Deep Learning–Based Inflation Prediction Using Economic Indicators with Early Stopping: A Comparative Study of LSTM and XGBoost Models

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ABSTRACT

Inflation forecasting plays a crucial role in economic policy formulation, financial planning, and macroeconomic stability, as inaccurate predictions can lead to ineffective monetary decisions and economic imbalance. The behaviour of inflation is influenced by multiple interacting economic factors and exhibits non-linear and temporal characteristics, making it challenging to model using conventional statistical approaches. In recent years, machine learning and deep learning techniques have demonstrated strong potential in handling such complex time-series forecasting problems.

Historical time-series data consisting of inflation rates along with key economic indicators such as **Consumer Price Index (CPI)**, **GDP growth rate**, **Interest rate**, and **exchange rate** are utilized in this study. The collected data is pre-processed through normalization, handling of missing values, and transformation into a multivariate time-series format suitable for deep learning models. This project presents a comparative analysis of two advanced predictive models—**Extreme Gradient Boosting (XGBoost) and Long Short-Term Memory (LSTM)** networks—for forecasting inflation using historical time-series data. **XGBoost**, **an ensemble learning method** based on gradient boosting, is utilized to model non-linear relationships and feature interactions efficiently, while **LSTM**, a **recurrent neural network architecture**, is employed to capture long-term dependencies and sequential patterns inherent in inflation data. Both models are trained and evaluated using standard performance metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Experimental results reveal that while XGBoost delivers strong predictive performance with lower computational complexity, the LSTM model demonstrates superior capability in capturing long-term inflation trends and temporal dynamics. The findings of this study confirm that deep learning–based models can significantly enhance inflation forecasting accuracy compared to traditional machine learning approaches.

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INTRODUCTION

1.1 Importance of Inflation Forecasting

- Inflation is a key macroeconomic indicator that measures the overall increase in price levels in an economy.
- Accurate inflation forecasting is essential for effective monetary policy, fiscal planning, and economic stability.
- Central banks and governments rely on inflation predictions to make decisions regarding interest rates, money supply, and economic growth.
- Incorrect forecasts can lead to policy failures, financial instability, and reduced purchasing power.

1.2 Limitations of Traditional Forecasting Methods

- Conventional statistical and econometric models often assume linear relationships and stationarity in data.
- Inflation behaviour is influenced by multiple economic factors, making it highly non-linear and dynamic.
- Traditional models struggle to capture long-term dependencies and complex interactions within time-series data.
- These limitations reduce forecasting accuracy in real-world economic scenarios.

1.3 Role of Machine Learning in Economic Forecasting

- Machine learning techniques offer data-driven approaches that do not rely on strict statistical assumptions.
- They are capable of modeling non-linear relationships and learning patterns directly from historical data.
- Machine learning models have been increasingly adopted in economic and financial forecasting applications.
- Their adaptability makes them suitable for handling complex macroeconomic indicators such as inflation.

1.4 XGBoost for Inflation Prediction

- Extreme Gradient Boosting (XGBoost) is an ensemble learning algorithm based on gradient boosting.
- It efficiently handles non-linear relationships and interactions among input features.
- XGBoost includes regularization techniques that prevent overfitting and improve generalization.
- Due to its robustness and computational efficiency, XGBoost serves as a strong baseline model for inflation forecasting.

1.5 LSTM for Time-Series Forecasting

- Long Short-Term Memory (LSTM) networks are a type of recurrent neural network designed for sequential data.
- LSTM models effectively capture long-term temporal dependencies in time-series datasets.
- They overcome limitations such as the vanishing gradient problem found in traditional RNNs.
- LSTM networks are well-suited for modeling inflation trends where historical values influence future outcomes.

1.6 Aim and Scope of the Project

- This project aims to forecast inflation using historical time-series data through machine learning and deep learning approaches.
- A comparative study is conducted between XGBoost and LSTM models.
- Model performance is evaluated using standard error metrics such as MAE, MSE, and RMSE.
- The study seeks to identify the most effective model for capturing inflation dynamics and improving forecasting accuracy.

LITERATURE REVIEW

2.1 Traditional Approaches to Inflation Forecasting

- Early studies on inflation forecasting primarily relied on statistical and econometric models such as AR, MA, ARIMA, and Phillips Curve–based models.
- These models assume linear relationships and stationarity in economic data.
- Although effective for short-term forecasting, their performance deteriorates when dealing with non-linear patterns and structural economic changes.
- Researchers have highlighted the inability of traditional models to capture complex interactions among economic variables.

