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Meta-learning for financial market prediction: An efficient approach with reduced computational cost

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ABSTRACT

In the era of advanced computational techniques and predictive modeling, the focus has shifted toward reducing latency and minimizing costs. Financial market prediction is not a novel concept, as it has been applied effectively over the past decades to support informed decisions by traders and investors, leading to improved returns. However, machine learning and deep learning models often demand substantial computational power and processing time due to their complex architectures. Meta-learning provides an efficient alternative by reducing computation time and resource requirements for financial forecasting. This study proposes a meta-SGD model to predict future prices of the S&P 500 index and NASDAQ, and compares its performance with deep learning models (CNN and GRU) and a hybrid CNN-GRU model. Evaluation using RMSE, MAE, and R^2 metrics shows that the meta-learning model outperforms both deep learning and hybrid models, achieving state-of-the-art predictive accuracy with significantly lower computational cost.

1. Introduction

Financial market prediction is one of the most attractive research domains for researchers. Accurate forecasting enables investors to anticipate future market conditions, thereby facilitating informed decisions aimed at maximizing returns while minimizing risks (Huy and Hang, 2021). Financial markets such as equity, commodity, bond, and cryptocurrency markets exhibit stochastic behavior influenced by numerous interrelated factors. Consequently, stochastic models are favored over deterministic ones for market forecasting. Various modeling approaches have been employed, including classical time series techniques (Arashi and Rounaghi, 2022), machine learning algorithms, and deep learning architectures (Chauhan et al., 2025), all demonstrating effective predictive capabilities within acceptable error margins. However, the performance of these models is contingent upon the availability of high-quality datasets that capture the intricate relationships between market prices and influencing features (Batool et al., 2025). Moreover, these models often demand substantial computational resources and extended training times to achieve optimal performance (Ahmed et al., 2023). When analyzing multiple financial instruments, models must be trained separately for each, further increasing computational load and processing time.

With the aim of better predictivity of future behavior of the financial market with limited time and resources, instead of an ordinary machine learning approach, Meta learning approach is a better alternative. Meta learning of learning to learn is an advanced machine learning framework that has the capacity to analyze a bigger picture of a dataset with minimal data. Besides, it enables the training models to quickly adapt to new tasks with improved efficiency. Meta-learning leverages prior knowledge to generalize across tasks and adaptability. Along with that, multiple target features can be trained by performing one-time training of a predictive model (Noor and Fatima, 2024). By focusing on learning patterns across multiple tasks, meta-learning enhances model performance, reduces computational costs, and accelerates learning, making it superior to conventional deep learning and reinforcement learning approaches in dynamic environments (Tian et al., 2022).

In this paper, a predictive model is designed using meta-learning for the forecasting of two international equity markets, including the S&P 500 index and NASDAQ, based on macroeconomic

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variables and events. The deep learning models have also been used for the same purpose, including CNN (Convolution Neural Network) and GRU (Gated Recurrent Unit). After that, a hybrid deep learning model is developed by the fusion of CNN and GRU. It was found that the developed meta-learning model is way better than deep learning models also better than the hybrid deep learning model. Deep learning models such as Convolutional Neural Networks (CNN) and Gated Recurrent Units (GRU) have been employed for financial market prediction. Building on these, a hybrid deep learning model combining CNN and GRU was developed to enhance predictive accuracy. However, the proposed meta-learning model demonstrated superior performance, not only outperforming individual deep learning models but also surpassing the hybrid model. The key contribution of this study lies in the development of a meta-learning framework capable of generating forecasts with minimal error while significantly reducing computational time. Unlike conventional models that require separate training for each financial instrument or target variable, the meta-learning approach enables simultaneous training across multiple targets in a single run. As illustrated in Fig. 1, the meta-learning model effectively minimizes computational resources by jointly training on datasets with multiple target variables, an advantage not offered by traditional machine learning or deep learning methods, which necessitate independent training for each target. The study focuses on addressing the following research questions:

- Is a meta-learning model a superior choice for equity market prediction compared to traditional deep learning frameworks?
- In what ways does our designed meta-learning model surpass conventional training models?
- Can a meta-learning model outperform hybrid deep learning models, which are currently regarded as the most effective approaches?

The remainder of this paper is organized as follows. Section 2 presents the literature reviewed in this domain. Section 3 explains the complete methodology, including data collection, preprocessing, model implementation, and testing. Section 4 discusses the results obtained. Section 5 outlines the limitations of the study, and Section 6 concludes the paper and highlights potential future research directions.

