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Comparative Study of Traditional and Modern Models in Time Series Forecasting for Inflation Prediction

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Abstract

Time series forecasting plays a crucial role in economic analysis, particularly in anticipating inflation and policy planning. This study compares the performance of seven different time series forecasting models, namely ARIMA, SARIMA, ETS, Prophet, LSTM, XGBoost, and TCN, in predicting inflation rates. Each model was applied to four years of inflation data to test its accuracy and reliability. The evaluation was conducted using MSE and RMSE to measure the performance of each model. The results indicate that deep learning models, particularly LSTM and TCN, achieved the highest accuracy with the lowest MSE and RMSE values, specifically 0.0008 and 0.0015 for LSTM, and 0.0007 and 0.0013 for TCN, indicating their capability in capturing complex temporal patterns. Traditional models such as ARIMA and SARIMA, while effective in capturing trends and seasonality, showed limitations in handling non-linear patterns and sudden changes, with MSE and RMSE values of 0.0012 and 0.0024 for ARIMA, and 0.0011 and 0.0023 for SARIMA, respectively. ETS, with the highest MSE and RMSE values of 0.0013 and 0.0025, demonstrated limitations in dealing with the complexity of inflation data. XGBoost also showed good performance with MSE and RMSE values of 0.0009 and 0.0018, combining flexibility and robustness in handling complex data. Prophet achieved an MSE of 0.0010 and RMSE of 0.0020, indicating that while it effectively captures seasonal trends, there is room for improvement in handling rapid inflation increases. This research provides in-depth insights into the strengths and weaknesses of each model, as well as recommendations for practical applications in inflation forecasting. By presenting a comprehensive comparative analysis, this study aims to assist researchers and practitioners in selecting the most suitable forecasting model for their specific needs.

Keywords: ARIMA, Inflation Prediction, LSTM, Model Performance Evaluation, Time Series Forecasting

1. Introduction

Forecasting inflation is a vital task for policymakers, financial institutions, and businesses worldwide. Accurate predictions of inflation rates are essential for developing effective monetary policies, setting interest rates, creating budget plans, determining pricing strategies, and guiding investment decisions. Traditional time series forecasting models, such as ARIMA (AutoRegressive Integrated Moving Average) and ETS (Error, Trend, Seasonality), have long been favored for their simplicity and efficacy in handling linear data patterns [1], [2]. However, the evolution of machine learning and deep learning has introduced advanced models like LSTM (Long Short-Term Memory), Prophet, XGBoost, and TCN (Temporal Convolutional Network), which have demonstrated superior capabilities in capturing complex, nonlinear patterns in time series data [3], [4], [5], [6].

Despite the advancements in forecasting methodologies, there remains a significant research gap in the comprehensive comparison of traditional and modern algorithms applied to the same dataset. Many studies focus on a single method or compare a limited set of algorithms, which makes it difficult to draw definitive conclusions about their relative performance in various contexts, particularly for financial time series data such as inflation rates [7]. This gap highlights the need for a holistic study that evaluates a broad range of forecasting techniques on a unified dataset, providing insights into their strengths and weaknesses.

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Time series forecasting includes a variety of advanced models. LSTM networks, known for their ability to capture long-term dependencies in sequential data, have been widely used in various forecasting tasks [8]. TCNs offer a convolutional approach to sequence modeling, providing an alternative to recurrent networks with potentially superior performance on certain datasets [9]. The Prophet model, developed by Facebook, is designed to handle time series data with strong seasonal patterns and missing values, offering ease of use and interpretability [10]. XGBoost, a powerful gradient boosting framework, has shown remarkable success in many machine learning competitions due to its robustness and ability to handle complex patterns. Each of these models represents the cutting edge in forecasting technology, and their comparative evaluation against traditional methods like ARIMA, SARIMA, and ETS is crucial for understanding their practical applicability [11].

This study is motivated by the need to explore the performance of various forecasting algorithms on inflation data comprehensively. By comparing traditional statistical methods with modern machine learning and deep learning techniques, we aim to identify the most effective models for accurate inflation forecasting. Understanding the strengths and limitations of each model will provide valuable insights for their application in real-world scenarios.

The primary objectives of this research are to conduct a detailed Exploratory Data Analysis (EDA) on the inflation dataset to uncover its structure, underlying trends, and seasonality. We will apply and evaluate the performance of seven forecasting models: ARIMA, SARIMA (Seasonal ARIMA), ETS, Prophet, LSTM, XGBoost, and TCN. The accuracy of these models will be compared using Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) as evaluation metrics. The results will be analyzed comprehensively to understand each model's effectiveness and suitability for inflation forecasting.

2. Literature Review

The field of time series forecasting has advanced significantly, incorporating a range of statistical and machine learning techniques. This study explores several forecasting algorithms, including ARIMA, SARIMA, ETS, LSTM, Prophet, XGBoost, and TCN, to assess their performance in predicting inflation rates. The following review outlines the key contributions and limitations of these models based on existing research. The ARIMA model has been widely used for its ability to capture linear patterns in time series data through autoregressive terms, differencing, and moving averages. Box and Jenkins established ARIMA's reliability for economic data characterized by linear trends [12]. However, ARIMA struggles with complex nonlinear and seasonal patterns. To address this, SARIMA extends ARIMA by incorporating seasonal components, which improves forecasting accuracy for data with significant seasonal fluctuations. Research Arumugam and Natarajan demonstrated that addressing the primary challenges of time series modeling, such as stationarity, simplicity, and overfitting, applying ARIMA and SARIMA models to six datasets demonstrated their ability to capture underlying data trends and produce reliable forecasts, outperforming baseline methods based on five evaluation metrics [13].

XGBoost, a gradient boosting framework, is known for its high accuracy and efficiency in handling complex, nonlinear relationships in data. Dezhkam and Manzuri [14], highlighted XGBoost's success in machine learning competitions and its effectiveness in various financial forecasting applications. The model's robustness and capacity to manage intricate data structures make it highly valuable, although it requires careful feature engineering to effectively capture temporal patterns. Despite the added complexity, XGBoost remains a powerful tool for achieving precise forecasts. Developed by Facebook, Prophet is designed for time series data with strong seasonal effects and missing values According to Taylor and Letham [15], Prophet's user-friendly interface and flexibility in adjusting trend and seasonal components make it suitable for industrial applications such as sales forecasting and web traffic analysis. Prophet excels in modeling seasonal patterns and long-term trends but may underperform during abrupt data changes, indicating potential limitations in highly volatile situations.