2.2 Machine Learning in Economic Time-Series Forecasting

- With the advancement of computational techniques, machine learning models have been increasingly applied to macroeconomic forecasting.
- Machine learning methods are capable of learning complex non-linear relationships directly from data.
- Studies indicate that machine learning models outperform traditional statistical approaches in many economic forecasting tasks.
- These models do not require strict assumptions regarding data distribution or linearity.

2.3 Application of XGBoost in Economic Prediction

- XGBoost has emerged as a powerful ensemble learning technique due to its high predictive accuracy and efficiency.
- Several studies have applied XGBoost for economic forecasting, including inflation, GDP growth, and stock market prediction.
- XGBoost's ability to handle feature interactions and incorporate regularization reduces overfitting.
- Research findings suggest that XGBoost performs well for structured economic datasets and short-to-medium-term forecasts.

2.4 Deep Learning Models for Time-Series Analysis

- Deep learning models, particularly Recurrent Neural Networks (RNNs), have shown strong performance in time-series forecasting.
- However, traditional RNNs suffer from issues such as vanishing gradients.
- To overcome these limitations, Long Short-Term Memory (LSTM) networks were introduced.
- LSTM models are capable of learning long-term dependencies in sequential data, making them suitable for macroeconomic forecasting.

2.5 Use of LSTM in Inflation Forecasting

- Recent research has demonstrated the effectiveness of LSTM networks in predicting inflation trends.
- LSTM models capture temporal dependencies better than traditional machine learning methods.
- Studies report improved forecasting accuracy when LSTM models are applied to historical inflation data.
- LSTM-based approaches are particularly effective in modeling economic time series with long-term dependencies.

2.6 Comparative Studies Between Machine Learning and Deep Learning Models

- Several studies have conducted comparative analyses between traditional machine learning models and deep learning architectures.
- Results generally indicate that while machine learning models offer computational efficiency, deep learning models provide superior performance for complex time-series data.
- Comparative evaluations using error metrics such as MAE, MSE, and RMSE are commonly employed.
- These studies support the need for comparative analysis, as conducted in this project, to determine the most suitable model for inflation forecasting.

2.7 Research Gap Identified

- Despite existing research, limited studies provide a direct comparison between XGBoost and LSTM for inflation forecasting using the same dataset.
- There is a need for systematic evaluation of machine learning and deep learning models under identical experimental conditions.
- This project addresses this research gap by implementing and comparing XGBoost and LSTM models for inflation prediction.

PROBLEM DEFINITION, MOTIVATION AND OBJECTIVES

3.1 PROBLEMS

3.1.1 Unpredictable Nature of Inflation

Inflation is affected by several economic indicators such as interest rates, GDP growth, money supply, exchange rates, and consumer demand. The interaction among these indicators is complex and non-linear, making accurate inflation forecasting difficult.

3.1.2 Limitations of Conventional Forecasting Methods

Traditional statistical and econometric forecasting models often assume linear relationships and stationarity in data. However, inflation time-series data frequently violates these assumptions due to structural changes, policy interventions, and economic shocks. These limitations restrict the ability of conventional models to capture complex non-linear patterns and long-term dependencies, leading to reduced forecasting accuracy.

3.1.3 Challenges in Inflation Time-Series Forecasting

Inflation data typically exhibits trends, volatility, and sudden fluctuations over time. Structural breaks caused by economic reforms or external shocks further complicate forecasting. Many existing models struggle to adapt to these variations, resulting in unstable or inaccurate predictions when applied to real-world economic data.

3.1.4 Overfitting in Advanced Predictive Models

While advanced models such as deep learning–based LSTM networks are capable of capturing non-linear and temporal patterns, they are susceptible to overfitting when trained on limited or noisy time-series data.

3.1.5 Need for Comparative Evaluation of Machine Learning and Deep Learning Models

Although machine learning and deep learning techniques have shown promise in economic forecasting, there is limited research that provides a systematic comparison between ensemble-based machine learning models like XGBoost and deep learning models such as LSTM for inflation prediction under the same experimental conditions.

3.2 Motivation

3.2.1 Economic Significance of Inflation

Inflation plays a crucial role in determining purchasing power, cost of living, interest rates, and overall economic stability. Accurate inflation forecasting is essential for effective economic planning and policy formulation.

