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# [Forecasting Financial Time Series Using Machine Learning Models]

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## ABSTRACT

Forecasting economic variables is crucial for policymakers, researchers, and financial institutions, since it facilitates informed decision-making and efficient planning. Monetary Aggregates (M3) are one of these variables that is very important for showing liquidity, guiding monetary policy, and measuring economic stability. In the literature, numerous classical and machine learning techniques have been utilized to predict monetary aggregates. This study utilizes four independent methodologies—Autoregressive Integrated Moving Average (ARIMA), Autoregressive Fractionally Integrated Moving Average (ARFIMA), Extreme Learning Machine (ELM), and Multilayer Perceptron (MLP)—to predict M3 using monthly data. We utilize well-known quality indicators like Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) to rate how well each model works. The results show that the MLP model always does better than the other techniques, with the lowest error values in both the training and testing stages. This shows that MLP neural networks are very good at capturing the nonlinear and complicated dynamics of monetary aggregates. The results show that machine learning approaches, especially MLP, could make economic forecasts more accurate and help make financial and monetary policy decisions based on facts.

**Keywords:** Financial Time Series, Machine Learning, Multilayer Perception (MLP)

## Introduction

Economic factors are the main reason why the global market is growing and stable. These factors are important for understanding how the economy is doing (Sachs, 2015). Financial variables like interest rates, exchange rates, stock prices, and commodity prices are especially important. Changes in these variables have a direct effect on business decisions, investment choices, and economic policies (Mishkin, 2019). Shiller (2015) said that it is important to be able to accurately predict these variables because their changes can have a big effect on people, businesses, and even whole societies.

For example, the investors may suffer financial losses due to inaccurate predictions of the financial variables, while these inaccurate and unreliable predictions can undermine the policy makers' efforts to manage systematic risk and stabilize the markets (Greenspan, 2007). Therefore, it is a very crucial element of effective decision-making, comprehensive risk management, and strategic planning to effectively understand and achieve precise forecasting of financial variables (Soros, 2013).

Historically, to examine and predict the analysts have depended on conventional statistical models like GARCH (Generalized Autoregressive Conditional Heteroskedasticity) and ARIMA (Autoregressive Integrated Moving Average). These models often fall short while dealing with the non-linear structures, dynamics, inherent complexities, and confused behavior of modern financial data, despite the fact that they provided valuable insights about linear relationships (Tsay, 2010; Brooks, 2014). Financial markets, having an impact of a wide range of interconnected variables, like as investor psychology, geopolitical events, and macroeconomic data, are complicated and dynamic. It is challenging to predict the financial markets using simple linear models, due to these interconnected variables (Taleb, 2007).

The advanced learning models are capable of capturing the hidden patterns and non-linear relationships in the financial data; therefore, they are becoming popular as traditional models have limitations (Ahmed, 2023; Cao & Gu, 2020). Long Short-Term Memory (LSTM) networks and Transformer models have shown better accuracy when working with time series sequential data, especially when the market is volatile (Chen et al., 2021). Deep learning models, such as LSTM networks, are good at modeling sequential data because they can remember things (Chollet, 2017). Conventional neural networks (CNNs), which were originally used for image recognition (Goh, 2019), can be used to find patterns in financial time series. The CNN extracts features for the LSTM to use in its prediction, combining the strengths of several architectures in hybrid models as the CNN-LSTM (Alonso-Betanzos et al., 2021). These models, by employing more sophisticated market analysis and risk management techniques, are enhancing financial predictions.

Previous research using traditional statistical techniques to capture sudden regime transitions, abrupt market shocks, or long-term relationships has been constrained since these studies usually assumed linearity and stationarity in financial data. However, machine learning models are proven to be more effective in managing non-linearities. Many studies focus on a single model or a specific financial variable, which makes it difficult to generalize results across diverse markets and time horizons. Furthermore, comparative analyses are limited, which restricts a comprehensive understanding of the strengths and weaknesses of different approaches. Therefore, there is a need for a comparison of traditional and advanced learning models under multiple evaluation frameworks. The purpose of the study is to compare and explore both traditional and advanced models for the prediction of financial time series. The objectives of the study are to (i) evaluate the prediction performance of selected models, (ii) examine their ability to capture non-linear dynamics, and (iii) identify the most effective model for practical decision-making in finance.