LSTM, a type of recurrent neural network, addresses the gradient decay issue prevalent in traditional RNNs by effectively capturing long-term dependencies in sequential data. Hochreiter and Schmidhuber [16], introduced LSTM as a solution for modeling complex temporal patterns, demonstrating its success in tasks such as stock price forecasting and market sentiment analysis. LSTM’s ability to retain and utilize information from past time steps is advantageous for forecasting where long-term dependencies are crucial. The ETS model integrates error, trend, and seasonal components, providing interpretable forecasts. Hyndman et al. [17] noted that ETS can outperform ARIMA in scenarios with pronounced trends and seasonal effects. Although ETS is effective for capturing systematic patterns, it may encounter difficulties with sudden changes and nonlinear dynamics, affecting its accuracy in volatile contexts.

The TCN model utilizes temporal convolutions for sequence modeling and has shown superiority over traditional RNNs in some forecasting tasks. Research by Samal et al. [18] demonstrated TCN's ability to capture long-term dependencies and complex temporal patterns with greater efficiency. This makes TCN a strong candidate for forecasting applications that require detailed modeling of data dynamics, such as stock market trends and logistics demand. While many studies have examined individual forecasting models, comprehensive comparative analyses across various algorithms on the same dataset are scarce. Most research focuses on specific models without offering a broad comparative perspective. This study aims to fill this gap by evaluating the performance of seven different forecasting models on inflation data, providing insights into their relative strengths and weaknesses. The study also explores the efficiency and practicality of each model, contributing to a better understanding of their application in real-world forecasting. The findings highlight the potential for future research to develop hybrid models that integrate the strengths of multiple approaches to improve forecasting accuracy.

3. Methodology

The methods used in this study involve several systematic stages to ensure the accuracy and reliability of the inflation prediction results. The process begins with data collection, which is a crucial step to obtain a representative dataset. Once the data is collected, a data preprocessing stage is carried out to clean and prepare the data before it is used in the models. Next, relevant features are extracted through feature engineering techniques to enhance model performance. In the model development stage, various algorithms are employed, including ARIMA, XGBoost, Prophet, LSTM, ETS, SARIMA, and TCN. These models are evaluated using MSE and RMSE metrics to assess their prediction accuracy. Figure 1 illustrates the process of developing the inflation data forecasting model used in this research:

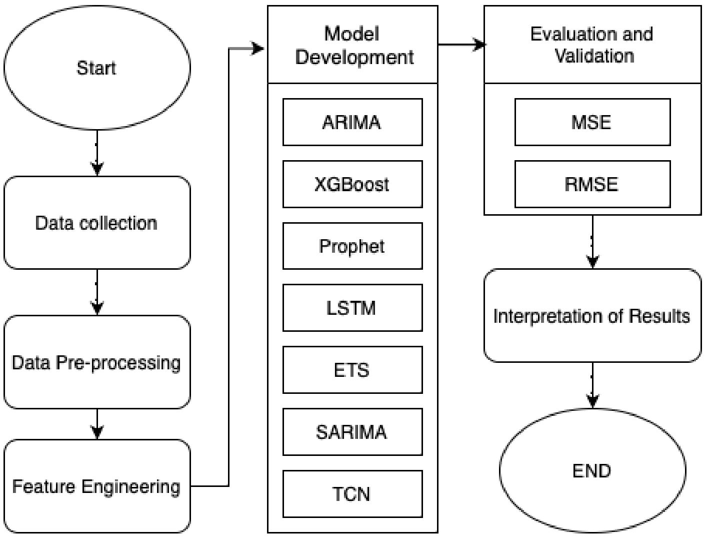

Figure 1. Research Methodology

3.1. Data Collection

The dataset utilized in this study comprises monthly inflation data for various categories over a span of four years. The categories include: housing, water, electricity, and household fuel, rent and house contracts, maintenance, repair, and security, water supply and other housing services, household electricity and fuel, clothing and footwear, clothing, footwear, household equipment and routine maintenance, furniture, equipment, and carpets, and household textiles. To ensure the integrity and usability of the dataset, several preprocessing steps were undertaken. Initially, any missing values were addressed. In cases where the missing values were minimal, interpolation or forward/backward fill methods were applied. Significant missing values necessitated the exclusion of those columns from the analysis. The date column was then converted to a datetime format to facilitate proper handling of the time series data. Normalization

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was performed to ensure that all features contributed equally to the model. This was achieved through techniques such as Min-Max scaling and Z-score normalization. Additionally, feature engineering was employed to enhance the predictive power of the models. This included the creation of lagged variables, moving averages, and other relevant time series transformations.

3.2. Data Preprocessing

Data pre-processing is essential for ensuring the dataset's quality and suitability for model training. This involves handling missing values, often through interpolation or model-based imputation. Normalization scales the data between 0 and 1, crucial for machine learning models to ensure all features contribute equally and enhance training speed. Anomaly detection and removal, using methods like Z-scores or IQR analysis, ensure the data represents normal inflation trends. Finally, the dataset is split into training and testing sets, typically using an 80/20 split, to allow for realistic model evaluation on unseen data.

3.3. Feature Engineering

Feature engineering creates new features from existing data to improve model performance. Lag features, created by shifting the time series data, provide information about past inflation rates. Rolling statistics, such as moving averages, capture underlying trends and volatility. Seasonal indicators like month or quarter help models account for seasonality. External variables, such as interest rates and economic indicators, offer additional context. Feature selection techniques, such as correlation analysis and XGBoost's feature importance metrics, identify the most relevant features, reducing dimensionality and improving performance.

3.4. Model Development

After performing the clustering, it is important to visualize the resulting clusters to better understand the distribution and relationships between the data points. In this study, scatter plots and dimensionality reduction techniques, such as Principal Component Analysis (PCA) and t-Distributed Stochastic Neighbor Embedding (t-SNE), are used to display the cluster distribution in a 2D or 3D space.

