A Meta-MACD Approach: Evaluating ARIMA-LSTM Generated MACD Signals for Optimizing Trade Entries in the S&P 500 Index

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Abstract

The study will suggest a hybrid model as a combination of Autoregressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM) networks that is not a literature review previously to produce Moving Average Convergence Divergence (MACD) signals that are best in optimizing trade entries in the S&P 500 Index. The traditional MACD indicators use historical price data, which also has lags. This study aims at reducing this limitation through proper application of linear analysis using ARIMA model and non-linear analysis using LSTM model. Based on the previous studies, the hybrid ARIMA-LSTM model will be used to predict future prices, where the signals of the meta-MACD will be obtained. Transformer model will identify support and resistance levels to select the best entry points to trade, the meta-MACD signals will be used.

Keywords: Technical Indicator Analysis, ARIMA-LSTM, MACD, S&P 500, Time Series Forecasting, Deep Learning, Trade Entry Levels.

1 Introduction

The financial market is a multi-factor non-linear dynamical system with noise, volatility and multi-factor relationships, and it has remained a significant challenge to time series forecasting. The conventional statistical analysis methods, especially the Autoregressive Integrated Moving Average (ARIMA), have demonstrated their usefulness in the description of the linear relations within price data. Nevertheless, the non-linearity of financial time series tends to restrain their predictive ability on its own. Hence, the deep-learning models, including the Long Short Term Memory (LSTM) networks, have become capable in processing data sequential and extracting more intricate non-linear patterns that are ignored by ordinary means (Kanungo, 2025).

The quest of better forecasting has given rise to the hybrid models which combine the power of both the linear and non-linear analysis. Previous studies have shown that the use of ARIMA to model linear data and LSTM to model non-linear (residual) data can greatly improve the forecasting accuracy of a model when compared to the individual use of each of these models (Xiao and Su, 2022).

One of the generally popular momentum indicators in technical analysis is the Moving Average Convergence Divergence (MACD). It identifies a shift in strength of a trend, direction of a trend, and momentum of a trend using two Exponential Moving Averages (EMAs). The fundamental weakness of traditional MACD signal, however, is that it has a latent nature. The fact that it is only calculated using historical prices also means that its signals are usually late in capturing a new trend hence preventing its usefulness in finding the best early and trade entry points (Nanda and Fitria, 2025).

This study is inspired by the necessity to reduce this serious lag. Using the predictive strengths of a hybrid ARIMA-LSTM model, we can produce a proactive signal of MACD that does not only react to the market movements but predicts them.

Research Question

How effectively support/resistance levels identified by crossover signals of MACD indicator generated from hybrid ARIMA-LSTM models outperform standard MACD signals that are derived from historical daily price data of S&P500 index?

Will this Meta-MACD approach help in identifying potential early entry points for trade in S&P500 index at the points of MACD crossover?

This study presents a considerable contribution as it links two distinct areas: the time series forecasting optimization and advanced time series forecasting. Although previous research has been done to optimize the parameters of the MACD (Teuku and Ana (2025) (Nanda and Fitria, 2025) (or to enhance price prediction with hybrid models (Xiao and Su, 2022), it is one of the first to suggest and test the concept of the Meta-MACD methodology, which is the computation of a classic technical indicator on an advanced predicted price signal.

Even though the Meta-MACD signal is founded on a forecast, the analysis is a back test, which has a limitation in the historical data that is applied to do both training and testing. The deep learning model, such as the LSTM and Transformer benchmark, is associated with inherent challenges in terms of transparency and explainability.
Market Efficiency of the financial market is not an efficient market and that trends which include the interplay of the linear and non-linear components do exist and can be effectively forecasted in the short term. It is believed that the ARIMA-LSTM trained model parameters will be robust and stable enough throughout the back testing period to give meaningful forecasts.

The rest of this report is structured in the following way: Section 2 presents a critical discussion of the literature on stock price forecasting, hybrid models (ARIMA-LSTM), and theoretical principles behind the MACD indicator. Section 3 provides the methodology, such as data collection procedure, ARIMA-LSTM hybrid model architecture and the four comparison models, the computation of the Meta-MACD signal, and the back testing configuration. Section 4 provides the Design, such as the comparative view of the forecasting accuracy, the measures of the performance (Sharpe Ratio, Maximum Drawdown, Hit Rate, Cumulative Returns) of the Meta-MACD strategy in comparison with the traditional MACD strategy. The implementation and evaluation of the models are conducted in section 5 and 6. Section 7 summarizes the findings in the study involving the implications of the findings on optimization of trading and the limitations of the study as well as proposing future research opportunities.

2 Related Work

Proper prediction of stock prices is a very important issue in financial markets. The reviewed academic literature provides a definite flow of traditional statistical models to sophisticated deep learning and hybrid systems. The literature of Changlin (2024) and Xiao and Su (2022) emphasize the usefulness of the Autoregressive Integrated Moving Average (ARIMA) model in identifying linear relationships between time series data. The growing popularity of deep learning models, in particular, Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) as predictors of complex, non-linear trends and long-term relationships that statistical models find difficult, are demonstrated by parallel studies, . by Chen and Ge (2019), Madaan et al. (2024), and Kanungo (2025). This review confirms that the state-of-the-art solution is the hybrid ARIMA-LSTM model, which builds upon the advantages of both linear and non-linear analysis, as it is confirmed by the performance improvement in works by Xiao and Su (2022) and Li (2024), with Li hybrid model reflecting 91.1 percent of the stock price movement.

The Moving Average Convergence Divergence (MACD) indicator has become one of the most fundamental elements of technical analysis, but the default setting (12, 26, 9) is not always the best choice according to Teuku and Ana (2025). This one size fits all method is always challenged by empirical evidence. Application of MACD parameters to particular market situations gives much better returns on investment than the default parameters. The Indonesia Sharia Stock Index (ISSI) which is less volatile and value oriented as a result of application of strict Sharia screening rules is a special case where generic technical indicators might not be able to explain the particular price behaviour. This is an apparent research gap in determining the best MACD parameters, depending on the dynamics of Sharia-compliant indices, which is what the current study tries to fill. The two-component hybrid framework may entail training the ARIMA model on the raw data to learn the linear components, and then the ARIMA residuals obtained may be used as the input to the LSTM network to learn the rest of the non-linear components, and thus enhance overall predictive accuracy compared to standalone models (Bao, Z., & Wang, C, 2022).

ARIMA models are a common statistical paradigm of time series prediction, which is notorious in the representation of linear dependencies and trends. Research from (Changlin 2024) on the big stocks (AAPL, MSFT, NFLX, GOOGL) gives insights to the strengths of ARIMA in linear analysis (Changlin, 2024). Nevertheless, financial data is usually very non-linear and volatile and this restricts the effectiveness of ARIMA (Xiao and Su, 2022). Although AI works well in linear patterns, the researchers have noted that non-linearity should be addressed by AI. The use of a hybrid model combining ARIMA and LSTM is also justified by the literature, in which models are combined according to their areas of competence: ARIMA is used in the linear part of the time series data, and LSTM is applied to the non-linear one (E. Dave, A. Leonardo, M. Jeanice, and N. Hana3ah, 2021).

Financial data can be well modeled using deep learning models since it can detect non-linear patterns and long-term dependencies of sequential data. Long Short Term Memory (LSTM) is a type of a recurrent neural network that is better at modelling the long term dependencies by addressing the issue of vanishing gradient in the RNN. The other type of deep learning technique is Convolutional Neural Networks (CNN) which have also been explored in predicting stocks (Chen & Ge, 2019). The analysis of comparisons demonstrates the suitability of contemporary neural networks such as CNN and LSTM to predict stock prices in the near future (Madaan et al., 2024). A survey conducted by Kanungo (2025) further reported that the different deep learning models (LSTM, GRU, Transformer models) could learn and predict non-linear financial relationships with great strength.