**Literature Review**

Financial forecasting is evolving significantly advanced technology and a deeper understanding of market complexities. The review produces key trends from traditional statistical models to advanced machine learning models, and also identifies critical gaps that the study aims to address.

**Traditional Statistical Approaches and Their Limitations**

Historically, traditional econometric and statistical models dominated forecasting and financial time series analysis. The Autoregressive Integrated Moving Average (ARIMA) family of models is commonly used to denote linear relationships and trends in data (Tsay, 2010). Similarly, Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models have been shown to be effective at modeling volatility clustering and heteroskedasticity, common features of financial data (Brooks, 2014). Despite offering a strong basis for comprehending market dynamics, these models' underlying assumptions of stationarity and linearity have turned out to be a major drawback. Now, it is commonly recognized that financial markets are It is now commonly acknowledged that financial markets are complicated adaptive systems that affect pricing, including a wide range of non-linear factors, such as changes in investor sentiment, adjustments to macroeconomic policies, and unanticipated geopolitical events (Taleb, 2007). Traditional models are frequently unable to achieve high forecasting accuracy due to the dynamic, frequently chaotic, and intrinsic non-linearity of contemporary financial data.

**The Rise of Machine Learning and Deep Learning in Finance**

In the domains of deep machine learning and deep learning, the constraints of conventional models have prompted a significant transition towards more versatile and robust computational frameworks (Ahmed, 2023). Goodfellow et al. (2016) assert that machine learning algorithms are especially adept at handling the intricate, concealed structures and non-linear networks characteristic of financial data. Early adopters effectively used models like Support Vector Machines (SVMs) and Random Forests, which were better than their statistical predecessors in finding non-linear patterns and subtle market signals (James et al., 2013).

Deep learning models have changed the field by making it easier to analyze time series data. Artificial Neural Networks (ANNs) are extensively utilized in finance for classification and regression tasks due to their ability to handle complex nonlinear interactions. Specialized models have demonstrated superior proficiency in handling sequential data. LSTM-type recurrent neural networks are great at finding long-term relationships in time series data, which is a very important skill for predicting the future of money (Chollet, 2017). CNNs that were first made to recognize images have been changed to find important patterns in financial time series by considering the data as a one-dimensional "image" (Goh, 2019). Hybrid models, such the CNN-LSTM, are providing a strong synergy for making predictions (Alonso-Betanzos et al., 2021). During times of high market volatility, Transformer models that use attention processes have shown an amazing ability to process consecutive data and make big increases in forecasting accuracy (Chen et al., 2021).

Additionally, through engagement with market dynamics, innovative methodologies like Reinforcement Learning (RL) are being explored to facilitate an agent's direct acquisition of optimal trading strategies (Deng, 2023).

The research has conclusively demonstrated the superior efficacy of machine learning compared to traditional methods in capturing non-linearities; yet, significant gaps persist. Much existing research is narrowly targeted, utilizing a single model for a specific financial variable or market, hence constraining the generalizability of their findings across many financial contexts. Secondly, comparative evaluations of various forecasting methodologies are frequently constrained by uneven evaluation metrics, data preprocessing methods, and forecasting timeframes, complicating the ability to do a thorough and equitable evaluation of the models' respective advantages and disadvantages. The research lacks a systematic and unified framework for assessing the performance of classical and contemporary machine learning models across many financial variables utilizing a consistent set of evaluation criteria. To give researchers and practitioners useful advice, it is important to lessen these problems.

This study aims to rectify the identified flaws by conducting a systematic and comprehensive comparative analysis of classical and contemporary machine learning models. This research will provide a thorough and pragmatic evaluation of the efficacy of various models by implementing them on diverse financial variables and analyzing their performance within a uniform framework utilizing multiple assessment criteria and forecasting horizons. The findings will validate the superiority of machine learning in managing non-linearities and will pinpoint the most successful techniques for diverse financial contexts, consequently improving decision-making, strategic planning, and risk management in finance.

**Methodology**

This chapter outlines the existing approaches and the research methodology for forecasting financial time series. It outlines the data sources and the statistical and machine learning techniques employed in the research. The analytical approach aims to identify intricate patterns, improve forecast precision, and establish a solid foundation for assessing future financial trends. This study employs two conventional statistical methods and two machine learning techniques to achieve the research aims. The subsequent section provides a succinct overview of each strategy. Classical methods typically denote statistical forecasting strategies that depend on historical time-series data. This study employs two classical methodologies for predicting, which are succinctly stated as follows.