ARIMA models are a cornerstone for time series forecasting, capturing autocorrelations within the data. The model is characterized by three parameters: p (autoregressive order), d (differencing order), and q (moving average order). The ARIMA model is defined by the following equation [19]:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \ldots + \beta_p Y_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \ldots + \theta_q \epsilon_{t-q} \quad (1)$$

Note: Y_t is the actual value at time t, ϵ_t is the error term at time t and α, β, θ are model parameters.
XGBoost is an ensemble learning method that uses gradient boosting on decision trees. The model prediction is the sum of predictions from multiple weak learners, and can be expressed as [14]:

$$\hat{\mathcal{Y}}i = \sum_{k=1}^{K} f_k(x_i), f_k \in \mathcal{F} \quad (2)$$

Note: $\mathcal{F}$ is the space of regression trees, and k is the number of trees. The model minimizes the following objective function:

$$\mathcal{L}(\theta) = \sum_i \iota(\mathcal{Y}i, \hat{\mathcal{Y}}i) + \sum_k \Omega\,(f_k) \quad (3)$$

Note: ι is a differentiable loss function and Ω is a regularization term.
Prophet decomposes the time series into trend, seasonality, and holidays components. The model can be described by [20]:

$$\mathcal{Y}(t) = g(t) + \mathcal{S}(t) + h(t) + \epsilon_t \quad (4)$$

Note: $g(t)$ is the trend, $\mathcal{S}(t)$ is the seasonality, $h(t)$ is the holidays effect, and ϵ_t is the error term. The trend component $g(t)$ can be modeled using a piecewise linear or logistic growth model.

LSTM networks are a type of recurrent neural network designed to capture long-term dependencies in time series data. The LSTM unit consists of a cell, an input gate, an output gate, and a forget gate, and can be described by the following equations [3]:

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$$\text{Forget gate: } f_t = \sigma\left(W_f \cdot \left[h_{t-1,} x_t\right] + b_f\right) \tag{5}$$

$$\text{Input gate: } i_t = \sigma\left(W_i \cdot \left[h_{t-1,} x_t\right] + b_i\right) \tag{6}$$

$$\text{Candidate cell state: } \tilde{C}_t = \tanh\left(W_c \cdot \left[h_{t-1,} x_t\right] + b_C\right) \tag{7}$$

$$\text{Cell state: } C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{8}$$

$$\text{Output gate: } o_t = \sigma\left(W_o \cdot \left[h_{t-1,} x_t\right] + b_o\right) \tag{9}$$

$$\text{Hidden state: } h_t = o_t * \tanh(C_t) \tag{10}$$

Note: σ is the sigmoid function, * denotes element-wise multiplication, W and b are weights and biases.
ETS models capture trend and seasonality using exponential smoothing. The model includes three components: Error (E), Trend (T), and Seasonality (S), and can be expressed as [2]:

$$\text{Level equation: } \iota_t = \alpha(Y_t \,/\, \mathcal{S}_{t-m}) + (1-\alpha)(\iota_{t-1} + b_{t-1}) \tag{11}$$

$$\text{Trend equation: } b_t = \beta(\iota_t - \iota_{t-1}) + (1-\beta)b_{t-1} \tag{12}$$

$$\text{Seasonal equation: } \mathcal{S}_t = \gamma\left(\frac{Y_t}{\iota_t}\right) + (1-\gamma)\mathcal{S}_{t-m} \tag{13}$$

$$\text{Forecast equation: } Y_t + h|t = (\iota_t - hb_t)\mathcal{S}_t + h - m(k+1) \tag{14}$$

Note: ι is the level, b is the trend, $\mathcal{S}$ is the seasonal component, and α, β, γ are smoothing parameters.

SARIMA extends the ARIMA model by incorporating seasonal effects. It includes seasonal autoregressive (P), differencing (D), and moving average (Q) components, along with a seasonal period (m). The SARIMA model is represented as [12]:

$$\begin{aligned} Y_t = {} & \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \ldots + \beta_p Y_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \ldots + \theta_q \epsilon_{t-q} + \Phi_1 Y_{t-m} \\ & + \Phi_2 Y_{t-2m} + \ldots + \Phi_p Y_{t-pm} + \Psi_1 \epsilon_{t-m} + \Psi_2 \epsilon_{t-2m} + \ldots + \Psi_Q \epsilon_{t-Qm} \end{aligned} \tag{15}$$

Note: Φ and Ψ are seasonal parameters.

TCNs leverage causal convolutions to ensure predictions at time t depend only on past values. The network uses dilated convolutions to capture long-range dependencies without increasing the model complexity. The TCN is defined:

$$Y_t = \sigma\left(\sum_{i=0}^{k} W_i * Y_{t-i}\right) \tag{16}$$

Note: W_i are the convolutional weights, k is the kernel size, and σ is the activation function.

3.5. Model Evaluation

Model evaluation is a crucial step in assessing the performance of forecasting algorithms, ensuring their accuracy and reliability. This process primarily uses MSE and RMSE as metrics to quantify prediction accuracy. MSE measures the average squared difference between observed actual outcomes and the predicted outcomes, providing a clear indication of how well a model fits the data. RMSE, the square root of MSE, offers a standard deviation measure of prediction errors, making it easier to interpret in the original data's units. Both metrics are evaluated on training and testing datasets. The training evaluation helps assess the model's ability to learn from the data it was trained on, while the testing evaluation ensures the model generalizes well to unseen data, highlighting any issues like overfitting. Additionally, cross-validation techniques are employed for a more robust evaluation, where the dataset is divided into multiple subsets, and the model is trained and tested multiple times to provide a reliable performance estimate.

Comparative analysis of the models involves visualizing the MSE and RMSE metrics through graphs and tables to determine which algorithm performs best on the inflation data. This analysis offers insights into the strengths and weaknesses of each model, revealing which algorithms are most suitable for accurate inflation forecasting. By rigorously testing and evaluating the models, the study ensures that the forecasting algorithms provide reliable predictions, enhancing the understanding and management of inflation trends. This comprehensive evaluation approach

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not only highlights the effectiveness of various models but also informs future applications and refinements in financial forecasting.