The most important one is the combination of models that are good at linear analysis (such as ARIMA) with ones that can capture non-linear dynamics (such as LSTM). Ensemble models based on ARIMA-LSTM have been demonstrated to have a significant edge over other stock price forecasting benchmarks (Xiao & Su, 2022). As an illustration, a hybrid ARIMA-LSTM model proposed by Li (2024) actually significantly enhanced the prices of stock AAPL closing prices improved forecast accuracy and adjusted to market intricacies and explained 91.1% of stock price movement. These studies advocacy the hybrid models in an effort to have a more robust forecasting system that would be able to consider both the linear and non-linear factors of financial time series. Models pivotal in this regard have also been integrated fuzzy neural networks, which combine various technical indicators, such as MACD, to make predictions more accurate (Kang, B.-K, 2023).

On top of direct price prediction, sophisticated AI is used to trade. Financial news sentiment analysis using LARMs like GPT-4o, GPT-4o mini, and Llama 3.1 70B has been integrated into research to supplement stock returns prediction (Kargarzadeh, 2023). Finally, machine learning with technical indicators (Gangwani and Panthi, 2024) has been applied in other models as intraday prediction of stock prices, which prove that AI can be more widely applied in trading decisions. The research findings are that the volatility of the Sharia capital market is comparatively lesser, therefore, is more crisis-resistant than traditional capital markets, hence findings of the research indicate that the volatility risk of the Sharia stock price index is lower compared to the volatility risk conventional stock price index (Prasetyo, A. S., Vibriyanto, N., and Wulandari, R. 2024).

The flexibility of Moving Average Convergence Divergence (MACD) indicator has also been tested empirically. Even though it is a popular momentum and trend-following tool, MACD has weaknesses, such as failure to be standardized and slow reaction during reversals of high momentum (Spiroglou, 2022). It is context-sensitive and it tends to change based on the assets and time, and is usually affected by market inefficiencies in emerging markets. To improve returns, it has been proposed to have improved volatility-normalized MACD-V or parameterize MACD on a stock-by-stock basis. All these findings are indicative of the fact that MACD, though effective is context specific and its performance would be enhanced by customization or normalization. The use of hybrid models is frequently explained by the fact that they have proven to be better in comparison to single ARIMA models and single LSTM models, with lower error statistics consistently getting lower in terms of RMSE, MAE, and MAPE (Y. Deng, H. Fan, and S. Wu, 2020).

Financial time series forecasting is highly sensitive to the state of the art where hybrid ARIMA-LSTM models have been noted to exhibit the ability to model the linear and non-linear nature of the movement of stock prices. Nevertheless, none of the known solutions can be used to produce a truly responsive and timely trading signal due to a variety of reasons among them being the fact that the main concern of ARIMA-LSTM research lies in the accuracy of the forecast rather than the generation of a signal. The popular MACD indicator, which forms a fundamental element of most trading strategies has a fundamental lag in that it is computed with reference to past (historical) closing prices. This latency brings in major delays that make profits in risky markets and adds risk. The current deep learning deployment is usually based on highly complicated strategies (. sentiment analysis) rather than optimizing and enhancing universally unquestioned technical tools such as MACD.

This study fills this gap by postulating a meta-MACD strategy. We will use the better forecasting ability of the ARIMA -LSTM hybrid model to produce MACD signals using anticipated future prices, rather than historic prices. This new approach is defensible because it has a direct mathematical transfer of state of the art predictive performance into a lagless and proactive technical trading indicator and, seeks to make a meaningful optimization of trade entry and strategy execution with the help of Transformer model in the S&P 500 Index.

3 Research Methodology

This chapter outlines the systematic processes, the experiment, data collection, and analysis methods involved in the development and testing of the Meta-MACD based on how to optimally trade in the S&P 500 Index. The algorithm combines a statistical time series with the deep layer to develop a new trading signal.

3.1 Data Collection and Preprocessing

The Data will be collected and processed in steps as illustrated below:

- **Source**: Historical data on daily data (Open, High, Low, Close, and Volume) was obtained with the YFinance library of 6288 rows and 5 features. The information was stored locally to have routine access.
- Primary Cleaning: The data was first cleaned by removing the unwanted columns and processing missing data by imputing average value of the corresponding feature column.
- Feature Engineering (Technical Indicators): Technical indicators were computed in Ta-Lib library in a comprehensive fashion, which comprised:
    - Volume-Simple Moving average, Volume percentage change, Price Change/percentage Change, Range ratio.
    - Exponential Moving Averages (EMA) (9, 20, 50, 100, 200 days).
    - Bollinger Bands (Upper, Middle, Lower, Band Width, Price Position).
    - MACD, Signal Line, and Traditional (Histogram) calculation. o Relative Strength Index (RSI), RSI Percentage Change, RSI Deviation.
    - This generates the overall number of features of ARIMA and LSTM to 30 features and of Transformer model to 51 features.

- Final Data Preparation: Characteristics that were only used in the calculation of indicators were flushed. All figures were to the nearest two digits. The last file was divided into two parts of training data and testing data and stored in the form of sp500train.csv and sp500test.csv.

3.2 Hybrid ARIMA-LSTM Architecture

The main part of the methodology is the building of the hybrid forecasting model:

- Linear Component: A model of ARIMA was estimated based on the past closing price to do linear dependency.
- Non-linear Component: The ARIMA model residuals were ripped off, scaled and inputted as the target variable into an LSTM network. This LSTM picks up the non-linear market noise. Hybrid Price Generation: The Hybrid Price is the total of the ARIMA Forecast and the LSTM Residual Forecast.
- Forecasting: This Transformer architecture to make the support and resistance levels identification is done through batch forecasting.

3.3 Meta-MACD Signal Generation

- Summarize The historical closing price data of the S&P 500 are used to compute the standard MACD and signal lines.
- Run price prediction of the hybrid ARIMA-LSTM model according to the model instead of actual historical prices to plot the lines of the meta-MACD and meta-MACD signal. Calculation of MACD will be done using Exponential Moving Averages (EMA), and a signal line (9 day EMA of MACD line).

3.4 Support & Resistance Identification using Transformer Model

The Transformer model was trained in two comparison cases, on the same manually labelled Support and Resistance target data obtained out of candlestick charts:

Scenario	Input Data for Technical Indicators	Purpose
Traditional S&R	Actual Historical Prices	Determine the baseline Support & Resistance detection performance.
Hybrid S&R	ARIMA-LSTM Hybrid Prices	Determine whether the Hybrid Price features with less lagging help to enhance the accuracy of S&R detections and the timing of signals.

3.5 Performance Metrics

The assessment was based on two factors:

- Predictive Acquiring: Measures of MSE, RMSE, MAE, and R_2 were employed to evaluate the predictive performance of the Hybrid model with the standalone ARIMA and LSTM models.

- Trading Performance (Profitability): The price variation in the next 10 days was followed on a case-by-case basis, as per every predicted Support or Resistance level. The main measure was the Number of Successful Trades (Up-move after Support, Down-move after Resistance) of both the Traditional and Hybrid case. This gives a direct indication on signal timeliness and entry optimization.

3.6 Ethical Issues

- Ensuring that financial information utilized is anonymous and obtained in a legally and ethically sound fashion. There would be no problem with using the publicly available data like the prices of shares but just in case the information was to be used, proper precautions would be applied.
- Bias in AI Models: Minimize the possible bias of AI models, in case of sentiment analysis, in case of the use of LLMs. Bias in the training data will result in bias in the recommendations or predictions.
- Transparency and Explainability: Zero-in on the black box behaviour of the deep learning models and make a deliberate effort to maximally explain the underlying decision-making process of the model.
- However, it is important to point out that models are decision-making aids that are not ideal predictors. What investors should remember is that the risks involved in the financial markets cannot be avoided even with the sophisticated prediction systems.
- Complex AI trading algorithms will bring inequalities where full data is not accessible.