Box and Jenkins (1970) developed the Autoregressive Integrated Moving Average (ARIMA) model, a widely utilized method for time series forecasting (Althobaiti, 2025). Three parameters—p (autoregressive order), d (degree of differencing), and q (moving average order)—characterize temporal correlations (Mulla et al., 2024). The autoregressive component addresses historical observations, differencing eliminates trends and seasonality, and the moving average component manages short-term dependencies and noise (Arumugam and Natarajan, 2023). ARIMA is a linear combination of historical data and errors. Mathematically,

$$(1\text{-}\emptyset_1 B\text{-}\emptyset_2 B^2 -- \cdots -- \emptyset_p B^p)(1-\mathrm{B})^d y_t = \delta + (1\text{-}\theta_1 B + \theta_2 B^2 - \cdots - \theta_q B^q)\,\varepsilon_t \qquad (1)$$

Where, t= 2,3,⋯n

The backward shift operator is B, and the actual value symbol $y_t$. They are important in these formulations $\delta$ is the constant value, $\varepsilon_t$ represented by the error term at time t. Using the least squares method, we find the model's coefficients, $\emptyset_p$ and $\theta_q$. Furthermore, the model has a systematic way of doing model identification, parameter estimation, and modeling diagnostics. To make sure the data is correct and strong, you need to be attentive while using the Akaike Information Criterion (AIC) to choose the best ARIMA (p, d, q) model. The "auto.arima" function in the R forecasting package is for the Arima model.

**Autoregressive Fractionally Integrated Moving Average (ARFIMA)**

The Autoregressive Fractionally Integrated Moving Average (ARFIMA) model characterizes long-memory processes by allowing fractional values for the differencing parameter d (Al-Gounmeein and Ismail, 2023). ARFIMA's flexibility enables it to represent persistent correlations in time series that diminish more gradually than those modeled by short-memory approaches (Ismail & Al-Gounmeein, 2022). The ARFIMA (p,d,q) model is effective for time series exhibiting short-term dynamism and long-term dependence. The Haslett and Raftery (1989) algorithm in R estimates and selects parameters p, d, and q utilizing statistical estimators. Wang et al. (2023) assert that ARFIMA adheres to the model identification, estimation, and diagnostic validation procedures of ARIMA, although it emphasizes the accurate capture of the fractional differencing parameter to represent persistent data behavior.

Machine learning methodologies are increasingly prominent in the domain of predictive analysis. This work employs two distinct machine learning techniques, each of which is briefly explained below.

Contemporary single-hidden-layer feedforward neural networks (SLFN) encompass the Extreme Learning Machine (ELM) proposed by Huang et al. (2006). Non-iterative training characterizes ELM (Izonin et al., 2024). In Extreme Learning Machine (ELM), input weights and hidden layer biases are randomly assigned and remain constant, while output weights are determined analytically, thus eliminating the necessity for iterative parameter adjustment (Vásquez-Coronel et al., 2023). This technique enables expedited learning and diminished processing costs relative to traditional neural networks, all while preserving enhanced generalization (Chegni et al., 2022). ELM has performed exceptionally in time series forecasting, categorization, and regression (Iamsa-At et al., 2024). The mathematical model for an Extreme Learning Machine (ELM) with K hidden nodes and activation function m(y) is as follows:

$$\sum_{i=1}^{K} \delta_i \ m_i\,(y_j) = \sum_{i=1}^{K} \delta_i \ \mathrm{m}\,(v_i . x_j + a_i) = \eta_j \ , \mathrm{j} \in \{1, 2, 3, \ldots, \mathrm{M}\} \quad (2)$$

The weight vector $v_i$ = $[v_{i1}, v_{i2}, \ldots, v_{im}]^{\,T}$ assumes a critical position, representing the fundamental link between the $i^{th}$ hidden node and the input nodes. $a_i$ is the value of the threshold of the $i^{th}$ hidden node, and $\delta_i$= $[\delta_{i1}, \delta_{i2}, \ldots, \delta_{im}]^{\,T}$ represent the weight vector integrating the $i^{th}$ hidden and output nodes. However, $v_i . x_j$ represent the inner product of both $v_i$, $x_j$.