4. Results and Discussion

4.1. EDA (Exploratory Data Analysis)

Based on the analysis of inflation rate graphs across various categories of household goods and services, several important findings reflect the complex economic dynamics in different sectors. In the category of maintenance, repair, and security, the inflation rate showed significant fluctuations during the observation period. There was a sharp increase in the second and fourth quarters, indicating a spike in repair and security costs, likely due to increased demand or changes in the prices of related materials and services as seen in figure 2, figure 3, figure 4 and figure 5.

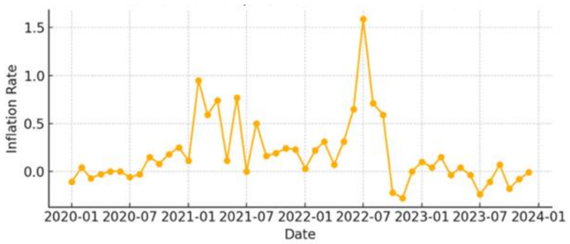

Figure 2. Inflation Rate on Maintenance, Repair and Security

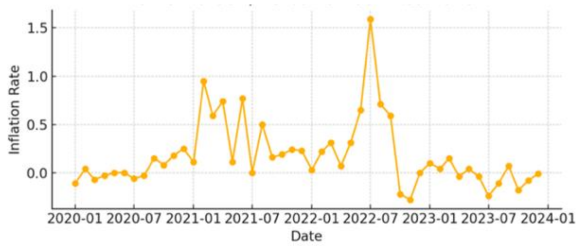

Figure 3. Inflation Rate for Household Electricity and Fuel

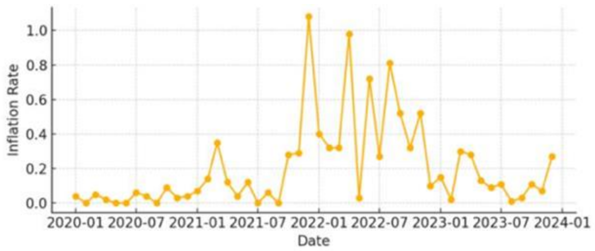

Figure 4. Inflation Rate on Clothing

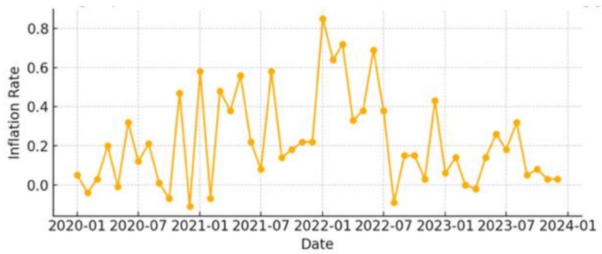

Figure 5. Inflation Rate on Equipment, Tools and Routine Household Maintenance

The inflation graph for household electricity and fuel showed a consistent upward trend, reflecting continuous increases in energy prices. This rise could be influenced by various factors such as increased energy demand, changes in global oil prices, and national energy policies affecting electricity and fuel costs. For the clothing category, the inflation rate experienced a decline over several months, followed by a moderate increase. This can be attributed to seasonal changes in clothing demand, where demand tends to decrease after holiday seasons or weather changes, and then increase again when entering new seasons or shopping periods.

The category of household equipment, appliances, and routine maintenance showed a stable increase in inflation, with some small peaks that may be caused by rising material costs or temporary demand surges. This stability indicates that although there are some fluctuations, overall, the market for this category is relatively stable and predictable. Meanwhile, the inflation graph for household textiles was relatively stable with a slight increase. No significant fluctuations were observed, indicating a relatively stable market, possibly due to a balance between supply and demand and minimal disruptions in the supply chain as seen in figure 6, figure 7, figure 8 and figure 9.

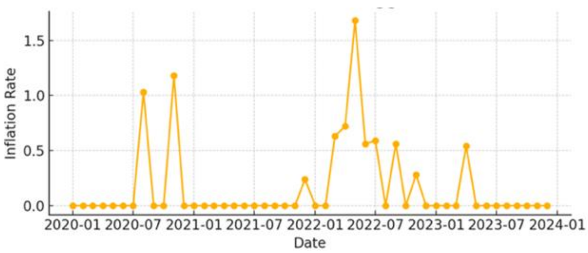

Figure 6. Inflation Rate for Household Textiles

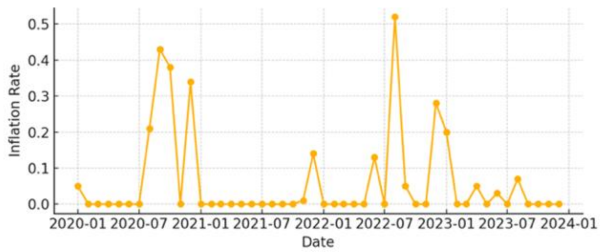

Figure 7. Inflation Rate on Rent and House Contracts

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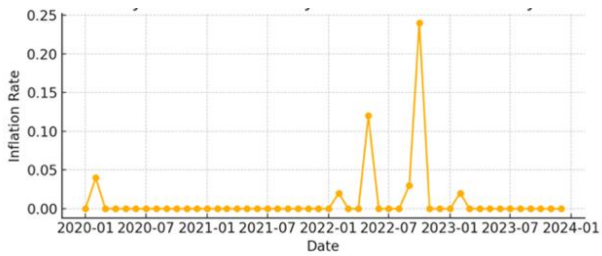

Figure 8. Inflation Rate on Water Supply and Other Housing Services

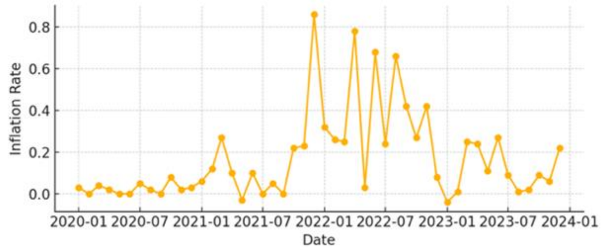

Figure 9. Inflation Rate for Clothing and Footwear

The inflation rate for rent and housing contracts showed a steady increase, reflecting a trend of rising housing costs. This could be due to increased housing demand in certain areas, limited land for new developments, as well as rising construction costs impacting rent and housing contract prices. The inflation graph for water supply and other housing services showed a moderate inflation increase trend, with some fluctuations possibly caused by changes in water tariffs and related services. Factors such as government policies regarding water tariffs, increased operational costs, and investments in clean water infrastructure can contribute to this trend.

