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Computational Analysis for Enhanced Forecasting of India's GDP Growth using a Modified LSTM Approach

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Abstract:

Forecasting GDP growth accurately is critical for effective legislation, investment strategies, and corporate planning decision-making. This study focuses on the creation of a novel modified Long Short-Term Memory (LSTM) model for forecasting India's GDP growth. Outlier identification employs strong statistical techniques, such as the modified Z-score method, to identify and deal with extreme observations that may significantly impact the forecasting model's performance. Missing data is a typical issue in economic datasets. Imputation approaches, such as the Expectation-Maximization (EM) or MissForest algorithms are used to impute missing values by leveraging the correlations between variables and observed data. These advanced imputation techniques consider the data's complexity and produce more reliable and accurate imputed values, reducing biases in the subsequent forecasting process. Lasso regression with lagged variables is applied to select relevant features for forecasting GDP growth. Furthermore, Time Series SMOTE is used to address the class imbalance challenge in GDP growth datasets. Then, the improved LSTM model is then trained on the pre-processed data using robust optimization methods. Cross-validation procedures are used to validate the model's capacity to generalize and minimize overfitting. Performance metrics such as MAE, RMSE, MPE and forecast bias are used to assess the accuracy and precision of GDP growth forecasts. The proposed system has achieved better performance compared to existing methods.

Keywords: Forecasting, GDP growth, Modified Long Short-Term Memory (LSTM) model, corporate planning, Investment strategies, Stochastic gradient descent (SGD), Accurate forecasting, Imputation approaches, Outlier identification, Missing data imputation.

1. INTRODUCTION

GDP (Gross Domestic Product) growth forecasting is critical in analysing a country's economic outlook. It provides vital insights into the predicted trajectory of economic performance, supports policy creation, and assists firms in making educated decisions. This topic focuses on estimating GDP growth for India, a fast-rising economy with diversified industries and a major worldwide presence. India's economic growth has drawn international interest due to its large population, market potential, and growing integration into the global economy. Accurate GDP growth forecasting allows governments, investors, and businesses to project future economic trends, detect risks, and capitalize on opportunities [1].

Forecasting GDP growth in India entails looking at a variety of factors such as domestic consumption, investment levels, government spending, global trade dynamics, inflation, and monetary policy. Furthermore, demographic trends, technical improvements, infrastructure development, and social indices all contribute to predicting [2,3]. Forecasts for GDP growth are often generated by government agencies, international organizations, academic institutions, and financial firms. These forecasts are useful for policymakers designing fiscal and monetary policies to generate growth, maintain price stability, and promote inclusive development [4].

The Indian economy has demonstrated endurance and adaptation over the years, with times of tremendous growth as well as occasional setbacks. Understanding and forecasting growth determinants is critical for successful planning, resource allocation, and policy interventions [5]. It is crucial to highlight that estimating GDP growth is subject to inherent uncertainties and limits. Natural disasters, geopolitical conflicts, global economic downturns, or policy changes can all have a substantial impact on actual growth outcomes. As a result, forecasting models include assumptions and sensitivity studies to account for potential risks and uncertainties. This discussion on GDP growth forecasting for India attempts to provide insights into the methodology, challenges, and importance of effectively projecting the economic growth trajectory. By understanding the elements that drive growth and the complexities of forecasting, stakeholders may make intelligent choices, avoid risks, and contribute to India's sustainable and inclusive economic growth.

Mohanty et al. (2019) [6] highlighted the importance of evaluating numerous elements in estimating India's GDP growth in a single study. The study emphasizes the need of evaluating domestic consumption, investment levels, government expenditure, global trade dynamics, inflation, and monetary policy as significant factors of economic growth. The writers also highlight the importance of demographic trends, technical breakthroughs, infrastructure development, and social factors in influencing India's developmental trajectory.

Kumar and Pal (2018) et al. [7] addresses the significance of financial and banking sector indicators in GDP growth prediction for India. According to the study, variables such as bank credit, interest rates, stock market performance, and financial stability indicators might provide essential insights into future economic growth tendencies. These statistics indicate the overall health and performance of the financial sector, which supports investment and economic activity.