3.2.2 Need for Improved Forecasting Accuracy

Even small errors in inflation prediction can result in incorrect policy decisions, inappropriate interest rate adjustments, and financial instability. This motivates the need for highly accurate and reliable forecasting models capable of handling the complexity and uncertainty associated with inflation data.

3.2.3 Limitations of Existing Forecasting Techniques

Traditional statistical models and conventional econometric approaches often rely on linear assumptions and fail to capture non-linear relationships present in inflation time-series data. These limitations reduce their effectiveness in modeling real-world economic behaviour, thereby motivating the exploration of advanced data-driven forecasting methods.

3.2.4 Advancements in Machine Learning and Deep Learning

Recent advancements in machine learning and deep learning techniques have demonstrated strong performance in time-series forecasting applications. Models such as XGBoost effectively capture non-linear patterns in structured data, while deep learning models like LSTM are capable of learning long-term temporal dependencies. These developments motivate their application to inflation forecasting problems.

3.2.5 Availability of Historical Economic Data

The increasing availability of historical inflation data and macroeconomic time-series datasets provides an opportunity to build robust data-driven forecasting models. Access to such data enables the development of predictive models that can learn complex temporal patterns and improve forecasting accuracy.

3.3 Objectives

3.3.1 Analysis of Inflation Trends

To analyse historical inflation data in order to identify long-term trends, seasonal patterns, and fluctuations over time.

3.3.2 Identification of Key Economic Indicators

To identify and analyse significant economic indicators that influence inflation behaviour.

3.3.3 Data Collection and Preprocessing

To collect historical inflation and economic indicator data and preprocess it for time-series forecasting, including handling missing values, scaling, and sequence generation.

3.3.4 Development of LSTM Model

To design and implement a Long Short-Term Memory (LSTM) model to capture non-linear relationships and long-term dependencies in inflation time-series data.

3.3.5 Development of XGBoost Model

To implement an Extreme Gradient Boosting (XGBoost) model for inflation prediction and evaluate its effectiveness in handling structured economic data.

3.3.6 Comparative Performance Evaluation

To compare the forecasting performance of LSTM and XGBoost models using appropriate evaluation metrics such as MAE, RMSE, and MAPE.

3.3.7 Selection of Optimal Forecasting Model

To identify the most suitable model for inflation prediction based on prediction accuracy, stability, and generalization capability.

3.3.8 Policy and Economic Interpretation

To interpret the forecasting results and highlight their significance for economic planning, policy formulation, and decision-making.

PROPOSED RESEARCH METHODOLOGY

4.1 Data Collection

- Historical inflation time-series data is collected from reliable economic data sources.
- The dataset represents inflation values over a continuous time period.
- The collected data serves as the foundation for model training and evaluation.

4.2 Data Preprocessing

- Missing or inconsistent values in the dataset are identified and handled appropriately.
- The inflation data is normalized using scaling techniques to improve model performance.
- For supervised learning, lagged features are created to represent past inflation values.
- The dataset is divided into training and testing subsets to evaluate model generalization.

4.3 Feature Engineering

- Historical inflation values are transformed into input-output pairs using time-lag windows.
- Lag-based features help models learn temporal dependencies.
- Feature engineering ensures compatibility with both machine learning and deep learning models.

4.4 XGBoost Model Development

- XGBoost is implemented as a regression-based machine learning model.
- The model learns non-linear relationships from lagged inflation features.
- Regularization parameters are used to reduce overfitting and improve accuracy.
- The trained XGBoost model generates inflation forecasts on unseen test data.

4.5 LSTM Model Development

- An LSTM neural network is designed for time-series forecasting.
- The input data is reshaped into three-dimensional format (samples, time steps, features).
- The LSTM model captures long-term temporal dependencies in inflation data.
- The model is trained using appropriate loss functions and optimization techniques.
- Early stopping is applied to prevent overfitting during training.

4.6 Model Training and Validation

- Both models are trained on historical inflation data.
- Validation is performed using unseen test data.
- Training ensures that models generalize well and do not memorize the data.

4.7 Performance Evaluation

- Model performance is assessed using:
  - Mean Absolute Error (MAE)
  - Mean Squared Error (MSE)
  - Root Mean Squared Error (RMSE)
- These metrics provide quantitative measures of forecasting accuracy.
- Comparative analysis helps identify the most effective model.

4.8 Result Analysis and Comparison

- Actual inflation values are compared with predicted values from both models.
- Graphical visualization is used to analyse prediction trends.
- The strengths and limitations of XGBoost and LSTM models are evaluated.