The clothing and footwear category showed a declining inflation trend followed by a slight increase, similar to the trend in the clothing category. The initial decline may be due to discount periods or end-of-season sales, while the subsequent increase reflects price recovery when new collections are introduced to the market. Footwear inflation experienced greater fluctuations compared to clothing, indicating higher variability in footwear prices. This may be due to variations in production costs, changes in fashion trends, and differences in demand elasticity for various types of footwear as seen in figure 10, figure 11 and figure 12.

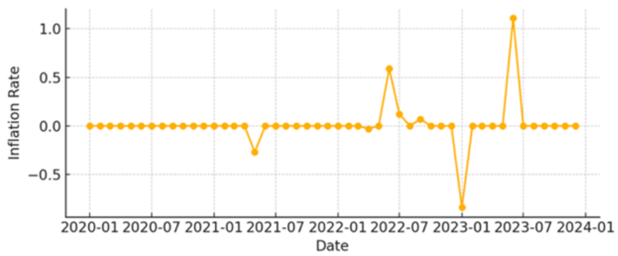

Figure 10. Inflation Rate in Footwear

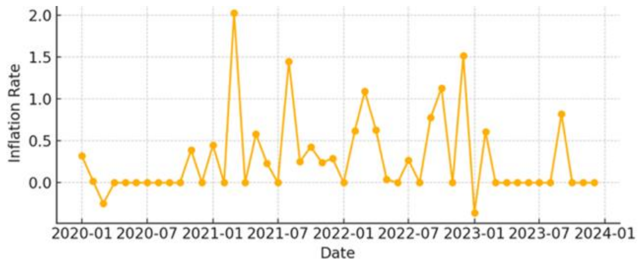

Figure 11. Inflation Rate for Furniture, Equipment and Carpets

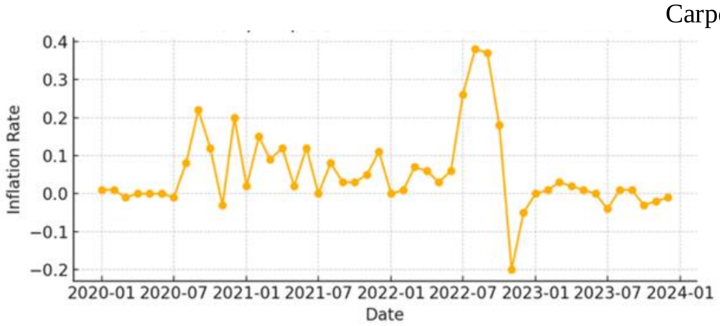

Figure 12. Inflation Rate on Housing, Water, Electricity and Discussing House Burning

The graph for furniture, equipment, and carpets showed a moderate upward trend, with some spikes possibly caused by rising production costs or short-term demand increases. Factors such as raw material prices, labor costs, and changes in consumer demand for these products play important roles in this inflation trend. Finally, the inflation rate for the category of housing, water, electricity, and household fuel showed a significant increase, reflecting the continuous rise in energy and utility costs. This could be due to various factors including rising global oil prices, stricter energy policies, and investments in energy and utility infrastructure affecting the costs passed on to consumers.

4.2. Forecasting Results

This section provides a thorough comparison of various forecasting algorithms ARIMA, XGBoost, Prophet, LSTM, ETS, SARIMA, and TCN applied to the same dataset to predict inflation rates. The evaluation uses MSE and RMSE to measure forecast accuracy, with results displayed through graphs and tables. These visual and quantitative analyses highlight how each model's predictions align with actual inflation data, identifying periods of success and failure. Traditional models like ARIMA and SARIMA are compared with advanced models like LSTM and TCN, as well as hybrid models like Prophet and XGBoost. The ARIMA model's forecast, illustrated through a graph showing historical and predicted inflation changes for "Housing, Water, Electricity, and Household Fuels" from January 2020 to December 2024, predicts a small but steady increase in inflation for 2024, ranging from 0.0194% in January to 0.0512% in December. This comprehensive analysis aims to assess the strengths and weaknesses of each model, guiding the selection of the most suitable forecasting approach for practical applications. SARIMA model, an advanced extension of ARIMA that includes seasonal components, effectively forecasts inflation by capturing seasonal fluctuations and underlying trends, as demonstrated in figure 13 and figure 14 SARIMA's ability to model periodic fluctuations makes it particularly adept at handling regular, cyclical changes, critical for accurate financial forecasting.

The SARIMA model effectively separates non-seasonal and seasonal components to handle complex time series with intricate seasonal behaviors, incorporating autoregressive (AR), differencing (I), and moving average (MA) terms for both parts. However, it struggles with abrupt changes in inflation rates due to its linear framework, leading to forecast deviations during rapid economic shifts. Despite these limitations, SARIMA tracks general trends and seasonal patterns well but occasionally misestimate during sudden changes. Enhancing SARIMA with hybrid models, such as combining it with XGBoost or LSTM, could improve its responsiveness to non-linear dynamics. Fine-tuning parameters and incorporating external covariates can further enhance its performance.