$$\text{Ή}\delta_i = \gamma \quad (3)$$

$$\text{Ή}= \begin{bmatrix} m(v_1 x_1 + a_1) & \cdots & m(v_M x_1 + a_M) \\ \vdots & \ddots & \vdots \\ m(v_1 x_M + a_1) & \cdots & m(v_M x_M + a_M) \end{bmatrix}_{M\times M} \quad (4)$$

$$\delta= \begin{bmatrix} \delta_1^T \\ \delta_2^T \\ \vdots \\ \delta_M^T \end{bmatrix}_{M\times 1} \quad (5)$$

$$\gamma= \begin{bmatrix} \gamma_1^T \\ \gamma_2^T \\ \vdots \\ \gamma_M^T \end{bmatrix}_{M\times 1} \quad (6)$$

A sufficiently large number of hidden nodes is typically required to ensure optimal generalization performance.

Many people use multilayer perceptron (MLP) feed-forward neural networks (FFNNs), which are made up of many layers of artificial neurons that are connected (Abiodun et al., 2019). An MLP architecture consists of an input layer, one or more hidden layers, and an output layer (Oral et al., 2012). A solitary hidden layer is often sufficient for several applications; however, the unique requirements of the problem dictate the number of neurons and the depth of the network. The activation functions are chosen to provide the best performance. The neurons in hidden layers usually use a logistic (sigmoid) activation function, while the output layer uses a linear activation function to make sure that predictions are correct across the goal range (Kangilaski, 2002; Oral et al., 2012).

This setup lets the hidden layer(s) change and compress inputs so that they can be mapped linearly in the output layer. There are two parts to MLP training. In the forward propagation phase, the input layer gets a vector from the training dataset, the hidden layers look at it, and the output layer makes predictions (Luo et al., 2025). Backpropagation uses a loss function and gradient descent to figure out the prediction error and then sends it from the output layer to the hidden layers. To reduce prediction error, network weights and biases are modified repeatedly (Madhiarasan and Deepa, 2017).

**Study Design**

This part of our study explains the approach we used to look at how well different models can predict the Monetary Aggregate (M3). The next steps outline the main parts.

**Step 1. Selection and Preprocessing of Monetary Aggregates Indicator**

The first step is to choose the monetary variable that is most important to you. In this case, it is Monetary Aggregates (M3), which shows how much money is in circulation and how stable the economy is. This indicator was chosen because it demonstrates how the economy's liquidity changes and how sensitive it is to changes in the macroeconomy. The dataset contains monthly observations for complete temporal analysis. To ensure comparability across values and to enhance the performance of forecasting models, the data was further scaled, which helps mitigate issues of varying magnitudes and improves the stability and efficiency of the estimation process

**Step 2. Forecasting Models**

In the second step, distinct forecasting techniques are applied. The rationale for using machine learning algorithms is due to their ability to capture nonlinear patterns and complex dependencies in financial time series, whereas statistical models are included to evaluate performance against simpler, well-established baselines. The detailed description of these forecasting models is provided in Chapter 3.

**Step 3. Training and Testing Phase**

In the third step, forecasting is implemented through the training and testing methodology. The dataset is partitioned into 80% for training and 20% for testing. The classical and machine learning models are trained using backpropagation, where the initial network parameters (weights and biases) are adjusted iteratively to minimize forecasting errors. This phase ensures that the models learn the intrinsic temporal behavior of M3 and can generalize effectively to unseen data.

**Step 4. Selection of the Appropriate Model**

The final step focuses on selecting the most suitable forecasting model based on quantitative performance criteria. In particular, RMSE is employed as the principal metric for model evaluation. The model yielding the lowest RMSE in both the training and testing phases is considered optimal for forecasting the future trajectory of Monetary Aggregates (M3).