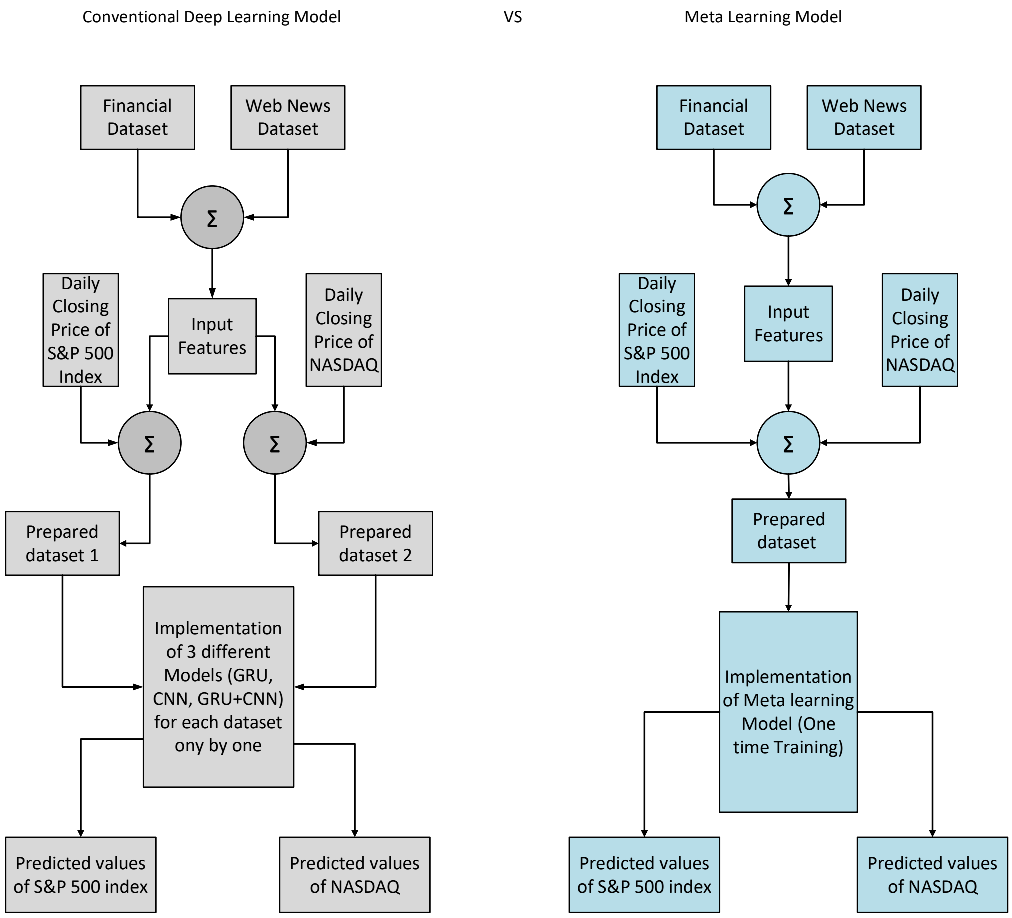

Fig. 1: Visualization of the meta-learning concept

2. Literature survey

To develop informed expectations about future financial market conditions, forecasting is essential for improving decision-making and designing effective policies. Traditional time series models are widely used to forecast financial markets. Models such as Auto-Regressive Moving Average (ARMA), Auto-Regressive Integrated Moving Average (ARIMA), and their advanced variations are commonly applied to predict future prices or returns. For example, Padma and Mishra (2022) used the ARIMA model to forecast the daily closing stock price of Apple Inc. This model is particularly effective for short-term forecasting and can support short-term investment decisions.

For informed decision-making, forecasting risk is as important as forecasting returns. Models such as Auto-Regressive Conditional Heteroscedasticity (ARCH), Generalized ARCH (GARCH), and other time series approaches are widely used for predicting financial market volatility. Jain et al. (2022) applied the GARCH (1,1) model to forecast the volatility of the Nifty Realty Index, while Mattera and Otto (2024) used the Log-ARCH model to estimate the volatility of the DJIA Index. These models can also be combined to predict both risk and return. For example, Arashi and Rounaghi (2022) forecasted the risk and return of the NASDAQ stock market using the ARMA-GARCH model.

To achieve better forecasting performance, researchers have applied machine learning models in addition to traditional time series models to predict financial market behavior. Both supervised and unsupervised machine learning techniques have been used for this purpose. Gorenc Novak and Velušček (2016) employed machine learning methods to predict daily prices using daily high prices and found that these methods provided better predictive accuracy than traditional models. Fraz et al. (2022) used a non-linear neural network alongside the GARCH model to forecast market volatility and reported that the neural network outperformed GARCH family models. Similarly, Al Mamun et al. (2024) compared supervised and unsupervised learning models and concluded that supervised machine learning models achieved higher prediction accuracy than unsupervised models.