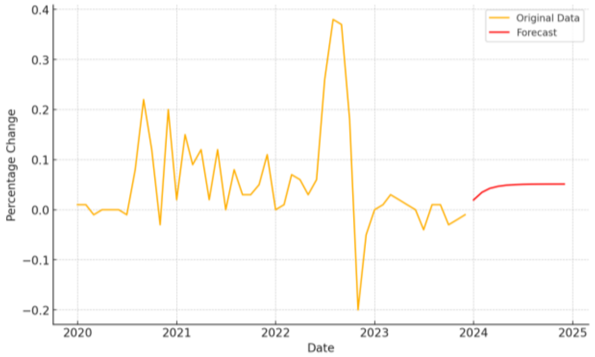

Figure 13. Result of ARIMA Forecast

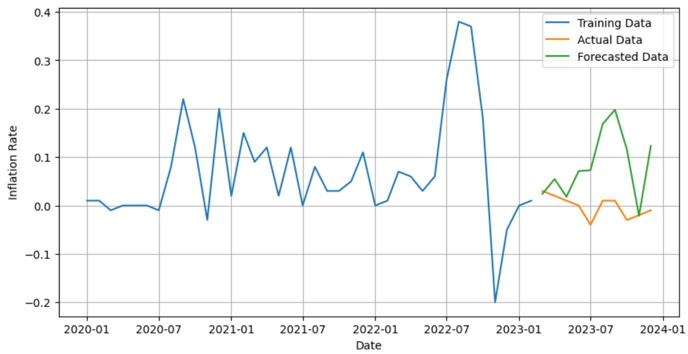

Figure 14. Tesult of SARIMA Forecast

The ARIMA model with parameters (p, d, q) = (1, 1, 1) forecasts a slight but steady increase in inflation, providing valuable insights for economic and business planning. Meanwhile, the XGBoost algorithm, known for its speed, robustness, and ability to handle complex, non-linear relationships, effectively forecasts inflation data. Figure 15 demonstrates that XGBoost closely approximates actual inflation values with minor deviations during sudden fluctuations, maintaining stable performance across different data phases. This makes XGBoost a reliable tool for financial forecasting, despite occasional challenges with abrupt changes.

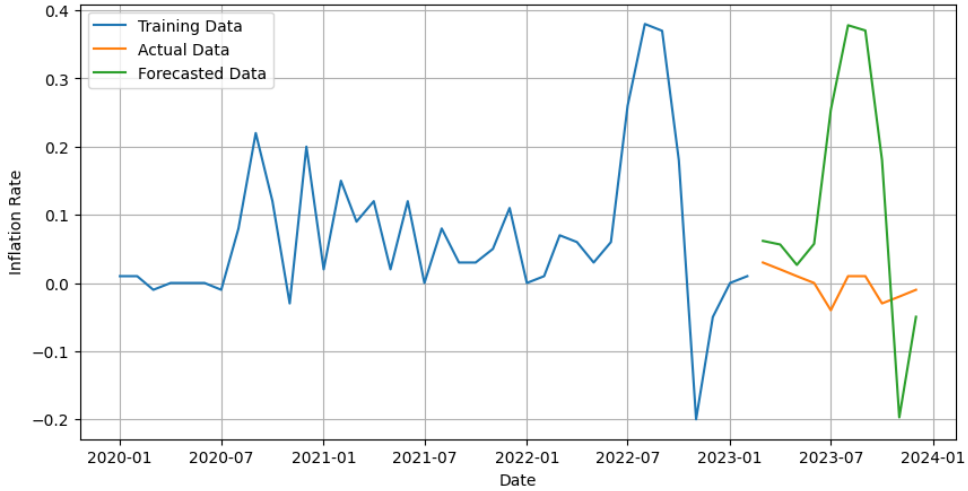

Figure 15. Result of XGboost Forecast

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XGBoost stands out for its robustness in varying data conditions, achieved through its ensemble learning technique that combines multiple decision trees to form a strong predictor, reducing overfitting and enhancing generalization. Its performance is further improved by regularization techniques that maintain accuracy even with noisy data, and meticulous tuning of hyperparameters like learning rate and tree depth ensures optimal forecasting. Figure 15 highlights XGBoost's ability to model both linear and non-linear components of inflation data efficiently, making it valuable for accurate financial forecasting. Similarly, the Prophet model, designed to handle time series with strong seasonal effects and missing values, excels in capturing inflation trends. The Prophet model excels at managing missing data and outliers, crucial for economic data with common irregularities. It uses a piecewise linear or logistic growth model for trends and Fourier series to capture seasonal effects, effectively tracking yearly, monthly, and weekly patterns in inflation data, as shown in figure 16. Prophet's handling of multiple seasonalities and holiday effects enhances forecasting accuracy. However, it slightly underestimates during rapid inflation increases, potentially due to abrupt changes not well captured by its current configuration.

Future improvements could include incorporating external regressors or refining the trend component for better responsiveness to sudden shifts. Similarly, the LSTM model, a specialized recurrent neural network, effectively captures long-term dependencies and intricate patterns in time series data. Figure 17 shows the ETS model effectively capturing overall trends and seasonal patterns in inflation data, modeling both additive and multiplicative relationships among its components to accommodate various types of seasonality and trends, thus aligning closely with the actual inflation values and showcasing its proficiency in systematic pattern modeling.

