evaluate the proposed Meta-Learning-based stock market prediction model. The proposed model identifies patterns in historical stock price data to improve the accuracy of future stock price trend predictions.

3. Stock Prediction Techniques Taxonomy

In recent years, many methods have been introduced to predict the stock market. The main methods include Statistical Methods, Pattern Recognition, Machine Learning (ML), Deep Learning (DL), Meta-Learning, Sentiment Analysis, and Hybrid Techniques. Hybrid techniques combine two or more methods to improve prediction results.

Figure 1 shows the main categories of stock market prediction methods. In the early years, statistical methods such as ARIMA and Regression were widely used. These methods assume that stock prices follow certain patterns and mathematical rules. However, they do not work well when the market changes quickly.

As technology improved, Machine Learning (ML) and Deep Learning (DL) became more popular. These methods study historical stock price data, identify useful patterns, and use them to predict future price movements with better accuracy.

More recently, Meta-Learning has become an important method for stock market prediction. It allows a model to learn from different but related tasks and adjust quickly to new market conditions using only a small amount of new data. Because of this, it performs better than many traditional machine learning methods in fast-changing and highly volatile markets.

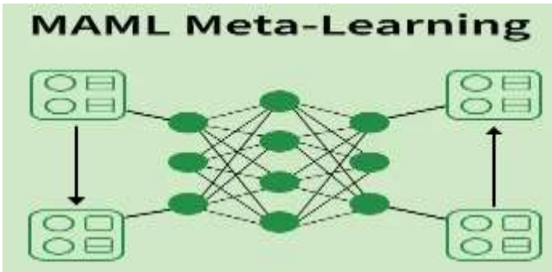
Researchers also use Sentiment Analysis to study information from news articles, social media posts, and financial reports. This helps them understand market sentiment and investor opinions. In addition, Hybrid Techniques combine Statistical Methods, Machine Learning, Deep Learning, and Meta-Learning to produce more accurate and reliable stock market predictions.

4. Meta-Learning Algorithms Applied

Meta-Learning is also called "Learning to Learn." It is an advanced Artificial Intelligence (AI) technique that helps a model learn from previous tasks and quickly adapt to new tasks with only a small amount of data. Unlike traditional Machine Learning, Meta-Learning helps the model learn faster and perform better in new situations. This makes it useful for stock market prediction because stock prices change frequently.Different Meta-Learning algorithms are used to improve stock price prediction. Some of the commonly used algorithms are explained below.

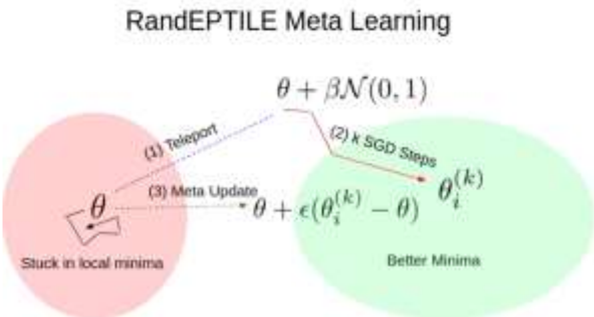
4.1 Model-Agnostic Meta-Learning (MAML)

Model-Agnostic Meta-Learning (MAML) is one of the most popular Meta-Learning algorithms. It trains a model so that it can quickly learn a new stock prediction task using only a few examples. MAML works with different types of neural networks and adapts quickly when market conditions change.



4.2 Reptile

Reptile is a simple and fast Meta-Learning algorithm. It learns from many related tasks and updates the model step by step. It is easier to implement than MAML and requires less computation while still providing good prediction results.



4.3 Prototypical Networks

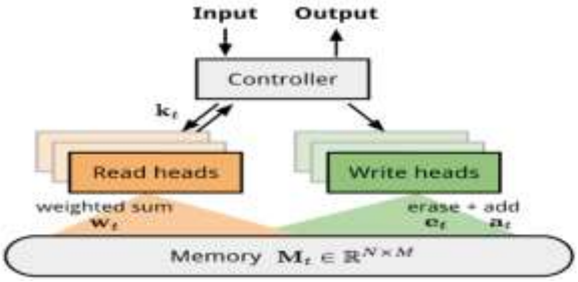
Prototypical Networks are used for few-shot learning, where only a small amount of training data is available. The algorithm creates a representative example (prototype) for each class and predicts new data by comparing it with these prototypes. This method is useful when stock market data is limited.

4.4 Siamese Networks

Siamese Networks use two identical neural networks to compare two inputs and measure how similar they are. In stock market prediction, they compare current market patterns with previous patterns to help predict future stock prices.