Deep learning models have also been widely used for forecasting financial markets. These models include Recurrent Neural Networks (RNNs) (Samarawickrama and Fernando, 2017), Long Short-Term Memory (LSTM) networks (Bhandari et al., 2022), Convolutional Neural Networks (CNNs) (Steinbacher et al., 2025), and others. Deep learning models generally produce better results than traditional machine learning models because their hierarchical learning structure allows them to uncover complex relationships among features. These multi-layer architectures are capable of capturing non-linear and high-level patterns, which leads to improved predictive performance (Hung et al., 2023).

Statistical models are effective for short-term forecasting and identifying linear relationships in data. In contrast, machine learning and deep learning models are capable of capturing non-linear and complex patterns, making them suitable for long-term predictions. Therefore, combining these methods to create hybrid models has become a popular approach, as it allows researchers to leverage the strengths of both techniques in a single framework.

Masalegou et al. (2022) developed a hybrid model for predicting the Dow Jones Industrial Average (DJIA) index by combining an autoencoder with an LSTM network. Batool et al. (2022) proposed a hybrid approach that integrates a Neural Network Autoregressive (NNAR) model with GARCH to forecast the volatility of the KSE-100 index. Zhao et al. (2024) designed a hybrid model by combining CNN and LSTM to predict stock prices using historical OHLCV (Open, High, Low, Close, Volume) data. Similarly, Chauhan et al. (2025) introduced a hybrid deep learning model that fuses GRU and CNN architectures and found that it outperforms conventional deep learning models such as standalone CNN and GRU.

Forecasting techniques for financial markets are not limited to statistical, machine learning, or deep learning models. Several other methods have been explored to predict future market movements, such as fuzzy logic (Marszałek and Burczyński, 2014), reinforcement learning, and network analysis (Magner et al., 2020). Meta-learning is another emerging approach used in financial market forecasting. Santara et al. (2017) introduced the MESA framework, which is based on meta-learning and incorporates a stochastic strategy for asset management. Fernández et al. (2019) used a meta-learning model combined with an extreme learning machine to enhance the accuracy of financial time series predictions. Xiang et al. (2020) developed ordinal optimization algorithms using cross-validation, offering a novel method for analyzing financial datasets.

A review of recent studies on financial market forecasting shows that prediction is not limited to the strategies discussed above; many other techniques may also be applied. In this research, a novel Meta-Stochastic Gradient Descent (Meta-SGD) framework is proposed, which achieves state-of-the-art performance in forecasting international equity markets. Meta-SGD is chosen over LSTM and MAML due to its simplicity, efficiency, and strong adaptability, as it simultaneously learns the initialization, update direction, and learning rate within a single meta-learning framework.

2.1. Research gap: A critical comparison of the proposed methodology with other efficient learning paradigms

As discussed in the previous section, a wide range of forecasting models has been applied in financial market prediction. However, most of these models are limited in terms of adaptability, as they typically perform well only on a single dataset or specific market condition at a time. In contrast, meta-learning offers the ability to learn from multiple datasets within a single training process, enabling better generalization across different markets and time periods. Furthermore, Fatima et al. (2025) demonstrated that meta-learning maintains high performance across varying time horizons without sacrificing accuracy.

3. Methodology

3.1. Data collection

In this study, the S&P 500 index is forecasted using deep learning models, a hybrid deep learning model, and a meta-learning model. These models are trained on a combined dataset created from multiple news sources and selected macroeconomic variables. The dataset includes both numerical and textual data, with the textual information converted into numerical form for model processing. The numerical data consists of closing prices of various financial instruments (referred to as the financial dataset), sourced from Investing.com. The textual data is derived from news content and headlines obtained from online news platforms such as Yahoo Finance and BBC News.

3.1.1. Financial dataset

Daily closing values of the S&P 500 index were collected from Investing.com. In addition, daily closing prices of EUR/USD, GBP/USD, and the U.S. Dollar Index were retrieved. Daily gold and crude oil prices were obtained from commodity market data, while daily Bitcoin prices were collected from the cryptocurrency market to analyze their influence on the movements of the S&P 500 index. The NASDAQ index was also included to further validate the relationship between the selected features and equity market performance.

3.1.2. News dataset

Textual data from online news sources was gathered from two platforms. News articles from BBC News were extracted using Python libraries such as BeautifulSoup and Selenium. Fig. 2 presents the first five rows of the BBC dataset, which consists of five columns: headline, date, author, content, and link. Similarly, news from Yahoo Finance was scraped using BeautifulSoup only, which retrieved daily financial news. Fig. 3 displays the first five rows of the Yahoo Finance dataset, comprising seven columns: title, author, date, content, read time, tags, and link.