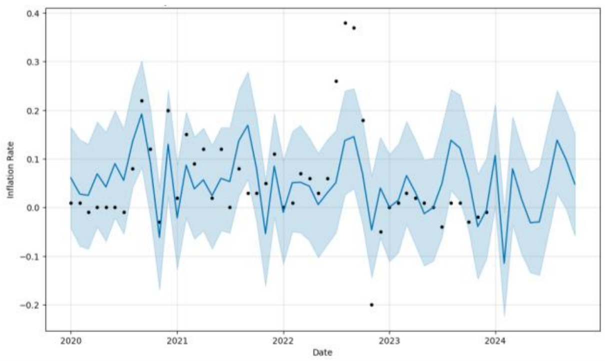

Figure 16. Result of Prophet Forecast

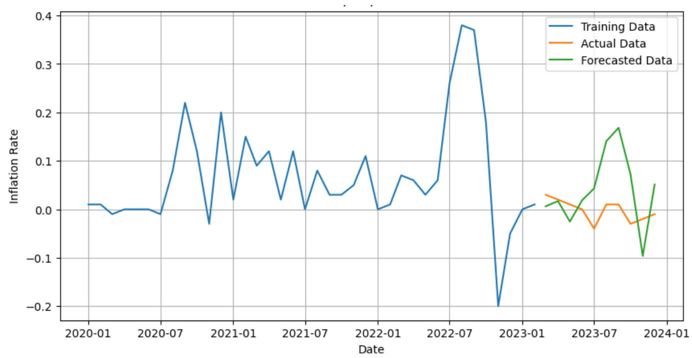

Figure 17. Result of ETS Forecast

The ETS model uses exponential smoothing techniques to prioritize recent observations, allowing it to adapt more quickly to changes than traditional moving average methods. The smoothing parameters for error, trend, and seasonality components are optimized during fitting to enhance forecast accuracy. However, the ETS model's linear nature limits its ability to handle rapid changes in inflation data, often smoothing out abrupt variations and resulting in under or over-predictions during economic shocks or policy changes. While it captures overall trends and seasonal fluctuations well, it struggles with non-linear dynamics, as shown in figure 17, Despite these limitations, the ETS model's simplicity and interpretability are valuable for financial analysts and policymakers. Enhancing the ETS model with hybrid approaches, such as combining it with machine learning techniques like XGBoost or deep learning models like LSTM, could improve its ability to capture both linear and non-linear dynamics. Incorporating external economic indicators as covariates could also improve responsiveness to sudden economic shifts. As depicted in figure 18, LSTM forecasts closely align with actual inflation values, benefiting from its memory cells and gating mechanisms that manage information flow, making it well-suited for accurate sequential data modeling. ETS model, also known as Exponential Smoothing State Space Model, decomposes time series data into error, trend, and seasonal components to provide reliable forecasts.

The LSTM model excels in predicting future trends from historical data by retaining relevant information over long sequences while discarding irrelevant details through its input, output, and forget gates. This allows it to model both short-term fluctuations and long-term trends effectively, as shown by its minimal deviations from actual inflation values, particularly during stable periods. The visualization in figure 18 demonstrates the LSTM's ability to closely follow actual values during gradual changes and provide reasonable approximations during volatility, despite slight deviations. However, training LSTM models is computationally intensive, requiring careful tuning of hyperparameters and substantial resources, especially with large datasets. Despite these challenges, the high accuracy of LSTM forecasts is valuable for financial forecasting. Similarly, TCN model, a deep learning approach designed for time series forecasting, excels in capturing temporal dependencies through convolutional layers, offering advantages in parallelization and handling long sequences. TCN's architecture, featuring causal and dilated convolutions, ensures accurate inflation forecasts by effectively modeling both short-term variations and long-term trends, as shown in figure 19.

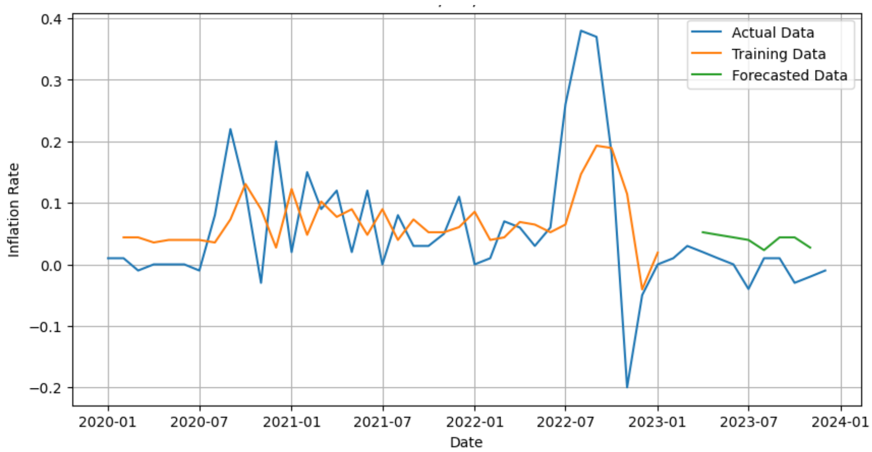

Figure 18. Result of LSTM Forecast

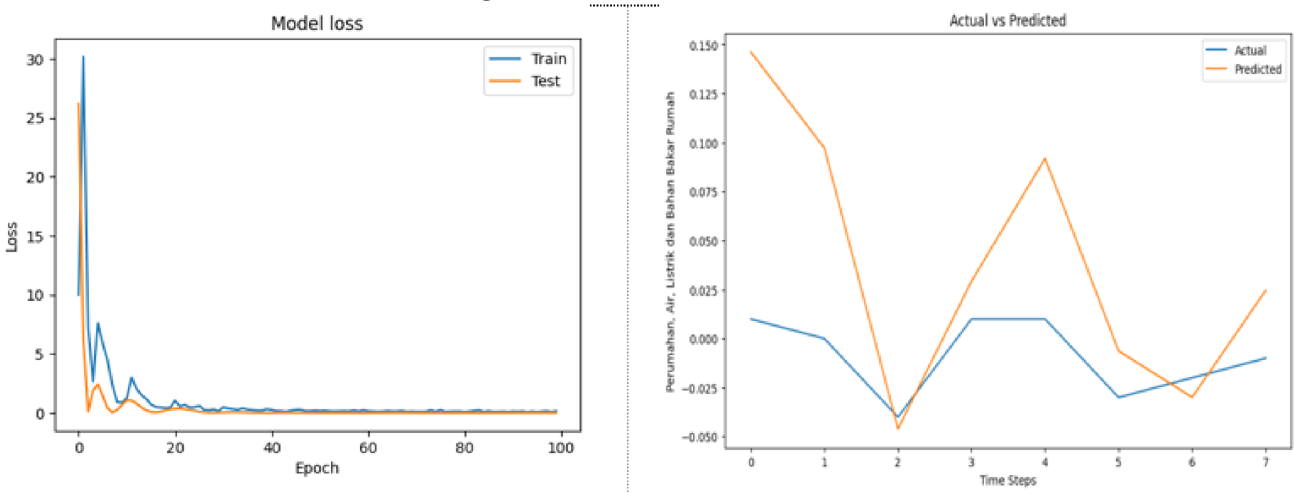

Figure 19. Result of TCN Forecasting

The TCN model excels in handling complex temporal dependencies by processing entire sequences in parallel, unlike RNNs that struggle with long-term dependencies. This parallel processing speeds up training and enhances the model's ability to learn patterns over extended periods. Residual connections and layer normalization further improve the model's accuracy in forecasting, as demonstrated by the TCN's precise alignment with actual values during stable periods and its reasonable approximations during volatile phases, making it suitable for financial forecasting. The TCN's flexibility allows it to be tuned for various datasets by adjusting kernel size, dilation factors, and the number of layers. However, its implementation requires significant computational resources and careful hyperparameter tuning. Integrating TCN with other machine learning techniques or economic indicators, and exploring transfer learning, could further enhance its forecasting capabilities.