SYSTEM ARCHITECTURE

5.1 Overview of the System Architecture

- The proposed system architecture is designed to forecast inflation using machine learning and deep learning models.
- It follows a modular and sequential approach, starting from data collection to result evaluation.
- The architecture ensures flexibility, scalability, and accurate model comparison.

5.2 Data Input Layer

- The system accepts historical inflation time-series data as input.
- The data consists of inflation values recorded over a specific time period.
- Input data serves as the foundation for model training and prediction.

5.3 Data Preprocessing Module

- Raw inflation data is cleaned to remove missing or inconsistent values.
- Data normalization is applied to scale values within a suitable range.
- Lag-based feature extraction is performed to convert time-series data into supervised learning format.
- Pre-processed data is prepared separately for XGBoost and LSTM models.

5.4 Model Layer

The model layer consists of two independent forecasting models:-

5.4.1 XGBoost Model

- XGBoost processes the pre-processed lagged features.
- It learns non-linear patterns and feature interactions efficiently.
- The model outputs predicted inflation values based on learned relationships.

5.4.2 LSTM Model

- LSTM receives sequential data in a three-dimensional structure.
- It captures long-term temporal dependencies in inflation time-series data.
- Early stopping is employed to avoid overfitting during training.
- The model generates future inflation forecasts.

5.5 Training and Optimization Module

- Both models are trained using historical data.
- Hyperparameters are optimized to improve predictive performance.
- Early stopping ensures efficient training and prevents unnecessary iterations.

5.6 Prediction and Output Layer

- The trained models produce inflation forecasts on test data.
- Predicted values are stored for comparison and evaluation.
- The system supports visualization of predicted versus actual inflation values.

5.7 Performance Evaluation Module

- The output from both models is evaluated using MAE, MSE, and RMSE.
- Quantitative metrics allow objective comparison of model accuracy.
- The best-performing model is identified based on evaluation results.

5.8 System Workflow Summary

- Data Collection → Data Preprocessing → Feature Engineering
- Model Training (XGBoost & LSTM) → Prediction Generation
- Performance Evaluation → Result Comparison

EXPERIMENTAL RESULTS AND DISCUSSION

6.1 Experimental Setup

- The experiments are conducted using historical inflation time-series data.
- The dataset is divided into training and testing sets to evaluate model generalization.
- Both XGBoost and LSTM models are trained under identical data conditions to ensure fair comparison.
- Model performance is evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).

6.2 Performance Evaluation Metrics

- **Mean Absolute Error (MAE):** Measures the average magnitude of errors without considering direction.

  Formula:

  $$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$$

  where:
  y_i= actual inflation value
  $\hat{y}_i$= predicted inflation value
  n= number of observations

  A lower MAE value indicates better model performance.

- **Mean Squared Error (MSE):** Penalizes larger errors more significantly by squaring the differences.

  Formula:

  $$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

  Lower MSE values represent more accurate and stable forecasts.

- **Root Mean Squared Error (RMSE):** Provides error magnitude in the same unit as inflation values.

  Formula:

  $$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

  RMSE is particularly useful for comparing the forecasting accuracy of different models.

- These metrics are widely used for time-series forecasting evaluation.

6.3 Results of XGBoost Model

- The XGBoost model demonstrates strong predictive performance on historical inflation data.
- It effectively captures non-linear relationships through ensemble learning.
- The model shows stable performance with relatively lower computational cost.
- XGBoost performs well in short-term inflation forecasting scenarios.

6.4 Results of LSTM Model

- The LSTM model successfully captures long-term temporal dependencies in inflation time-series data.
- It demonstrates improved accuracy in tracking overall inflation trends.
- The use of early stopping prevents overfitting and improves model generalization.
- LSTM exhibits better performance in scenarios involving complex temporal patterns.