Heading	Date	Author	Content	Link
Train firms mass closures of ticket offices	5-Jul-23	By Michael Race & Katy Austin	Train companies are pressing ahead with plans	https://bbc.com/news/business-66097850
Asia is spending big to battle low birth rates..	16-May-23	By Mariko Oi	Falling birth rates are a major concern for so...	https://bbc.com/news/business-65478376
Netflix password crackdown fuels jump in subsc...	20-jul-23	By Natalie Sherman	A burst of people signed up for Netflix this s....	https://bbc.com/news/business-66240390
Netflix: Streamer's expansion into gaming is '...	30-Aug-23	By Steffan Powell	Think of Netflix and memorable television sh....	https://bbc.com/news/entertainment-arts-66639477
E-bike fires prompt call for better re...	27-jul-23	By Tom Gerken & Chris Vallance	Batteries for e-bikes should be regulated in t....	https://bbc.com/news/technology-66304564

Fig. 2: First five rows of raw data collected from BBC News

Title	Author	Datetime	ReadTime	Content	Tags	Link
UPDATE 1-Russian rouble drops to over one-week....	Reuters	December 1, 2023 at 1:50 AM	2 min read	(Updates at 0937 GMT)MOSCOW, Dec 1 (Reuters)...	['Russian rouble' , 'oil prices']	https://finance.yahoo.com/news/1-russian-roubl...
European Stocks Extend $1.2 Trillion Rally Bet ..	Allegra Catelli	December 1, 2023 at 12:16 AM	3 min read	(Bloomberg)-European stocks kicked off Dece....	['Bloomberg' , 'Jerome Powell' , 'Ulta Beauty',....	https://finance.yahoo.com/news/european-stocks...
UPDATE 2-Toyota partially halts output at Tian...	Reuters	December 1, 2023 at 1:15 AM	2 min read	(adds no comment from Toyota and FAW, context ...	['Toyota' , 'Tianjin' , 'China' , 'FAW' , 'strong sa....	https://finance.yahoo.com/news/2-toyota-partia......
UN flags 127 major climate-warning methae plu...	Gloria Dickie	December 1, 2023 at 1:15 AM	2 min read	By Gloria DickieDUBAI, Dec 1 (Reuters) – A Uni	['methane emissions' ,'space satellites; 'UNE...	https://finance.yahoo.com/news/un-flags-127-ma...
COP28 Latest:Saudi's MBS Among Leaders Kickin...	Malaika Kanaaneh Tapper and Siobhan Wagner	November 30, 2023 at 9:45 PM	3 min read	(Bloomberg)-Sign up for the Green Daily new	['Bloomberg' , 'Prince Mohammad Bin Salman' , "...	https://finance.yahoo.com/news/cop28-latest-sa...

Fig. 3: First 5 rows of raw data collected from Yahoo Finance

3.2. Data preprocessing

The textual data collected from the two news sources contained different attributes. Since this study only requires two features—daily news headlines and news content—all other attributes were removed. The two datasets were then merged into a single dataset based on the variable Date and subsequently preprocessed using Natural Language Processing (NLP) techniques, as illustrated in Figs. 4 and 5.

Using the NLTK (Natural Language Toolkit) library, the text was first tokenized, followed by the removal of stop words. Part-of-Speech (PoS) tagging was then applied. After these steps, word frequency and syntactic features were calculated. Additionally, the average word length and sentence length were computed for further interpretation. Sentiment polarity for daily news was obtained using the TextBlob library, which applies a sentiment intensity analyzer. Lexical diversity was also measured by calculating the ratio of unique words to the total number of words in each text.

Fig. 6 shows the processed dataset obtained after applying the NLP techniques to both news sources. Finally, this processed textual dataset was merged with technical indicators, as depicted in Fig. 7, to forecast the S&P 500 and NASDAQ indices.

3.3. Model training

Deep learning models were trained to forecast international financial markets, specifically the S&P 500 and NASDAQ indices. The models implemented include Convolutional Neural Networks (CNN) and Gated Recurrent Units (GRU). After developing these individual models, a hybrid deep learning model was constructed by combining CNN and GRU to enhance forecasting performance. Separate models—both individual and hybrid—were trained on each dataset. Additionally, a Meta-Stochastic Gradient Descent (Meta-SGD) model was developed using the same dataset for future forecasting. Unlike the other models, the Meta-SGD framework was trained only once and applied to both financial markets.