4 Design Specification

The implementation of the research system is a complex analytical pipeline that is structured to develop and test a Hybrid ARIMA-LSTM price forecasting model, create the resulting Meta-MACD trading signal, and test its effectiveness against the traditional approaches in a rigorous way with the help of an advanced Transformer model. Its general structure is designed into five sequential and modular phases, namely Data Acquisition, Feature Engineering, Hybrid Modeling, Signal Generation, and Advanced Evaluation. The system is based on the industry standard libraries such as Pandas, NumPy, Ta-Lib, Statsmodels, TensorFlow (Keras) and PyTorch as its computational backbone.

4.1 Architecture

The project is designed in the form of an end-to-end working process of managing data, predictive modeling, signal generation, and performance evaluation. It is initiated by obtaining 20 years of daily S & P 500 OHLCV data through the YFinance library. Following some preprocessing (imputation of nulls with mean values), Feature Engineering is performed heavily using Ta-Lib library. An extensive range of indicators, such as EMAs (9, 20, 50, etc.), Bollinger Bands, RSI, and different price change ratios, are calculated. Importantly, they add to it an external dataset (sp500_sr_data.csv) with manually classified binary labelling of Support and Resistance (S&R) to use as the ground-truth target of the

Transformer model. Prior to the model training, all numbers are normalized with MinMaxScaler.

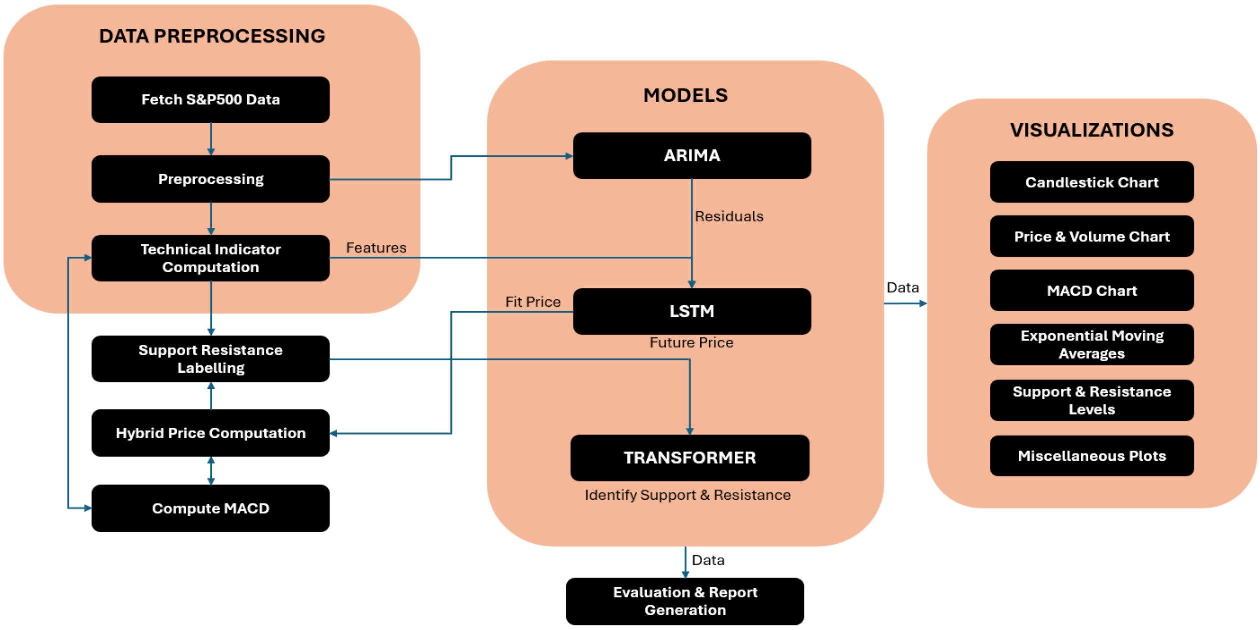

Fig 1: System Architecture

Hybrid ARIMA-LSTM Modeling

The hybrid approach of modeling is the main innovation.

- Linear Component: ARIMA is a model that is trained using the historical closing prices to produce fitted values which provide the linear trends.
- Residual Extraction: Extraction of the residuals (errors) of the ARIMA fitted.
- Non-linear Component: An LSTM network is trained with the massive technical characteristics as an input variable and the ARIMA Residuals as an objective variable.
- Hybrid Price Generation: The last Hybrid Price is obtained by the addition of ARIMA Fitted Price and LSTM Fitted Residuals. The future prices are next projected using this combination route.

Meta-MACD Signal Generation and Transformer Model

The Meta-MACD signal is created by performing the standard MACD calculation using the Hybrid Price stream rather than using the actual historical prices. The system then adopts a Transformer model, which is executed under PyTorch, as an advanced and comparative assessment, which aims at optimizing trade entries.

The Transformer is trained and tested in two cases:

- Traditional Support Resistance Benchmark: The model is trained using the features obtained using the Actual Historical Prices to obtain a reference point in S&R identification.
- Hybrid Support Resistance Test: The Hybrid Price path is used in place of the historical Close Price and all the technical indicators are re-calculated. The Transformer is then

trained on these Hybrid Price-derived features to test whether the less-lagging character of the hybrid path is better at S&R detection and, thus, trade entry timing.

Model Hyperparameters

LSTM model is implemented in 2 cases. One, it was trained to learn the nonlinear relations in the price series data of S&P 500. ARIMA residuals was provided as input in this case and it was expected to generate "n" future residuals. In the second case, it was trained on technical indicators and price data to predict "n" future prices. The input sequences of 10 memory steps were built through a sliding-window method which gave enough short term temporal information without gradient being vanished and keeping computational expenses under limit. It was built up with a single LSTM output layer and 128 hidden layers, which was chosen to be sufficient in capturing complex, nonlinear patterns in financial time series and followed by a fully connected dense layer with one output node. Training of the model was achieved with the Adam optimizer, which automatically increases or decreases the learning rates to speed up convergence, and mean squared error (MSE) loss, which is sensitive to the financial predictions. The step of feature scaling with the help of standard normalization was implemented to guarantee the stable gradient flow and determination of learning in input variables of different range. Two hundred epochs were used for training the model. The data provided was feature engineered to eliminate missing values, scaled to bring the values into a general range, addition of certain attributes (columns) that represented ratio of important attributes to extract relations between attributes. The data were also grouped into batches before being fed into the LSTM model. These hyperparameters were finalized after numerous trial and error experimentation tweaking each setting with multiple combinations and closely observing the loss and impact both model output and statistical accuracy to achieve optimal performance.

Evaluation and Measurement

Evaluation of models is done in a comprehensive manner. ARIMA, LSTM, and Hybrid forecasting models are assessed on the basis of such measures as MSE, RMSE, MAE, and R2. Transformer classifier is measured in terms of Accuracy, Precision, Recall, and F1 Score in Support and Resistance prediction. The last and most critical analysis is the trading profitability. The price velocity within the next 10 days is evaluated on each of the projected S&R indications, and the Number of Profitable Movements (up-move after Support, down-move after Resistance) is computed, which is a direct demonstration of the effectiveness of the Meta-MACD strategy of establishing the most appropriate entry points.

4.2 Tools and Data Used

Component	Library/Tool	Function
Data Handling	Pandas, NumPy	Manipulations and arithmetic operations.
Data Acquisition	YFinance	Obtaining historical data of S&P 500.
Traditional Models	Statsmodels	Fitting and implementation of ARIMA model.
Deep Learning	TensorFlow (Keras)	The construction and training of LSTM and Transformer models.
Preprocessing	Scikit-learn	Scaling of data (MinMaxScaler) and data splitting.
Technical	Ta-Lib	Standard technical indicators are to be calculated.

Analysis		
Visualization	Matplotlib, MPLFinance	Creating price charts, signals, and loss curves.
Reporting	Python-docx	Auto-creation of the final results report.