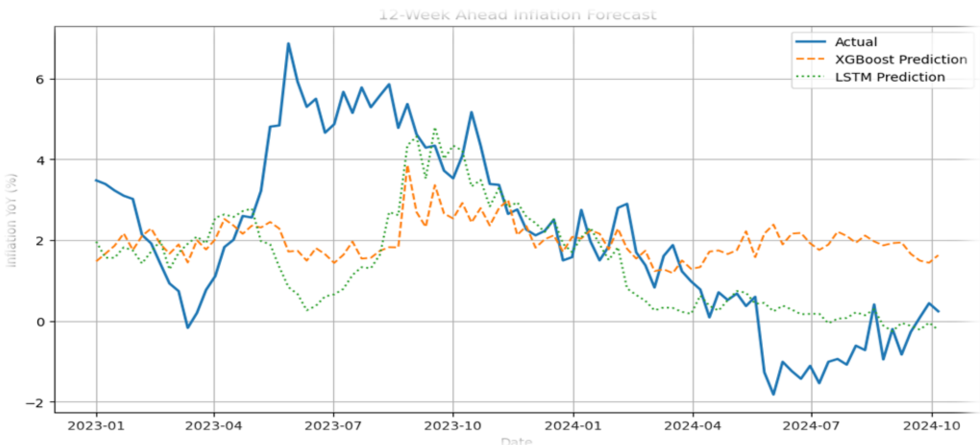
6.5 Comparative Analysis

- Both models produce accurate inflation forecasts, validating the effectiveness of machine learning approaches.
- XGBoost offers faster training and simpler implementation.

- LSTM provides superior ability to model sequential dependencies and long-term trends.
- The comparative results indicate that LSTM generally achieves lower forecasting errors than XGBoost.
- However, XGBoost remains competitive and efficient for structured regression tasks.

6.6 Visualization of Results

- Actual and predicted inflation values are plotted for both models.
- Graphical analysis shows that LSTM predictions closely follow actual inflation trends.
- XGBoost predictions show minor deviations during periods of rapid inflation changes.
- Visualization aids in understanding model behaviour beyond numerical metrics.



6.7 Discussion

- The experimental results confirm that deep learning models are more effective in capturing long-term inflation dynamics.
- Machine learning models such as XGBoost provide reliable performance with lower computational requirements.
- The choice of model depends on forecasting horizon, data complexity, and computational constraints. The findings support the integration of artificial intelligence techniques in economic forecasting.

CONCLUSION AND FUTURE SCOPE

7.1 Conclusion

This project focused on forecasting inflation using historical time-series data and key economic indicators through advanced machine learning and deep learning techniques. Inflation forecasting plays a vital role in economic planning and policy formulation due to its impact on purchasing power, interest rates, and overall economic stability. The complex and non-linear behaviour of inflation makes traditional statistical models less effective, thereby necessitating data-driven predictive approaches.

In this study, two powerful models—Long Short-Term Memory (LSTM) and XGBoost—were implemented and evaluated for inflation prediction. Proper data preprocessing techniques, including normalization and time-series transformation, were applied to ensure reliable model performance. The LSTM model demonstrated its ability to capture temporal dependencies and sequential patterns in inflation data, while the XGBoost model effectively learned non-linear relationships among economic indicators with high predictive accuracy and computational efficiency.

The comparative analysis revealed that both models are capable of producing reliable inflation forecasts, with each exhibiting distinct strengths. LSTM performed well in modeling long-term trends in time-series data, whereas XGBoost showed strong generalization ability and faster convergence. The results confirm that machine learning–based approaches significantly enhance forecasting accuracy when compared to conventional methods.

Overall, the findings of this project highlight the effectiveness of using advanced machine learning techniques for inflation forecasting. The proposed framework provides a practical and scalable solution that can support economists, policymakers, and financial analysts in informed decision-making. Additionally, this work lays a strong foundation for future research involving hybrid models, additional economic indicators, or real-time forecasting systems.

7.2 Future Scope

While this project successfully demonstrates the use of LSTM and XGBoost models for inflation forecasting using economic indicators, several opportunities exist for further enhancement. Future research can improve forecasting accuracy and model robustness by incorporating additional macroeconomic variables such as employment rate, fiscal deficit, crude oil prices, commodity indices, and global economic factors.

More advanced deep learning architectures may also be explored to enhance prediction performance. Models such as GRU, attention-based networks, and Transformer architectures have shown strong potential in time-series forecasting and can be applied to inflation prediction. Hybrid approaches combining deep learning and ensemble learning techniques may further improve forecasting reliability.

Another important extension of this work involves automated hyperparameter tuning methods such as Bayesian optimization or genetic algorithms to achieve optimal model configurations. Additionally, model interpretability techniques like feature importance analysis and SHAP values can be integrated to enhance transparency and support policy-level decision-making.

Future studies may also focus on real-time inflation forecasting systems that update predictions dynamically as new economic data becomes available. Deploying the forecasting models through web-based or cloud platforms can make the system more accessible and practical for economists, policymakers, and financial analysts.