3.3.1. GRU

A Gated Recurrent Unit (GRU) model was developed to forecast the S&P 500, DJIA, and NASDAQ indices. The architecture consists of two stacked GRU layers. The first layer contains 64 units and is configured to return the full sequence of outputs, while the second layer consists of 32 units. Fig. 8 illustrates the architecture used to forecast the daily closing values of the NASDAQ and S&P 500 indices.

Headline	Datetime	Content	Source
Mortgage rates: Five ways to save money	Aug 10, 2023	Headlines about are generally g...	BBC
Next says prices to rise by less than expected...	Mar 29, 2023	High Street retailer Next has said it wil put...	BBC
Nationwide latest lender to raise mortgage rat...	Jun 1, 2023	Nationwide will become the latest lender to ra...	BBC
Maersk cuts 10,000 jobs as shipping demand falls	Nov 03, 2023	One of the world's biggest shipping firms is t...	BBC
First look at new entertainment venue revealed	May 04, 2023	Images showing how entertainment venue c....	BBC

Fig. 4: First 5 rows of data obtained after merging news data from BBC News and Yahoo Finance

Headline	Datetime	Content	Source
Wall Street's stock market upgrades are now do...	January 9, 2024 at 3:01 AM	This is The Takeaway from today's Morning Brie...	YFin
Cinven Raises $14.5 Billion for UK Buyout Firm...	January 9, 2024 at 12:30 AM	(Bloomberg) -- Cinven has raised $14.5 billion...	YFin
Trump promises another trade war if he wins. H...	January 9, 2024 at 2:00 AM	Donald Trump is promising that if voters retur...	YFin
US small business sentiment up, but labor, inf...	January 9, 2024 at 3:02 AM	By Amina NiasseNEW YORK (Reuters) - U.S. small...	YFin
The Supreme Court cases (other than Trump) tha...	January 9, 2024 at 2:00 AM	All eyes are on the Supreme Court as it consid...	YFin

Fig. 5: Last 5 rows of data obtained after merging news data from BBC News and Yahoo Finance

Date	Sentiment	avg_sentence_length	avg_word_length	lexical_diversity
10/25/2023	0.141563	209	6.416268	0.751196172
10/25/2023	0.102188	382	6.230366	0.628272251
10/27/2023	-0.01655	259	6.30888	0.675675676
10/27/2023	0.015726	624	6.450321	0.676282051

Fig. 6: Prepared data of sentiments extracted from the fetched web news dataset

Datetime	Sentiment	EUR USD	GBP USD	USD Index	Bitcoin Close	Crude oil Close	Gold Close	DJI Close	avg_ sentence_ length	avg_ word_l ength	lexical_ diversity	NASDAQ	S&P_ 500_ Price
1/31/2024	0.04381	1.08	1.27	103.38	42580.5	75.85	2067.4	38175.34	215	6.92093	0.693023	15254.02	4848.87
1/31/2024	-0.01783	1.08	1.27	103.38	42580.5	75.85	2067.4	38175.34	170	6.517647	0.664706	15254.02	4848.87
1/31/2024	0.105442	1.08	1.27	103.38	42580.5	75.85	2067.4	38175.34	337	6.931751	0.58457	15254.02	4848.87
1/31/2024	-0.1	1.08	1.27	103.38	42580.5	75.85	2067.4	38175.34	55	5.981818	0.890909	15254.02	4848.87
1/31/2024	0.266667	1.08	1.27	103.38	42580.5	75.85	2067.4	38175.34	85	6.482353	0.658824	15254.02	4848.87