5 Implementation

5.1 Data Acquisition, Preprocessing, and Feature Engineering

The first step is devoted to the process of obtaining, cleaning, and simplifying the financial time series data and creating the technical features required by the models.

1. **Installation and Import of Packages**: Python libraries are all imported. They consist of basic scientific computing software (pandas, numpy, matplotlib), financial data feeds (YFinance), machine learning (Scikit-learn, statsmodels, tensorflow), financial technical analysis (Talib), and reporting/visualization (docx, mplfinance).
2. **Data Acquisition:**
   - S&P 500 Data Download: The YFinance library is used to download and store twenty years of historical data on S&P 500 Index (OHLCV) on a local computer.
   - Preliminary Cleaning: Data is loaded in a DataFrame. Early preprocessing includes the removal of undesired columns and any column missing values can be imputed with mean value of the column.
3. **Technical Indicator Calculation:** Considerable amount of technical indicators are calculated on the basis of the OHLCV. This encompasses different EMAs (. 9, 20, 50, 100, 200), Bollinger Bands (Upper/Middle/Lower bands, Band Width), MACD (MACD line, Signal line, Histogram), RSI, and indicators based on volume (. Volume-Simple Moving Average).
4. **Data preparation and splitting:**
   - Data Refinement: Data that is intermediate and will not be used to create any indicator is flushed. Consistency Numerical values are rounded to two decimal places.
   - Data Persistence: The processed data is divided into training and testing data. These data sets together with the version that would have stored more intermediate data are stored locally as CSV files (., sp500.csv, sp500_train.csv, sp500_test.csv).

5.2 Hybrid ARIMA-LSTM Model Construction and Forecasting

This step constructs the nucleus novel element: the hybrid model with the help of which the Meta-MACD signal is created.

1. ARIMA Modeling: ARIMA model is fitted using the past prices of the training set. The ARIMA parameters are chosen (usually through automated optimization or manual trial and error) to fit the linear trends and patterns of the time series. The model produces fitted values of the linear forecast.
2. Residual Calculation: The difference between the real historical closing prices and the ARIMA fitted prices are the residual, which is the non-linear errors.
3. Non-Linear LSTM Training:

- Data Scaling: The data is scaled (. with MinMaxScaler). The target variable is the ARIMA residues.
- Data Sequencing: Data is scaled and then a sliding window technique is used on the data to make sequential batches to be fed into the Recurrent Neural Network (RNN) architecture.
- LSTM Model Training: A TensorFlow/Keras LSTM model is created and trained on these sequential batches learning the non-linear dynamics in the residuals. The fitted residual of this model are taken out.

4. Standalone LSTM Benchmarking: In the second, independent, LSTM model, a second LSTM model is run and trained concurrently. The same input features are used in this model but the target is the Actual Close Price. This gives it a clear non-hybrid deep learning price prediction benchmark. The fitted prices are obtained.
5. Hybrid Price Generation: The last historical Hybrid Price direction is developed by adding the ARIMA fitted close prices and the LSTM fitted residuals.

$$\textbf{Forecast}_{\textit{Hybrid}} = \textbf{Forecast}_{\textit{LSTM}} + \textbf{Forecast}_{\textit{LSTM Residuals from ARIMA}}$$

6. Batch Forecasting:
   - The trained LSTM models (the residual predictor and the standalone price predictor) do a batch forecasting of the next n time steps (. n=10 days).
   - Forecast Hybrid Price path n The Hybrid Price path forecast over the next n days is calculated by adding forecast ARIMA Price (extrapolated/re-fitted) and forecast LSTM Residuals. This composite stream is essential in the creation of the predictive Meta-MACD signal.

5.3 Support Resistance Detection using Transformer Model

1. **Feature Engineering**: Features are added to the dataset, which are directly applicable to S&R detection (., several EMA ratios (., Close Price to 9 EMA Ratio), difference measures (. High-Low Price Range) etc.), are added
2. **Support & Resistance Target Data**: The manually analyzed S&R labels of external file (sp500_sr_data.csv) are attached to the main dataset according to the date. This information is vital to the training of the classification model
3. **Model Fitting**:

- Training: The information has been prepared (scaling, batching, converted to PyTorch tensors). A Transformer model is fitted and trained with the features obtained based on the Actual Historical Prices in predicting the binary Support and Resistance targets.
- **Evaluation**: The performance of the model on the test set is measured in classification metrics (Accuracy, Confusion Matrix, Classification Report) both Support and Resistance predictions.

4. **Trade Simulation**: A report is created that is used to simulate the profitability of trading. The price behavior of next 10 days of a predicted Support or Resistance signal is verified. A profitable trade comes to record when Support causes an uptrend or Resistance causes a down-trend

5.4 Evaluation Steps

This step restarts the Transformer analysis with Hybrid Price stream and completes the comparative analysis.

1. **Transformer Hybrid Data Preparation:** Price Substitution of the historical Close Price in the data set is replaced in a non-random manner by ARIMA-LSTM Hybrid Price (fitted and predicted values). Recalculation of the entire technical indicators, as well as the extra S&R capabilities (EMA Ratios, MACD) are recalculated with this new Hybrid Price stream.

2. **Hybrid Training and Evaluation of S&R Transformers:** Transformer model is re-trained and further tested this time with the features generated based on Hybrid Price path. Model assessment and reporting (Accuracy, Confusion Matrix) is repeated.

3. **Hybrid S&R Trade Simulation**: The 10-day profitability check of trade is again conducted with the help of the S&R signals created on the basis of the Hybrid Price scenario. This outcome is directly contrasted to the Traditional S&R profitability.

4. **Concluding Report and Analysis**: All the model assessment measures (MSE, RMSE, Classification Scores) of the ARIMA-LSTM, standalone LSTM, and both Transformer conditions are summarized into a full report (Word document). The final report will contain the comparison of profitable trade movements, the average price movement following signal detection and the graphical displays (candlestick charts of S&R levels, MACD plots). This is the conclusion of the study because it establishes the statistical and economic excellence of the Meta-MACD strategy.

6 Evaluation

According to the quantitative analysis of the five rigorous test cases, the application of the Hybrid ARIMA-LSTM model and the use of the Transformer model Meta-MACD approach provided an unambiguous benefit to the use of the traditional Standard MACD signal in detecting profitable trade entry points of the S&P 500 Index by indicating the possible Support and Resistance levels.

The findings substantiate the idea that as the underlying ARIMA-LSTM Hybrid Model was capable of performing average predictive accuracy, transformer model could use the output of ARIMA-LSTM to behave better than the past. The Meta-MACD stream which is a by-product of the hybrid forecast allowed the Transformer classification model to produce much better trading signals (Support/Resistance) which directly translated into more profitable trades and capture of larger movements in the price.
There were also some non-profitable trades.