**Evaluation Measures**

To ensure the reliability and accuracy of model selection, two widely used error metrics are employed, RMSE and MAE. RMSE quantifies the square root of the average squared differences between predicted and observed values. On the other hand, explains prediction accuracy, without unduly penalizing big deviations by measuring the average magnitude of errors in absolute terms. Together, these metrics offer a balanced assessment of model performance. Lower values of RMSE and MAE indicate better predictive capability. In this study, both measures are used to identify the optimal forecasting model and to assign weights in the ensemble approach. The mathematical formulation of RMSE is expressed as:

$$RMSE = \sqrt{\frac{\sum_{j=1}^{n}(z_j - \hat{z}_j)^2}{n}} \qquad (7)$$

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|(z_j - \hat{z}_j)\right| \qquad (8)$$

Where, $z_j$ is the actual and $\hat{z}_j$is the fitted values across models.

**Application of Model**

The present study focuses on the monetary and financial system of Pakistan, with particular emphasis on the aggregated money supply indicators published by the State Bank of Pakistan (SBP). Monetary aggregates, especially M3 and its components, play a crucial role in understanding the liquidity position, credit availability, and overall financial stability of the country. These indicators are central to evaluating the effectiveness of monetary policy, as changes in money supply directly influence inflation, interest rates, and economic growth. Given their significance, forecasting these aggregates provides valuable insights for policymakers, financial institutions, and investors. The geographical scope of the study is national, encompassing all monetary activities within Pakistan's formal financial system. The dataset used in this research is sourced from the State Bank of Pakistan's Easy Data portal (https://easydata.sbp.org.pk), specifically from the Monetary Aggregates (M3) – Monthly Profile. The dataset covers the period from Jan 2017 to May 2025, providing almost 9 years of continuous monthly monetary aggregate data. The values are expressed in million PKR, ensuring consistency across the dataset. The temporal coverage is continuous every month to provide a reliable forecast, using classical and machine learning models. Table 1 presents the descriptive statistics of the Monetary Aggregates (M3). Furthermore, Figure 1 shows the visual representation of Monetary Aggregates (M3) data.

**Results and discussion**

**Modeling probabilistic and machine learning methods across Monetary Aggregates (M3)**

Table 2 presents the comparative performance of the four forecasting models—ARIMA, ARFIMA, ELM, and MLP—applied to the Monetary Aggregates (M3) time series, evaluated using RMSE and MAE for both training and testing datasets. For the training phase, the MLP model achieved the lowest RMSE (0.002741) and MAE (0.001311), indicating exceptional in-sample accuracy. ARIMA also demonstrated strong training performance with RMSE of 0.031048 and MAE of 0.019796, closely followed by ELM with RMSE of 0.031915 and MAE of 0.023444. In contrast, ARFIMA exhibited notably higher training errors (RMSE = 0.134073, MAE = 0.086287), suggesting weaker in-sample fit. In the testing phase, which better reflects the models' generalization capabilities, MLP again outperformed all counterparts, recording the lowest RMSE (0.131858) among the methods, along with an impressively low MAE of 0.189803. ARIMA ranked second in testing accuracy with RMSE = 0.189803, while ELM showed a moderate decline in performance (RMSE = 0.332596). ARFIMA performed poorest in the testing stage, with RMSE reaching 1.304832, highlighting substantial forecasting errors. Overall, the results clearly indicate that while ARIMA and ELM delivered competitive in-sample accuracy, their predictive performance in the testing dataset was inferior to MLP. The MLP model consistently provided the lowest errors across both datasets, confirming its superior ability to capture the complex nonlinear dynamics in the M3 series.

These findings establish MLP as the most optimal and robust model for forecasting Monetary Aggregates among the probabilistic and machine learning methods evaluated. Figure 2 illustrates the actual and fitted behavior of the Monetary Aggregates (M3) series using four forecasting models: ARIMA, ARFIMA, ELM, and MLP. In Figure 2a, the ARIMA model demonstrates a close alignment between the actual (blue line) and fitted (red line) values over the entire study period, with minimal deviations during most years, although slight underestimations appear in the late 2024 to 2025 period. Figure 2b presents the ARFIMA model, where the fitted series generally follows the trend of the actual values but exhibits more noticeable discrepancies, particularly at the beginning of the series (2017–2018) and in the latter portion (2024–2025), reflecting less stable adaptation to abrupt variations. Figure 2c displays the ELM model, which produces fitted values that almost perfectly trace the actual series throughout the time horizon, with only minor deviations in peak points, indicating strong pattern-learning capability. Finally, Figure 2d shows the MLP model, where the fitted line exhibits an almost complete overlap with the actual series, both in short-term fluctuations and long-term growth, suggesting an exceptional ability to capture the nonlinear and complex structure of the M3 time series. Overall, visual inspection confirms that while ARIMA and ELM achieve good fits, and ARFIMA maintains a reasonable though less precise match, the MLP model achieves the closest alignment with actual data, reinforcing its superior forecasting performance as also supported by the quantitative error metrics.