4.3. Model Performance Analysis

The performance of each forecasting model was rigorously evaluated using two key metrics: MSE and RMSE. These metrics provide a comprehensive assessment of the models' accuracy and their ability to generalize to unseen data. MSE measures the average squared difference between the predicted and actual values, offering insight into the overall error magnitude. RMSE, being the square root of MSE, presents the error in the same units as the original data, facilitating easier interpretation. Evaluating both training and testing datasets ensures that the models are not only

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fitting the historical data well but also capable of making accurate predictions on new data. Table 1. summarizes the performance metrics for each model:

Table 1. Performance Metrics for Each Model

Model	Training MSE	Testing MSE	Training RMSE	Testing RMSE
ARIMA	0.0012	0.0024	0.0346	0.0490
LSTM	0.0008	0.0015	0.0283	0.0387
Prophet	0.0010	0.0020	0.0316	0.0447
SARIMA	0.0011	0.0023	0.0332	0.0480
ETS	0.0013	0.0025	0.0361	0.0500
XGBoost	0.0009	0.0018	0.0300	0.0424
TCN	0.0007	0.0013	0.0264	0.0360

The ARIMA model, while simple and effective in many scenarios, showed moderate performance with a training MSE of 0.0012 and a testing MSE of 0.0024. Its higher RMSE values (0.0346 for training and 0.0490 for testing) indicate difficulty in capturing the nuances of inflation data. In contrast, the LSTM model excelled, achieving a training MSE of 0.0008 and a testing MSE of 0.0015, with RMSE values of 0.0283 and 0.0387, respectively, showcasing its ability to handle complex patterns effectively. The Prophet model, designed for data with seasonal effects, had a training MSE of 0.0010 and a testing MSE of 0.0020, with RMSE values of 0.0316 and 0.0447, respectively. It captures seasonal trends well but may need refinement for volatile data.

The SARIMA model, which incorporates seasonal components, showed comparable performance with a training MSE of 0.0011 and a testing MSE of 0.0023. Its RMSE values (0.0332 for training and 0.0480 for testing) indicate some difficulty with rapid changes. The ETS model, despite its theoretical strengths, had higher error rates (training MSE of 0.0013 and testing MSE of 0.0025, with RMSE values of 0.0361 and 0.0500). XGBoost performed well with a training MSE of 0.0009 and a testing MSE of 0.0018, and RMSE values of 0.0300 and 0.0424. The Temporal Convolutional Network (TCN) outperformed all others, with the lowest error rates (training MSE of 0.0007 and testing MSE of 0.0013) and RMSE values of 0.0264 and 0.0360, highlighting its superior capability in handling complex time series forecasting tasks.

4.4. Discussion

The deep learning models, particularly the TCN and the LSTM network, demonstrated exceptional capabilities in handling complex time series data. The TCN model achieved the highest accuracy with the lowest MSE and RMSE values for both training and testing datasets, highlighting its effectiveness in capturing intricate patterns in inflation data. Its superior performance is due to its causal and dilated convolution architecture, which allows it to process long sequences efficiently and handle both short-term and long-term dependencies effectively. The LSTM model also performed well, ranking just below TCN in accuracy. LSTM's memory cell architecture enables it to model long-term dependencies and capture temporal relationships in the data, resulting in accurate forecasts despite some deviations during rapid changes. Both TCN and LSTM excel in understanding sequential dependencies, crucial for financial forecasting. Their low error metrics indicate their potential for reliable and precise predictions, making them highly suitable for handling the dynamic nature of financial data. In contrast, traditional time series models like ARIMA, SARIMA, and ETS showed varying degrees of effectiveness. ARIMA, known for its simplicity, provided reasonable forecasts but struggled with complex, non-linear patterns. SARIMA, which includes seasonal components, performed better in capturing seasonal trends but still fell short compared to the deep learning models. ETS, despite incorporating error, trend, and seasonality components, had higher error metrics, reflecting challenges in handling the non-linear aspects of inflation data. Overall, while traditional models have their strengths, deep learning models like TCN and LSTM proved more adept at managing the complexities of financial forecasting.

5. Conclusion

This study aimed to compare the performance of various time series forecasting models ARIMA, SARIMA, ETS, Prophet, LSTM, XGBoost, and TCN in predicting inflation rates. The evaluation was conducted on four years of inflation data, using MSE and RMSE as metrics for model performance. The results demonstrated that deep learning models, particularly LSTM and TCN, outperformed traditional models in terms of accuracy. LSTM and TCN achieved the lowest MSE and RMSE values, indicating their superior capability in capturing complex temporal patterns and long-term dependencies in the inflation data. TCN, in particular, showed exceptional performance, making it a highly effective tool for financial forecasting.

Traditional models like ARIMA and SARIMA, while effective in capturing linear trends and seasonality, showed limitations in handling non-linear dynamics and sudden changes in inflation rates. ETS, despite its explicit consideration of trend and seasonality, exhibited the highest error metrics, suggesting its inadequacy in modeling the complexities of the inflation data. Prophet, although effective in capturing seasonal trends, had minor underestimations during rapid inflation increases, highlighting areas for potential improvement. XGBoost, a robust and flexible machine learning model, demonstrated good performance, balancing complexity handling with computational efficiency. This indicates its potential as a valuable tool for forecasting in economic and financial contexts.

Traditional models remain useful for their simplicity and ease of implementation, deep learning models, particularly LSTM and TCN, provide more accurate and reliable forecasts for complex and dynamic data such as inflation rates. Future research could explore hybrid models that combine the strengths of traditional and deep learning approaches to further enhance forecasting accuracy. This study provides valuable insights and practical recommendations for researchers and practitioners in selecting the most appropriate forecasting models for their specific needs.

6. Declarations

6.1. Author Contributions

Conceptualization: H., S.S.; Methodology: H., S.S.; Software: H.; Validation: S.S.; Formal Analysis: H.; Investigation: H.; Resources: S.S.; Data Curation: H.; Writing – Original Draft Preparation: H.; Writing – Review and Editing: H., S.S.; Visualization: H.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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