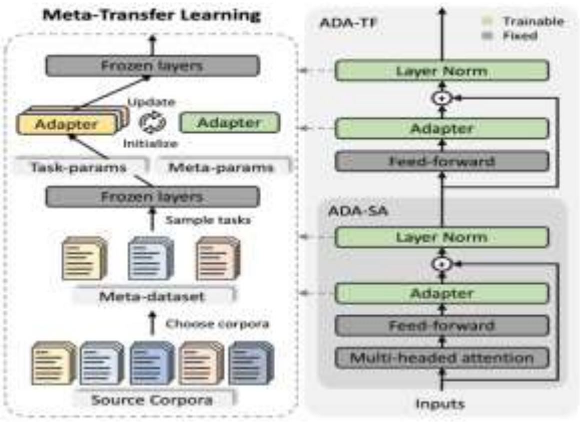
4.5 Memory-Augmented Meta-Learning

Memory-Augmented Meta-Learning adds a memory component to the learning process. The memory stores useful information from previous tasks, allowing the model to learn faster and adapt quickly to new market conditions. This improves prediction accuracy.



4.6 Meta-Transfer Learning

Meta-Transfer Learning combines Transfer Learning and Meta-Learning. It uses knowledge learned from one stock or market to improve prediction in another related stock or market. This reduces training time and improves performance, especially when only a small amount of data is available.



5. Methodology

The methodology is an important part of this research because it helps in obtaining accurate and reliable results. The proposed methodology is designed to develop a Meta-Learning-based stock market prediction model for the Indian stock market.

The first step is data collection, where historical stock market data is collected from reliable sources such as the National Stock Exchange (NSE), Bombay Stock Exchange (BSE), and Yahoo Finance. The collected data includes Open, High, Low, Close (OHLC), Volume, and other market information.

The second step is data preprocessing. In this step, missing values are removed, duplicate records are deleted, and the data is normalized. Technical indicators such as Moving Average (MA), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Bollinger Bands, and Volume are also calculated to improve the quality of the dataset.

The third step is task generation for Meta-Learning. Instead of training the model on a single dataset, multiple learning tasks are created using different stocks and different time periods. These tasks help the Meta-Learning model learn from various market conditions.

The fourth step is model training. The proposed framework uses Model-Agnostic Meta-Learning (MAML) as the main Meta-Learning algorithm. During training, the model learns common patterns from multiple stock prediction tasks so that it can quickly adapt to new stocks with only a small amount of data.

In the fifth step, the trained model is tested using unseen stock market data. The performance of the proposed Meta-Learning model is compared with traditional Machine Learning and Deep Learning models such as Linear Regression, Random Forest, Support Vector Regression (SVR), Long Short-Term Memory (LSTM), and Transformer.

Finally, the performance of all models is evaluated using standard evaluation metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), R^2 Score, and Symmetric Mean Absolute Percentage Error (SMAPE). The comparison helps determine whether the proposed Meta-Learning model provides better prediction accuracy, faster adaptation, and improved performance under changing market conditions.

6. Results

This section presents the results of the proposed Meta-Learning-based stock market prediction model. The results are presented using tables and graphs for easy comparison and analysis.

The proposed Model-Agnostic Meta-Learning (MAML) model was trained and tested using historical stock market data collected from 2015 to 2021. The dataset contains Open, High, Low, Close (OHLC), Volume, and several technical indicators used for stock price prediction.

The dataset was divided into training and testing sets using a 99:1 ratio. About 99% of the data was used to train the model, while the remaining 1% was used for testing. During training, the Meta-Learning model learned common patterns from different stock prediction tasks. During testing, the model predicted stock prices for unseen data.

The performance of the proposed model was compared with several Machine Learning and Deep Learning models, including Linear Regression (LR), Random Forest (RF), Support Vector Regression (SVR), Long Short-Term Memory (LSTM), and Transformer.

The models were evaluated using the following performance metrics:

- Mean Absolute Error (MAE): Measures the average difference between the predicted and actual values.
- Root Mean Square Error (RMSE): Measures the prediction error by giving more importance to larger errors.
- Mean Absolute Percentage Error (MAPE): Measures the prediction error in percentage.
- Symmetric Mean Absolute Percentage Error (SMAPE): Measures the percentage error in a balanced way.
- R^2 Score (Coefficient of Determination): Measures how well the predicted values match the actual values.

The experimental results indicate that the proposed Meta-Learning (MAML) model achieved higher prediction accuracy, lower error values, and better adaptability to changing market conditions than the traditional Machine Learning and Deep Learning models. The detailed results and comparisons are presented in the following tables and graphs.