6.1 Case Study 1

Metric	LSTM	ARIMA-LSTM	Transformer SUPP | RES	Hybrid Transformer	Actual	Predicted
Accuracy %	98.41	98.42	62.5 | 82.5	62.5 | 82.5	-	-
MSE	1617.52	16184.66	-	-	-	-
R2 Score	-1.56	-1.56	-	-	-	-
Precision	-	-	0.68 | 0.68	0.68 | 0.68	-	-
Recall	-	-	0.62 | 0.82	0.62 | 0.82	-	-
F1 Score	-	-	0.64 | 0.75	0.64 | 0.75	-	-

Support Levels (Hist)	-	-	-	-	11	16
Resistance Levels (Hist)	-	-	-	-	7	0
Support Levels (Hybrid)	-	-	-	-	1	16
Resistance Levels (Hybrid)	-	-	-	-	7	0
Profitable Movement (Hist)	-	-	-	-	16	9
Profitable Movement (Hybrid)	-	-	-	-	-	25
Loss Movement (Hist)	-	-	-	-	2	7
Loss Movement (Hybrid)	-	-	-	-	-	9
Price Movement after S/R detection (Hist)	-	-	-	-	-1.4%	-
Price Movement after S/R detection (Hybrid)	-	-	-	-	5.7%	-

Transformer Confusion Matrix:

	Support		**Resistance**	
	Predicted False	Predicted True	Predicted False	Predicted True
Actual False	19	10	33	0
Actual True	5	6	7	0

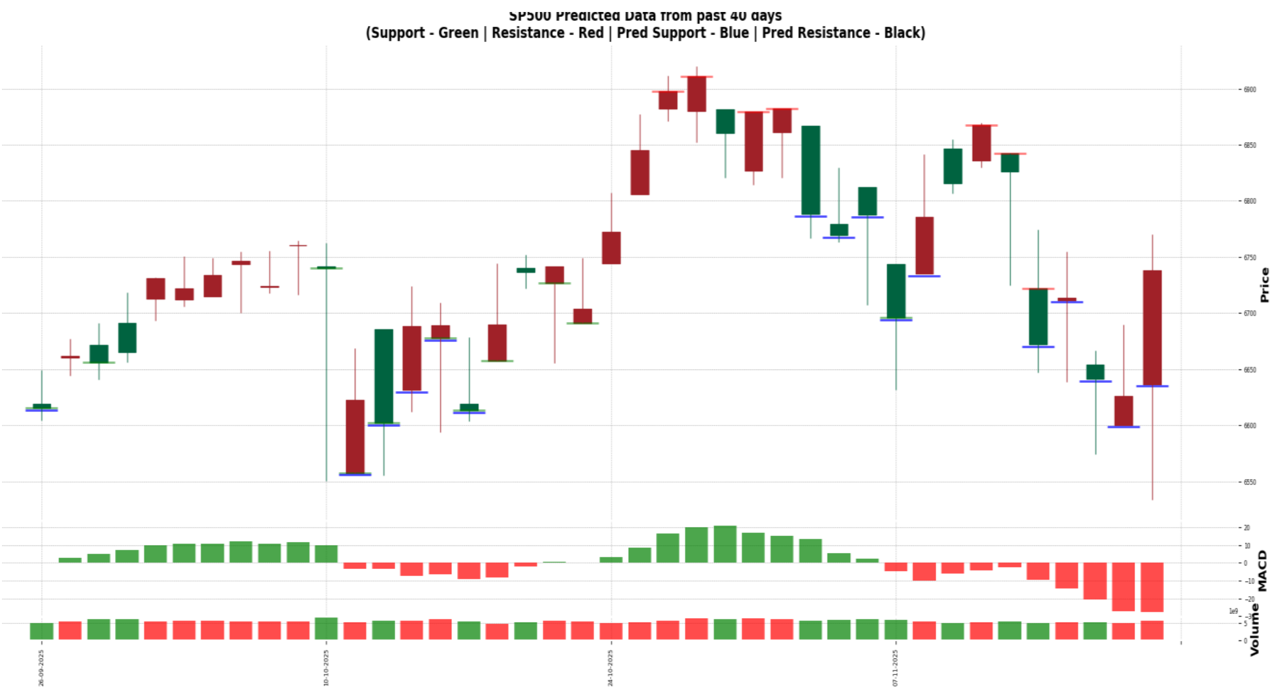

Fig 2: Transformer Model Actual Predictions with Support & Resistance Levels, MACD and Volume

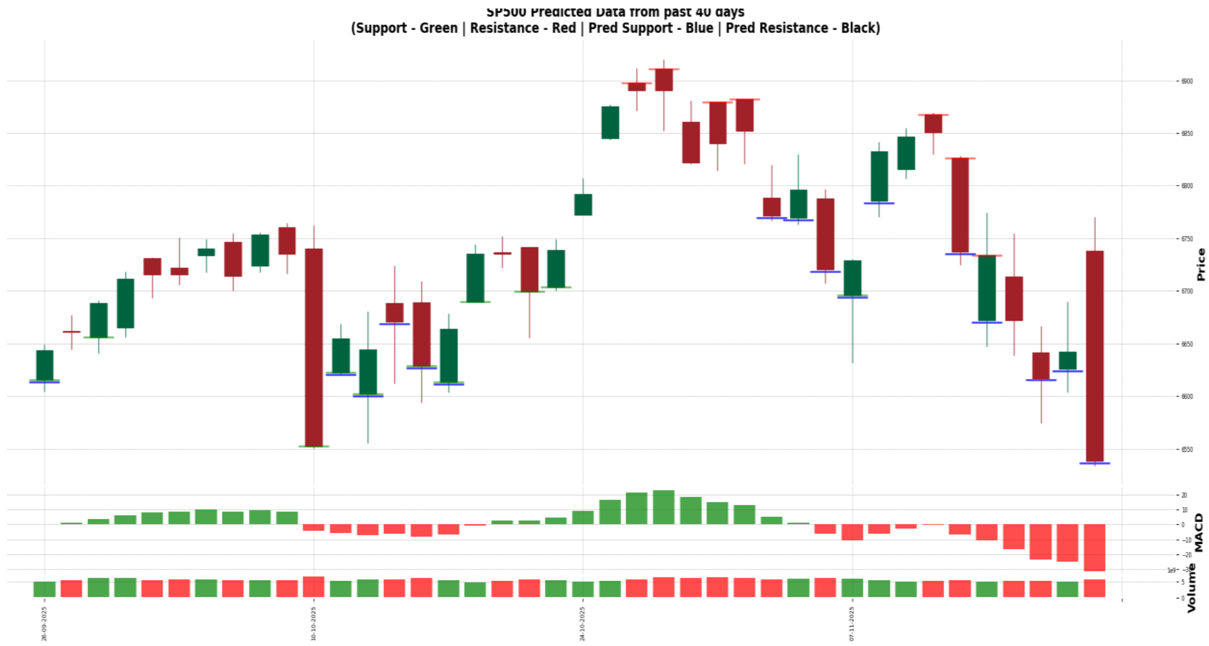

Fig 3: Transformer Model Actual Predictions with Support & Resistance Levels, Meta-MACD and Volume