**Analyzing optimal model across Monetary Aggregates (M3) series**

Figure 3 presents the combined actual and fitted behavior of the Monetary Aggregates (M3) series obtained from the four competing forecasting models—ARIMA, ARFIMA, ELM, and MLP. The actual series (black line) reflects the observed historical pattern, while the colored lines represent the fitted outputs from each model. Visually, the MLP model (purple line) demonstrates the closest alignment with the actual data across the entire period, capturing both the gradual upward trend and short-term fluctuations with minimal divergence.

The ELM model (green line) similarly closely matches the real series, although it has a little more trouble picking up local peaks and troughs. ARIMA (blue line) stays on a mostly correct path, but it does show some tiny changes during the high-growth period from late 2024 to 2025. ARFIMA (red line), on the other hand, exhibits the most differences, especially in the first few years (2017–2018) and at turning points. This means that it is less flexible when it comes to structural changes in the series. The comparative graphic backs up what we found in the error metrics analysis, showing that MLP not only has the lowest RMSE and MAE values but also matches the usual behavior of the actual

M3 dynamics. This shows that it is better at modeling the nonlinear and complicated time relationships that are common in financial time series data.

**Conclusion**

This study set out to evaluate the forecasting performance of classical probabilistic and machine learning methods for Monetary Aggregates (M3). Monetary Aggregates (M3) is a critical indicator for monetary policy formulation and economic stability. Four models, such as ARIMA, ARFIMA, ELM, and MLP, are rigorously compared based using widely recognized error measures, RMSE and MAE, across both training and testing phases. The results reveal several important insights. While ARIMA and ELM models demonstrated relatively good in-sample performance, their predictive strength weakened in the testing phase, indicating limited robustness in capturing future variations. ARFIMA consistently exhibited the highest forecasting errors, suggesting that its long-memory property did not adequately align with the underlying structure of M3. In contrast, the MLP model significantly outperformed its counterparts, achieving the lowest error metrics across both phases. The close agreement between the MLP forecasts and the actual series underscores its ability to effectively model both short-term fluctuations and long-term dynamics in complex monetary data. Beyond the methodological comparisons, the findings carry notable implications. The superiority of MLP highlights the value of machine learning techniques in economic and financial forecasting, particularly when data exhibit nonlinear and evolving patterns that traditional models struggle to capture. Reliable forecasts of monetary aggregates such as M3 are crucial for central banks and policymakers in guiding decisions related to inflation targeting, liquidity management, and financial stability. These findings support the use of neural networks and other advanced learning architectures in macroeconomic forecasting models.

But the study does have some problems. The study used a singular monetary aggregate and constrained forecasting models. Future research could enhance this framework by including machine learning algorithms, hybrid methodologies, or collaborative procedures, and by applying the study to various economies and financial metrics. These extensions may elucidate the models' generalizability and resilience across diverse economic environments. This research shows that the MLP is the best model for predicting Monetary Aggregates (M3). Its ability to change and provide accurate predictions makes it a methodological advancement and a useful tool for policymakers and financial institutions that need reliable estimates to help them plan and make decisions about the economy.

**Table 1. Descriptive statistics of the Monetary Aggregates (M3) monthly profile data**

| Statistics | Value |
|---|---|
| Mean | 8923766 |
| Median | 8528901 |
| Variance | 7.45E+12 |
| Standard Deviation | 2728981 |
| Minimum | 5159769 |
| Maximum | 15246291 |
| Range | 10086522 |
| 1st Quartile | 6426009 |

| | |
|---|---|
| 3rd Quartile | 10949009 |
| Interquartile Range | 4523000 |
| Skewness | 0.462219 |
| Excess Kurtosis | -0.89817 |
| Skewness2 | 0.46675 |
| Excess Kurtosis2 | -0.90481 |