Fig. 7: Final merged dataset used in model training

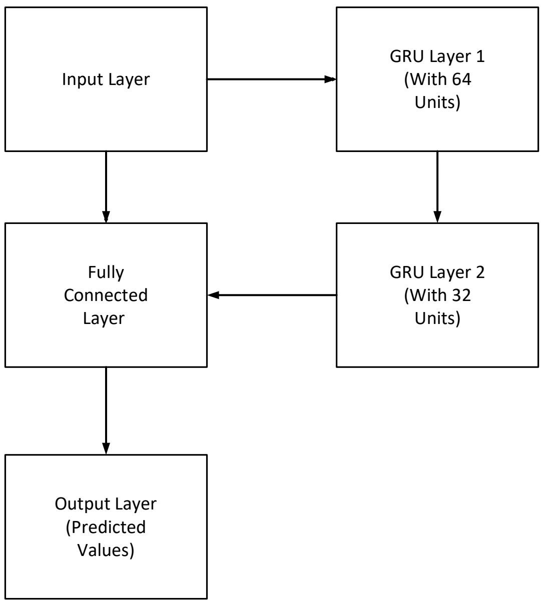

Fig. 8: Proposed architecture of GRU

3.3.2. CNN

The Convolutional Neural Network (CNN) model implemented in this study is designed for financial time series forecasting using a 1D convolutional architecture. The model consists of an input layer that uses sequential data with a shape of (1, 10), as the number of features considered is 10. The first Conv1D layer applies 64 filters with a kernel size of 1, using the ReLU activation function to extract important patterns from the input features. A second Conv1D layer with 32 filters further refines these extracted features. The output is then flattened to convert the multi-dimensional feature maps into a 1D vector, which is processed by a dense layer with 32 neurons for feature transformation. Finally, a fully connected output layer generates the final prediction as shown in Fig. 9. The model is compiled using the Adam optimizer with Mean Squared Error (MSE) as the loss function and trained for 500 epochs with a batch size of 16. After training, predictions are made on the test dataset, and the results are inverse-transformed to match the original scale of the financial data.

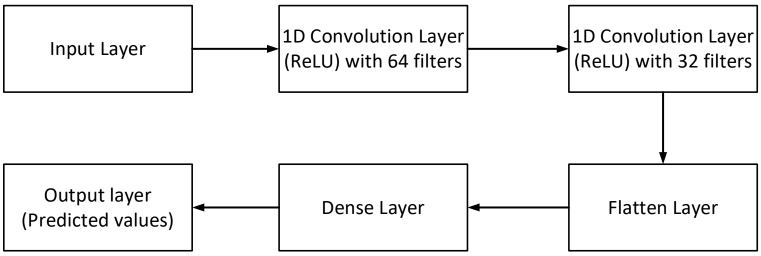

Fig. 9: Proposed architecture of CNN

3.3.3. Hybrid GRU-based CNN

After designing two deep learning models, they are merged to form a hybrid deep learning model. The designed hybrid GRU-CNN model integrates GRU and CNN to effectively capture both temporal dependencies and local feature patterns in financial time series data. At first, a GRU-based recurrent layer is created, where the first GRU layer consists of 64 units with return sequences enabled, allowing it to pass information to the next GRU layer with 32 units. The final GRU output is then reshaped to be compatible with the CNN input structure. A 1D convolutional layer with 64 filters is applied to extract localized patterns from the sequential data. The output is subsequently flattened and passed through a dense layer with 32 neurons before reaching the final output layer. The architecture of the designed hybrid model is described in Fig. 10.

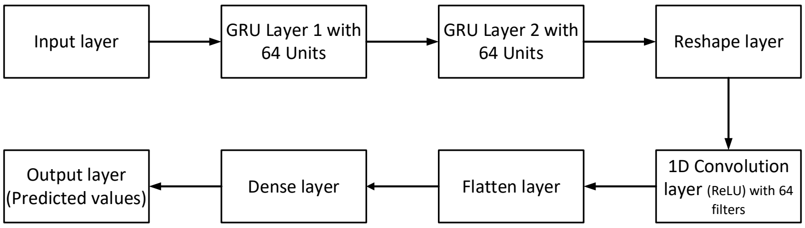

Fig. 10: Proposed architecture of hybrid GRU-CNN

3.3.4. Meta-SGD

The Meta-SGD model is a deep feedforward neural network designed to forecast multiple stock indices (NASDAQ and S&P 500) using a shared set of feature variables. The model consists of three dense layers with ReLU activation, followed by a linear output layer that predicts three target values simultaneously. It is trained using the Meta-SGD optimizer with Mean Squared Error (MSE) loss, ensuring efficient learning across multiple stock indices. The training process runs for 500 epochs with a batch size of 32, leveraging scaled input data for better optimization. After training, predictions are made and inverse-transformed to obtain actual stock index values, enabling accurate market forecasting. The complete architecture of our designed Meta-SGD model is described in Fig. 11.

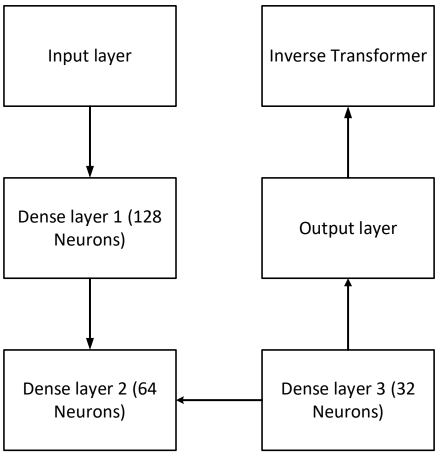

Fig. 11: Proposed architecture of meta learning model

3.4. Model testing and validation

The training models are tested on a test dataset of 30%. RMSE, MAE, and R^2 are used to evaluate all 4 models. In order to validate the obtained results, the daily closing price of NASDAQ is considered to validate the obtained results in order to interpret if the same output is obtained or not as that of the S&P 500 index.