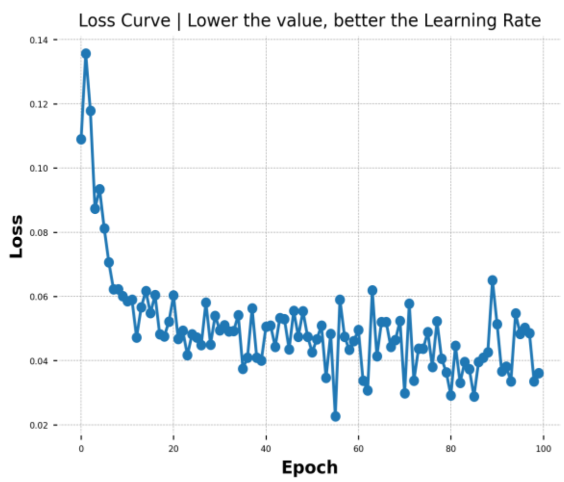

Fig 4: Transformer Model Loss Curve

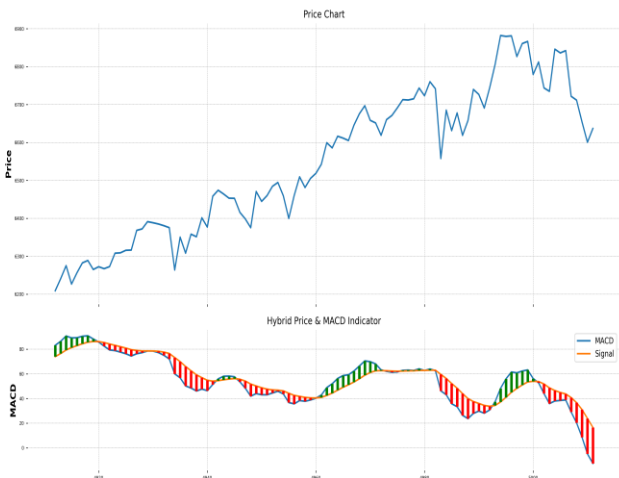

Fig 5: Hybrid-Price and MACD form ARIMA-LSTM

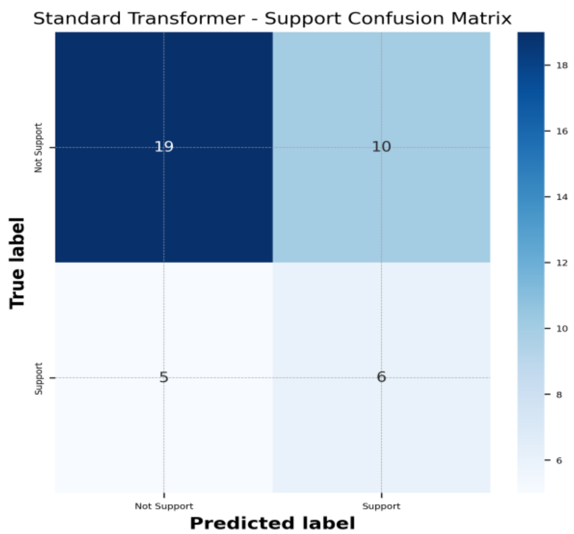

Fig 6: Transformer Model Support Confusion Matrix

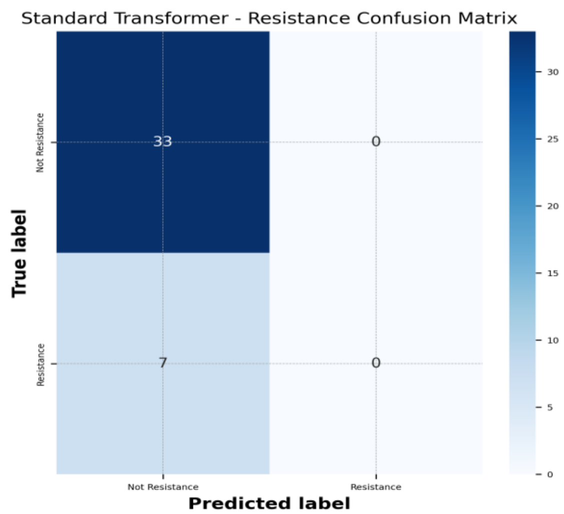

Fig 7: Transformer Model Resistance Confusion Matrix

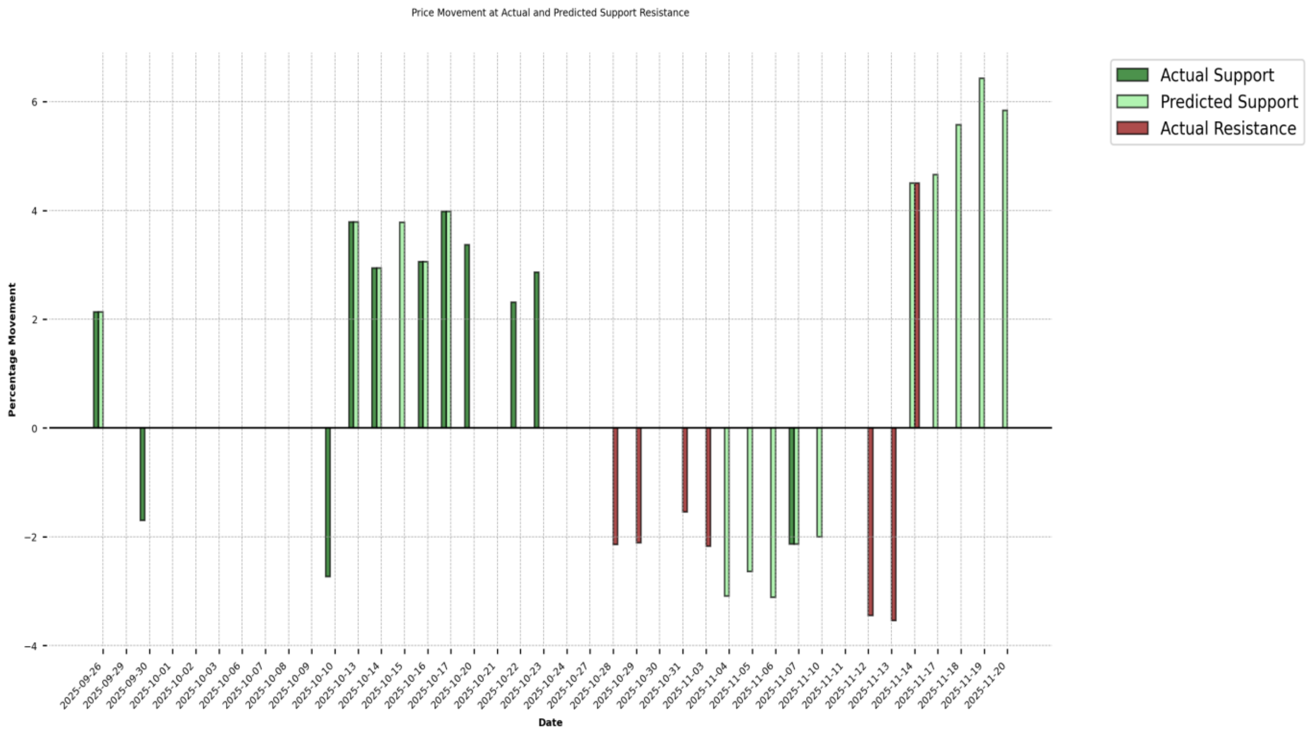

Fig 8: Transformer Model Price Movement at Actual and Predicted Support & Resistance