Overall, these enhancements can significantly improve the applicability, accuracy, and usability of inflation forecasting models, making them valuable tools for economic planning and decision-making.

REFERENCES

8.1 Global Inflation Forecasting and Uncertainty Assessment: Comparing ARIMA with Advanced Machine Learning Approaches.

This paper analyses global inflation forecasting by comparing traditional ARIMA models with modern machine learning techniques, highlighting differences in accuracy and uncertainty assessment.

Available : Global_inflation_forecasting_ARIMA_vs_ML.pdf

8.2 Real-Time Inflation Forecasting Using Non-Linear Dimension Reduction Techniques.

This study focuses on real-time inflation prediction using non-linear dimension reduction methods to improve forecasting performance in complex economic environments

Available: Real_time_inflation_forecasting_non_linear_dimension_reduction.pdf

8.3 Inflation Forecasting in an Emerging Economy: Selecting Variables with Machine Learning Algorithms.

This research explores the use of machine learning algorithms to identify key macroeconomic variables influencing inflation in emerging economies.

Available: Inflation_forecasting_emerging_economy_ML_variables.pdf

8.4 Inflation Prediction Method Based on Deep Learning.

This paper proposes a deep learning–based approach for inflation forecasting and demonstrates the effectiveness of neural network models in capturing non-linear economic relationships.

Available: Inflation_prediction_deep_learning.pdf

8.5 Inflation Prediction in Emerging Economies: Machine Learning and FX Reserves Integration for Enhanced Forecasting.

This study integrates foreign exchange reserves with machine learning techniques to enhance inflation prediction accuracy in emerging market economies.

Available: Inflation_prediction_emerging_economies_ML_FX_reserves.pdf

ANNEXURE

Source Code Implementation

Annexure A presents the complete source code developed and used for implementing the inflation forecasting models in this project. The code is written in **Python** and executed using the **Jupyter Notebook** environment. This annexure is included to ensure transparency, reproducibility, and a clear understanding of the implementation process followed in the study.

The source code covers all major stages of the research methodology, starting from data preprocessing to final prediction and comparison of models. Proper comments and structured programming practices have been followed to improve readability and ease of interpretation.

A.1 Programming Environment

The implementation was carried out using the following programming environment and tools:-

- Python programming language
- Jupyter Notebook environment
- Anaconda distribution (for package management)

A.2 Libraries and Frameworks Used

The following Python libraries and frameworks were used in the implementation:

- **NumPy** – for numerical computations
- **Pandas** – for data handling and manipulation
- **Scikit-learn** – for preprocessing, scaling, and evaluation metrics
- **XGBoost** – for machine learning-based regression model
- **TensorFlow and Keras** – for implementing the LSTM deep learning model
- **Matplotlib** – for visualization of results

A.3 Data Preprocessing and Transformation

The code includes preprocessing steps to prepare the historical inflation data for model training. These steps include handling missing values, normalizing the data using feature scaling techniques, and transforming the data into suitable formats for machine learning and deep learning models. For the LSTM model, the time-series data is reshaped into sequential input format.

A.4 Model Implementation

A.4.1 XGBoost Model

The **XGBoost** regression model is implemented to predict inflation values based on historical data. The model learns complex non-linear relationships between input features and inflation values. After training, the model is used to generate predictions on unseen data.

A.4.2 LSTM Model

The **LSTM** model is implemented using the **TensorFlow** framework to capture temporal dependencies in inflation time-series data. The model is trained using sequential input data, and early stopping is applied during training to prevent overfitting and enhance generalization performance.

A.5 Model Training and Prediction

Both models are trained using the training dataset and evaluated on unseen test data. The trained models are then used to generate inflation forecasts for future periods. The same preprocessing and scaling techniques are applied to ensure consistency between training and prediction phases.

A.6 File Description

The complete implementation is provided in the following file:

File Name:

Inflation Prediction comparing XGBoost and LSTM.ipynb

This file contains all code blocks related to data loading, preprocessing, model training, evaluation, and prediction.

A.7 Purpose of Including Source Code

The inclusion of source code in this annexure allows examiners and readers to:

- Verify the implementation methodology.
- Reproduce the experimental results.
- Understand the practical application of machine learning and deep learning models for inflation forecasting.

Annexure A Summary

Annexure A documents the complete technical implementation of the inflation forecasting models used in this project. It serves as a supporting section that strengthens the credibility and reliability of the research work by providing full access to the computational methodology.