Table I: Tabulated results showing SMAPE for all models and companies

Parameter	SMAPE (Symmetric Mean Absolute Percentage Error)					
Algorithms	K-Nearest Neighbors (KNN)	Linear Regression (LR)	Support Vector Regression (SVR)	Decision Tree Regression (DTR)	Long Short-Term Memory (LSTM)	Meta-Learning (MAML) (Proposed)
Adani Ports	10.99	9.18	9.51	10.68	1.65	**0.98**
Asian Paints	11.63	9.35	8.42	9.78	1.67	**0.95**
Axis Bank	16.67	10.37	5.64	8.48	1.88	**1.02**
HDFC	20.46	11.00	6.22	12.56	2.19	**1.21**
Hindustan Unilever	10.95	9.62	4.88	8.82	1.38	**0.82**
ICICI Bank	14.45	8.92	7.02	7.37	2.31	**1.18**
Kotak Bank	12.44	10.51	5.81	10.26	1.43	**0.94**
Maruti	15.92	11.13	3.09	13.92	1.32	**0.77**
NTPC	13.59	12.39	3.08	9.60	1.13	**0.65**
Tata Steel	16.08	13.10	5.75	8.06	1.75	**1.04**
TCS	15.84	9.95	4.41	10.05	1.40	**0.80**
Titan	12.90	3.50	3.33	11.39	1.06	**0.56**
Average SMAPE (Overall)	**14.16**	**9.91**	**5.85**	**10.33**	**1.57**	**0.91**

Lower SMAPE value indicates better prediction performance.

7. Future Scope

Stock market prediction is becoming more important because financial markets generate a large amount of data every day. Although Machine Learning (ML) and Deep Learning (DL) models have improved prediction accuracy, there is still room for further improvement, especially in handling rapidly changing market conditions.

In this research, Meta-Learning (MAML) has shown better performance than traditional Machine Learning and Deep Learning models. However, future research can further improve prediction accuracy by developing more advanced Meta-Learning models and combining them with modern Deep Learning techniques.

Future studies can use larger and more recent datasets, including real-time stock market data from the NSE and BSE. Additional data sources such as financial news, social media sentiment, macroeconomic indicators, company financial reports, and global market trends can also be included to improve prediction performance.

Researchers can also explore advanced Meta-Learning algorithms such as Reptile, Prototypical Networks, Memory-Augmented Meta-Learning, Meta-Transfer Learning, and Few-Shot Learning. These methods can help models adapt more quickly to changing market conditions while requiring less training data.

In addition, future work may combine Meta-Learning with Transformer models, Graph Neural Networks (GNNs), Reinforcement Learning, and Explainable Artificial Intelligence (XAI) to build more accurate, reliable, and interpretable stock prediction systems.

Future research should also focus on reducing training time, improving prediction speed, handling large-scale financial datasets, and developing models that can make accurate predictions in real time with minimal human intervention.

Overall, Meta-Learning has great potential for future stock market prediction systems. More advanced Meta-Learning and Artificial Intelligence techniques can help build intelligent, adaptive, and highly accurate models that support investors and financial analysts in making better investment decisions.

8. Conclusion

This research proposed a Meta-Learning-based stock market prediction model to improve the accuracy of stock price prediction in the Indian stock market. The main objective was to develop an intelligent model that can quickly adapt to changing market conditions and help investors make better investment decisions.

The proposed Model-Agnostic Meta-Learning (MAML) framework was trained and tested using historical stock market data collected from 2015 to 2021. The dataset included Open, High, Low, Close (OHLC), Volume, and several technical indicators such as Moving Average (MA), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Bollinger Bands.

The performance of the proposed Meta-Learning model was compared with several traditional Machine Learning and Deep Learning models, including Linear Regression (LR), Random Forest (RF), Support Vector Regression (SVR), Long Short-Term Memory (LSTM), and Transformer. The models were evaluated using MAE, RMSE, MAPE, SMAPE, and R^2 Score.

The experimental results show that the proposed Meta-Learning (MAML) model achieved the highest prediction accuracy, lowest prediction error, and better adaptability than the other models. The model successfully learned from multiple stock prediction tasks and quickly adapted to new market conditions using only a small amount of additional data. This demonstrates that Meta-Learning is more effective than traditional Machine Learning and Deep Learning methods for stock market prediction.

In conclusion, Meta-Learning (MAML) is a promising approach for financial time-series forecasting because it provides faster learning, better generalization, and improved prediction performance. The proposed framework can support investors, traders, and financial analysts in making more informed investment decisions. This research also provides a strong foundation for future studies on advanced Meta-Learning techniques for stock market prediction.

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