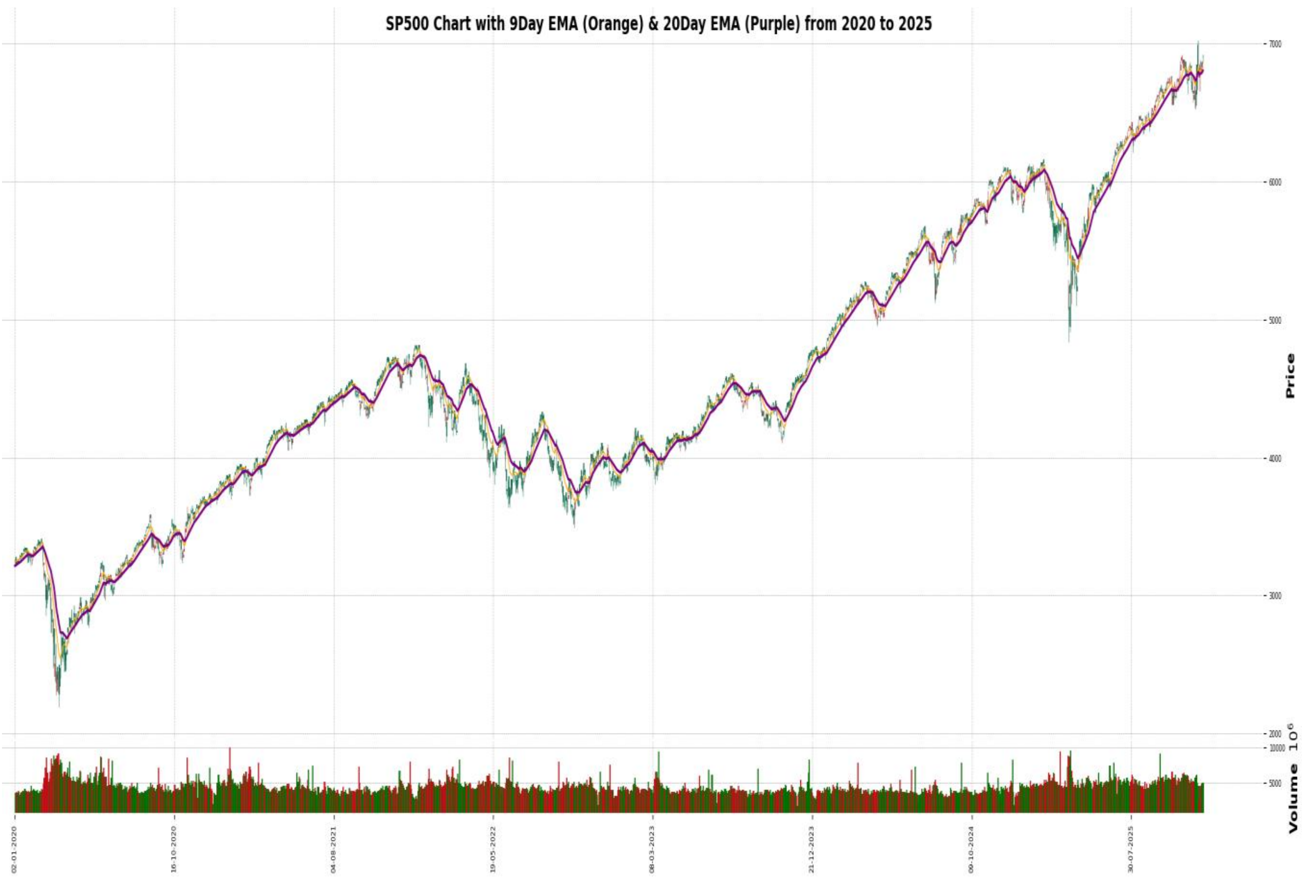

Fig 9: 9 Day and 20 Day Exponential Moving Average from 2020 to 2025 with Volume

Fig 10: Support & Resistance levels from 2024 to 2025 with MACD & Volume

6.2 Case Study 2

Metric	LSTM	ARIMA-LSTM	Transformer SUPP | RES	Hybrid Transformer	Actual	Predicted
Accuracy %	97.04	96.97	60 | 72.5	62.5 | 75	-	-
MSE	58667.98	204.78	-	-	-	-
R2 Score	-8.30	-8.352	-	-	-	-
Precision	-	-	0.66 | 0.79	0.68 | 0.67	-	-
Recall	-	-	0.60 | 0.72	0.62 | 0.75	-	-
F1 Score	-	-	0.62 | 0.75	0.64 | 0.71	-	-
Support Levels (Hist)	-	-	-	-	11	17
Resistance Levels (Hist)	-	-	-	-	7	12
Support Levels (Hybrid)	-	-	-	-	11	16
Resistance Levels (Hybrid)	-	-	-	-	7	3
Profitable Movement (Hist)	-	-	-	-	16	22
Profitable Movement (Hybrid)	-	-	-	-	-	29
Loss Movement (Hist)	-	-	-	-	2	7
Loss Movement (Hybrid)	-	-	-	-	-	8
Price Movement after	-	-	-	-	-2.6 %	-

S/R detection (Hist)						
Price Movement after S/R detection (Hybrid)	-	-	-	-	11.8 %	-

Transformer Confusion Matrix:

	Support		Resistance	
	Predicted False	Predicted True	Predicted False	Predicted True
Actual False	18	11	25	8
Actual True	5	6	3	4