4. Results and discussion

In this study, four forecasting approaches were applied to financial markets: deep learning models, a hybrid deep learning model, and a meta-learning model. The S&P 500 and NASDAQ indices were forecasted using news data and selected macroeconomic variables. Fig. 12 presents a visual comparison of the predicted values from each model against the actual index values. The results show that the hybrid deep learning model outperforms the individual deep learning models. Specifically, the GRU-CNN hybrid model achieved lower RMSE (Fig. 13) and MAE (Fig. 14) compared to standalone GRU and CNN models. This trend was also confirmed when the models were tested on the NASDAQ dataset. The meta-learning approach was then evaluated, and it demonstrated superior performance compared to both individual and hybrid deep learning models. The Meta-SGD model achieved the lowest RMSE and MAE values. Furthermore, the R^2 values (Table 1) indicate that the Meta-SGD model performs significantly better than the other models, while the deep learning and hybrid models produced negative R^2 values, suggesting their performance was worse than the mean predictor.

Additionally, a t-test conducted on the NASDAQ predictions showed that the Meta-SGD model produced a t-statistic closest to zero. This indicates that its prediction errors are nearly centered around zero, reflecting minimal bias. However, the slightly negative value suggests a minor tendency toward overprediction. In contrast, the other models produced larger absolute t-statistics, indicating greater bias in their predictions.

The designed Meta learning model has a minimum error among all designed models, but its efficiency is not limited to this. Along with the mentioned factor, Meta learning is effective because of its minimum computation time. Both of the predictions (S&P 500 index and NASDAQ) are performed by designing a single training model, unlike the hybrid model, in which the training has to be performed separately for different time series.

Table 1: Evaluation indices obtained after testing of the models

No.	Model	NASDAQ			S&P 500		
		RMSE	MAE	R^2	RMSE	MAE	R^2
1	GRU	2001.4	1323.6	-377.3	5161.1	3218.9	-208.7
2	CNN	246	185.8	-4.8	916.6	663.1	-5.6
3	Hybrid GRU-CNN	135.5	112.4	-0.7	969.5	672.7	-6.4
4	Meta-SGD	48.4	37.2	0.8	332.3	257.7	0.1