**Table 2. Analyzing error metrics to comprehend the best-fit model for forecasting Monetary Aggregates (M3).**

| | Training | | Testing | |
|---|---|---|---|---|
| Models | **RMSE** | **MAE** | **RMSE** | **MAE** |
| ARIMA | ARIMA | 0.031048 | 0.019796 | 0.189803 |
| ARFIMA | ARFIMA | 0.134073 | 0.086287 | 1.304832 |
| ELM | ELM | 0.031915 | 0.023444 | 0.332596 |
| MLP | MLP | 0.002741 | 0.001311 | 0.131858 |

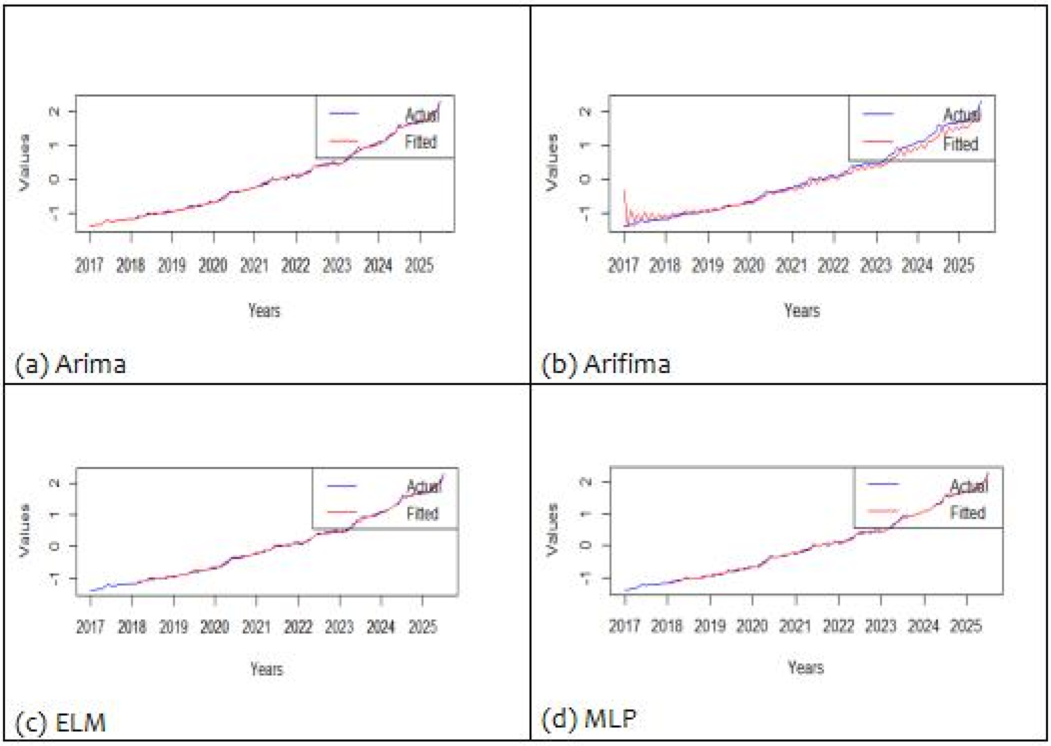


**Figure 1. Visual representation of Monetry Aggregation (M3) data**

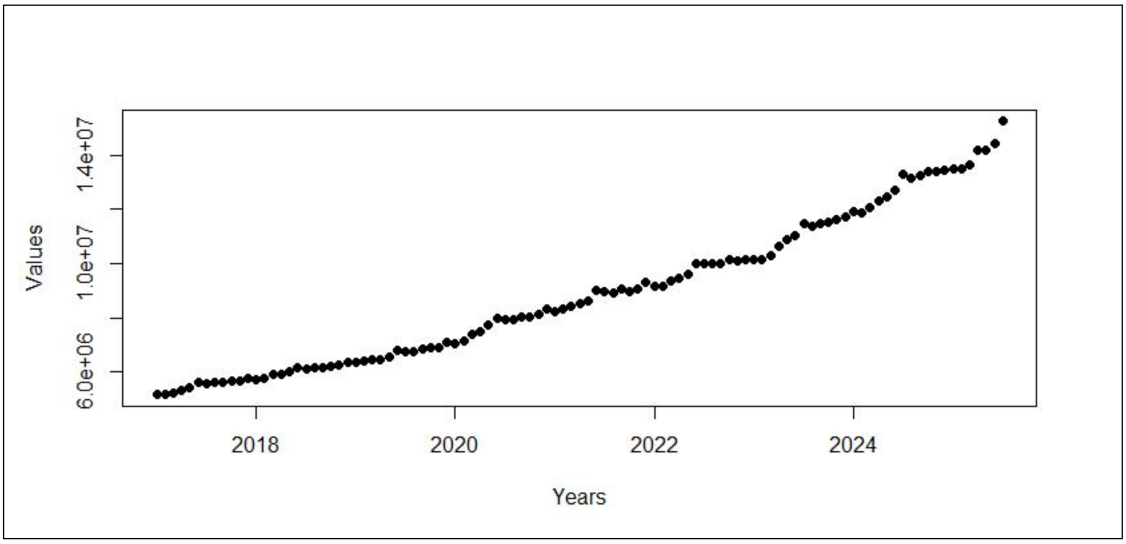


**Figure 2. Actual and fitted behavior of the Monetary Aggregates (M3) using classical and machine learning methods**

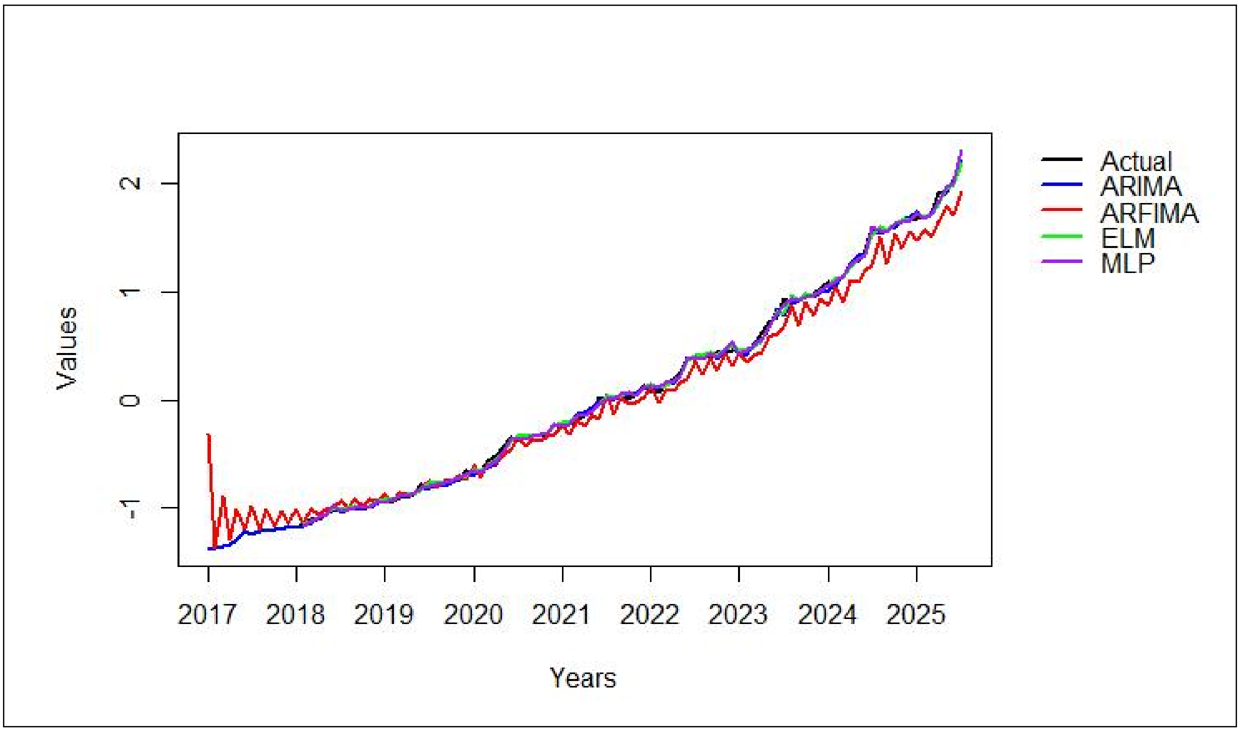


**Figure 3. Analyzing optimal model for forecasting Monetary Aggregates (M3)**

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