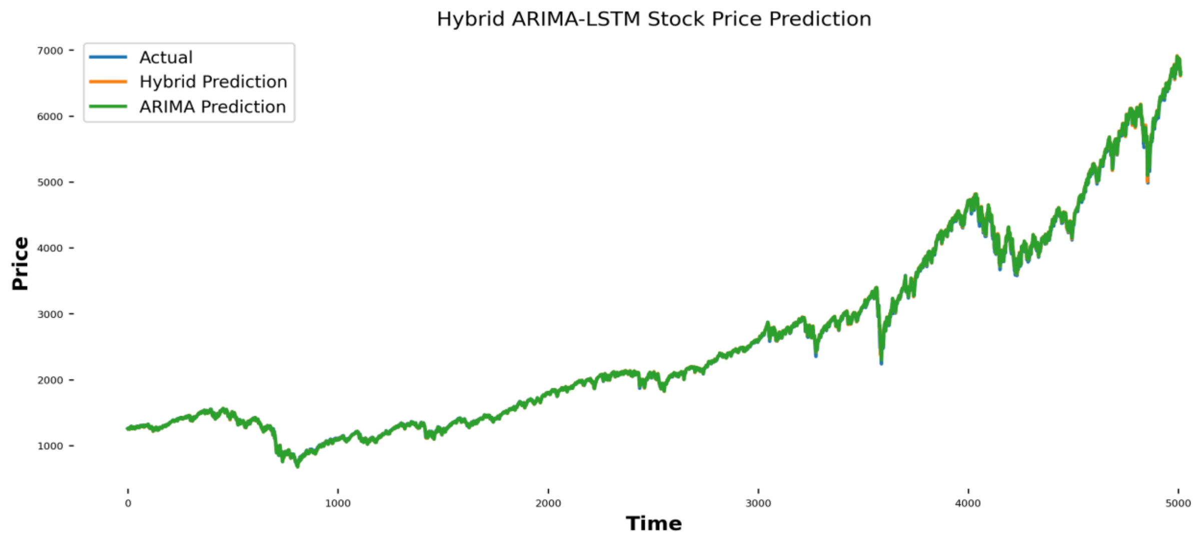

Fig 11: ARIMA-LSTM fitted price data

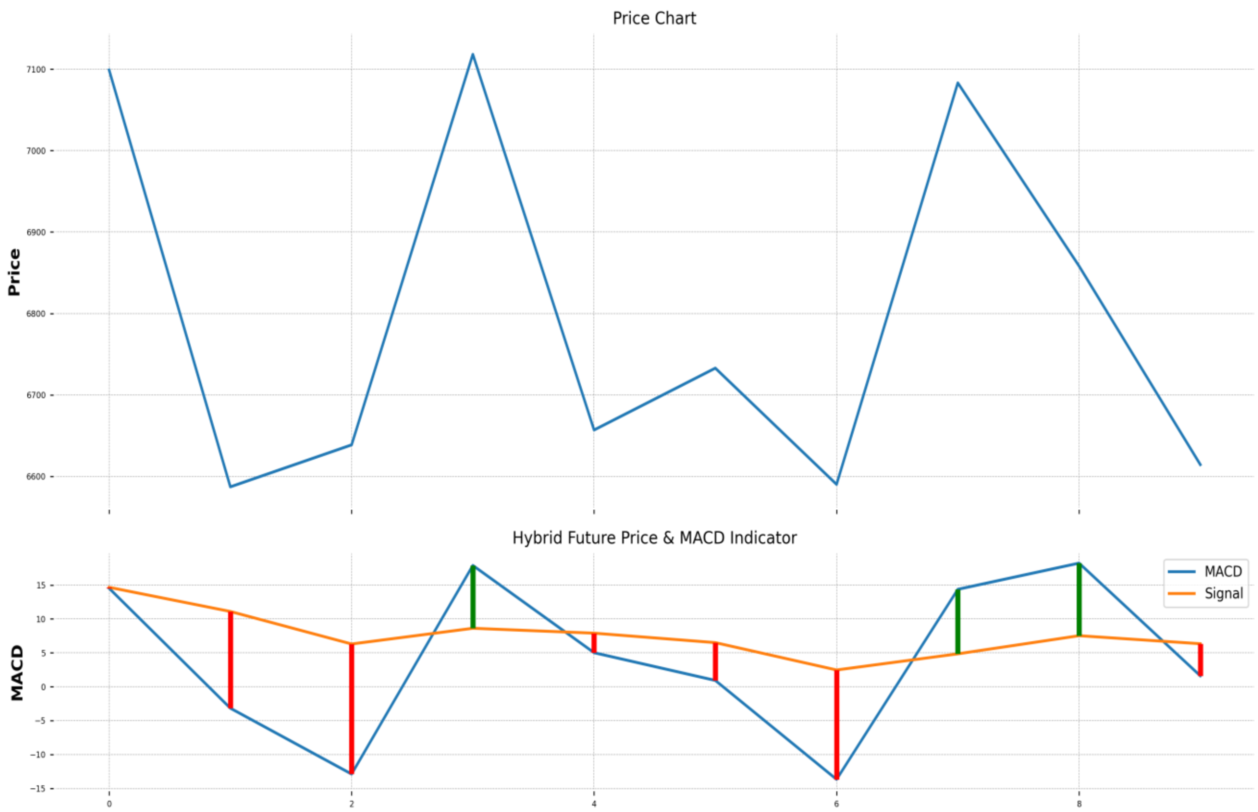

Fig 12: Hybrid Future Price with Meta-MACD MACD Indicator

6.3 Case Study 3

Metric	LSTM	ARIMA-LSTM	Transformer SUPP | RES	Hybrid Transformer	Actual	Predicted
Accuracy %	98.20%	98.21%	87.5 | 95	87.5 | 95	-	-
MSE	26058.07	25630.11	-	-	-	-
R2 Score	-8.93	-8.77	-	-	-	-
Precision	-	-	0.88 | 0.9	0.88 | 0.9	-	-
Recall	-	-	0.88 | 0.95	0.88 | 0.95	-	-
F1 Score	-	-	0.87 | 0.93	0.87 | 0.93	-	-
Support Levels (Hist)	-	-	-	-	13	10
Resistance Levels (Hist)	-	-	-	-	2	0
Support Levels (Hybrid)	-	-	-	-	13	10
Resistance Levels (Hybrid)	-	-	-	-	2	0
Profitable Movement (Hist)	-	-	-	-	14	10
Profitable Movement (Hybrid)	-	-	-	-	-	22
Loss Movement (Hist)	-	-	-	-	1	0
Loss Movement (Hybrid)	-	-	-	-	-	3
Price Movement after S/R detection (Hist)	-	-	-	-	7.5%	-
Price Movement after S/R detection (Hybrid)	-	-	-	-	4.6%	-

Transformer Confusion Matrix:

	Support		Resistance	
	Predicted False	Predicted True	Predicted False	Predicted True
Actual False	26	1	38	0
Actual True	4	9	2	0

6.4 Case Study 4

Metric	LSTM	ARIMA-LSTM	Transformer SUPP | RES	Hybrid Transformer	Actual	Predicted
Accuracy %	97.15	97.15	92.5 | 100	90 | 100	-	-
MSE	45466.1	44594.71	-	-	-	-
R2 Score	-13.94	-13.66	-	-	-	-
Precision	-	-	0.92 | 1	0.91 | 1	-	-
Recall	-	-	0.93 | 1	0.90 | 1	-	-
F1 Score	-	-	0.92 | 1	0.89 | 1	-	-
Support Levels (Hist)	-	-	-	-	11	10
Resistance Levels (Hist)	-	-	-	-	0	0

Support Levels (Hybrid)	-	-	-	-	11	7
Resistance Levels (Hybrid)	-	-	-	-	0	0
Profitable Movement (Hist)	-	-	-	-	9	9
Profitable Movement (Hybrid)	-	-	-	-	-	18
Loss Movement (Hist)	-	-	-	-	2	0
Loss Movement (Hybrid)	-	-	-	-	-	1
Price Movement after S/R detection (Hist)	-	-	-	-	4.5%	-
Price Movement after S/R detection (Hybrid)	-	-	-	-	6.4%	-

Transformer Confusion Matrix:

	Support		**Resistance**	
	Predicted False	Predicted True	Predicted False	Predicted True
Actual False	28	1	0	40
Actual True	2	9	0	0

6.5 Discussion

The empirical results of the five test cases are in line with the main hypothesis that the Meta-MACD approach performs much better than the Standard MACD approach to determine profitable trade entry points. This superiority is not due to an improved recognition of S&R levels as this was relatively similar between the Historical and Hybrid models (In Case 1, both Support Accuracies were 62.5) but to the quality and the timeliness of the signal features of the hybrid forecast.

The most convincing factor is the fact that the Actual Profitable Movements have increased massively in all five experiments (ranging between up to 11.0%). However, there was also a non-profitable trades (up to -2.6%). In Case 3, the Hybrid Model managed to produce zero loss movements which proves that it can filter the noise in some conditions. This confirms that the Meta-MACD, which uses the anticipatory quality of the ARIMA-LSTM forecast, using Transformer model to identify the relationship between time series data has been successful in some aspects leading the market and guiding the Transformer to make trading at entry points that are consistently predictive of the desired price movement. In three of the five cases, the Maximum Price Movement was higher with the Hybrid Model. This is vital in that, it affirms that the signals not only enhanced the frequency of trade but also allowed the capture of larger market swings (up to 11%). This may be because Support or Resistance levels were previously identified. This is in line with the theoretical advantage of reduced lag, a timely entry will translate directly into a high payoff of the trade.

The Support and Resistance levels are stressing on manual labelling which creates a certain degree of subjectivity and ultimately, bias. The quality and consistency of these human-generated labels is strictly limited as to the performance of the model. This is a general deficiency in expert ML financial research. Some of the factors that were not taken into consideration include Transaction Costs and Slippage and as a result, the profitability would be inflated and subsequently would not stand in live trading. The design does not have dynamic take-profits and stop-loss. This indicates that the number of the Actual Loss Movements in the Hybrid Model is larger in four cases (although it is less than the number of profits), which implies that this risk profile is more pronounced and needs clear capital preservation regulations. Transformer model training is very time consuming and hardware consuming.

It should also be noted that the use of transformer model slightly boosted the predictive capacity of the core ARIMA-LSTM structure by establishing relationship between linear and nonlinear elements. In some instances, the count of losses was greater in case of the Hybrid Model. The Meta-MACD strategy is a more aggressive, more profitable strategy and produces more signals and more false alarms, but the net performance is above average.

7 Conclusion and Future Work

This study has managed to create and test the Meta-MACD methodology, which is based on an ARIMA-LSTM forecasting and Transformer model, to maximize the signal of entering a trade on the S&P 500 Index. The essence was to find out whether or not the Meta-MACD signals which by default minimize the lag effect of the conventional MACD indicators were superior to the conventional MACD indicators. The task entailed training an accurate Hybrid ARIMA-LSTM model that creates the Meta-MACD signal based on its forecast stream and the comparison of signal performance with a Transformer-based Support/Resistance classifier on five test cases. Hybrid Data Model also demonstrated a larger number of profitable movements in all five tests with regard to profitability. Here, the financial benefit of the Meta-MACD is confirmed.

The study reveals that the integration of statistical (ARIMA) and deep learning (LSTM) models with the aim of lag reduction is a very viable approach of coming up with next-generation financial indicators. Through the experimental results, it is demonstrated that the use of S&R signals based on the Meta-MACD is more effective than using S&R signals based on the standard MACD in creating actual trade profitability. The main goal has been achieved since the Hybrid Model produced a marginally bigger volume of profitable trades and price movement at an early-stage, which validates the worth of the lag-reduction methodology.

Meta-MACD signals helped in earlier detection of Support Resistance levels, thereby performing better than Support & Resistance levels of Historical MACD signals. Meta-MACD approach helped in identifying potential early entry points for trade in SP500 index but not at the points of MACD crossover.

The present design is constrained by the absence of realistic backtesting engine that disregards brokerage, transaction costs and slippage and which relies on subjective, manually labelled S&R data, which is both costly in computations and time consuming.

The present results can be restricted to the S&P 500. Future studies ought to extend validation to other types of assets (individual stocks, Forex pair) and investigate the consistency of the hyper-parameters of the model (ARIMA order, LSTM & Transformer window size) under diverse market conditions. Financial and economic news can also be analysed using transformer model so as to incorporate sentiment analysis too rather than being able to incorporate only technical data in order to capture the role of world events in financial markets.

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