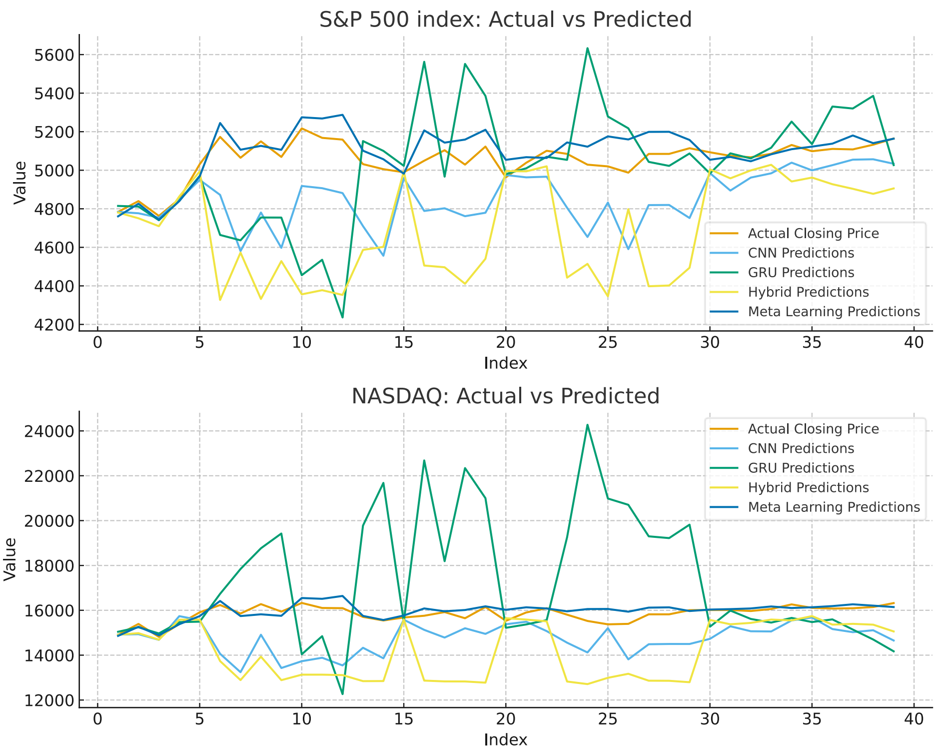

Fig. 12: Actual vs predicted results of considered models

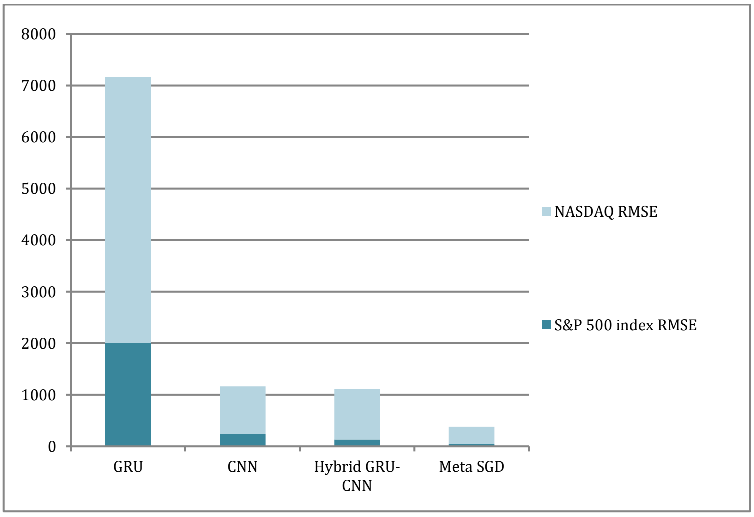

Fig. 13: RMSE of all 4 models

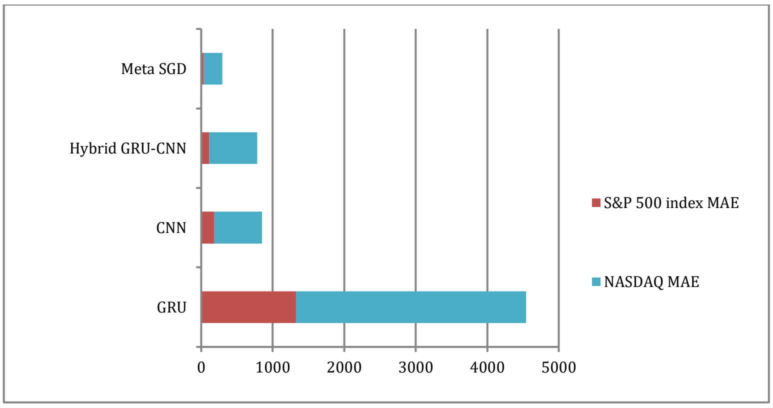

Fig. 14: MAE of all 4 models

5. Limitations

- This study focuses solely on financial market data. For applying meta-learning in other domains, domain-specific knowledge is essential for accurate interpretation of results.
- The meta-learning approach is limited by the number of datasets that can be used simultaneously. Due to variations in domains, geographical locations, time periods, and market conditions, only a small number of datasets (typically three to four) can be effectively incorporated.
- Not all recent advanced models have been critically compared with the proposed Meta-SGD method, which may limit the completeness of the comparative analysis.
- The models used in this study were not cross-validated. Incorporating cross-validation could provide a more robust and realistic evaluation of model performance in financial forecasting.

6. Conclusion and future work

Deep learning models have been extensively applied to forecasting tasks in finance and other real-world domains. To further improve predictive accuracy, researchers have also developed hybrid deep learning models. In this study, a Meta-learning model was proposed for forecasting the S&P 500 index. The results demonstrate that the proposed Meta-SGD model outperforms both standalone deep learning models and hybrid deep learning models—not only by achieving lower prediction errors but also by reducing computational time. These findings were further validated using the NASDAQ index, where the same conclusions were observed.

Future research can extend this work by investigating other meta-learning techniques that may yield even better predictive performance. Additionally, applying these methods to other real-world datasets beyond financial markets would help evaluate the generalizability and robustness of meta-learning models across different domains.

List of abbreviations

ARMA	Auto-Regressive Moving Average
ARCH	Auto-Regressive Conditional Heteroscedasticity
ARIMA	Auto-Regressive Integrated Moving Average
BBC	British Broadcasting Corporation
CNN	Convolutional Neural Network
DJIA	Dow Jones Industrial Average
GARCH	Generalized ARCH
GRU	Gated Recurrent Unit
KSE-100	Karachi Stock Exchange 100 Index
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAML	Model-Agnostic Meta-Learning
MESA	Meta learning for Stochastic Asset

	management
MSE	Mean Squared Error
NASDAQ	National Association of Securities Dealers Automated Quotations
NNAR	Neural Network Autoregressive
NLP	Natural Language Processing
NLTK	Natural Language Toolkit
OHLCV	Open, High, Low, Close, Volume
PoS	Part-of-Speech
ReLU	Rectified Linear Unit
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
R^2	R-squared
SGD	Stochastic Gradient Descent

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Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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