Furthermore, Mohapatra and Ghosh (2017) [8] investigated the role of global influences in estimating India's GDP growth. According to the report, global economic growth, commodity prices, exchange rates, and international trade dynamics all substantially impact India's financial performance. Understanding the interplay of domestic and global factors is critical for estimating GDP growth and analyzing the vulnerabilities and risks associated with foreign economic shocks.

It is crucial to remember that projecting GDP growth is challenging due to the inherent uncertainties and complexities of the global economic environment. Research studies frequently highlight the limitations and potential risks connected with forecasting. For example, Vohra and Singh (2019) [9] explore the difficulties of estimating India's GDP growth, including data limitations, structural changes, and the problem of capturing the influence of policy improvements. They underline the need for robust forecasting models that account for these issues to give credible projections. Given the significance of GDP growth forecasting, different entities make forecasts for India's economic performance. The International Monetary Fund (IMF), World Bank, and Reserve Bank of India (RBI) are among the leading organizations that issue GDP growth predictions for India. These projections are based on an extensive study considering domestic and global concerns, providing helpful information to politicians, investors, and enterprises. Understanding the context and methodology of GDP growth forecasting in India, as outlined in research work, allows stakeholders to make decisions based on information, analyze risks, and contribute to sustainable and inclusive economic development.

GDP (Gross Domestic Product) growth forecasting in India involves continual study and analysis to increase the accuracy and reliability of estimates. Several studies demonstrated the necessity for ongoing study in this area in order to solve various issues and improve the accuracy of GDP growth predictions in India.

Bhatia and Rana [10] underline the importance of research in building more sophisticated forecasting models that use advanced statistical approaches and use fresh data sources. According to the authors, big data analytics, machine learning algorithms, and high-frequency indicators can increase the accuracy and timeliness of GDP growth estimates. Such research investigations can help to improve forecasting approaches and increase understanding of India's economic dynamics.

Furthermore, research by Roy and Biswas [11] emphasizes the need for sector-specific assessments in GDP growth projections for India. According to the authors, analyzing the heterogeneity between sectors might provide useful insights into the drivers of growth and potential hazards. Research studies focusing on certain sectors, such as agriculture, industry, or services, can assist policymakers and investors in making sector-specific actions and decisions.

In the light of the challenges above, projecting GDP growth requires a framework that captures the underlying structure and variables affecting GDP growth in India. The methods used for projection is equally important. Traditionally VAR, ARIMA, Bayesian Vector Auto Regression (BVAR) models have found favour with researchers and economists, (Iyer and Gupta,2019). Machine Learning and Deep Learning Algorithm like ANN. LSTM, RNN and ED-LSTM are observed to be superior models, Sa'adah et al, 2020) as they can capture GDP changes with greater accuracy particularly during economic shocks. Of all these methods, LSTM has emerged as a robust method to process sequential data in a time series format, LSTM also prevents errors due to noises in dataset. RSME and MAE has been used as a standard statistical metric to test model performance.

This study proposes a modified LSTM model to increase the predictive accuracy of existing LSTM model. The novelty of this modified model is fourfold:

1) Extreme observations can affect models forecasting accuracy. The modified LSTM model proposed can deal with extreme observations through outlier treatment through Modified 'z' score method.
2) Missing data is a typical concern in economic datasets, The proposed model incorporates Expectation Maximisation (EM) or MissForest algorithm to address this issue.
3) Selection of relevant factors is critical for GDP growth forecasts. The proposed model uses Lasso Regression with lagged variables to select relevant factors for modelling.
4) Class imbalances in economic events affects forecasting. The proposed model uses Time Series SMOTE to address this challenge.

The proposed model was applied to GDP dataset for India for the period 1960 to 2022 and has shown encouraging results. With an RMSE of 1.05, MAPE of 1.26 and accuracy of 94.58%, the proposed model has outperformed the existing LSTM models. The modified MSTM model proposed will lead to better and more efficient GDP forecasting.

The remaining part of this article is structured as follows: Section 2 provides a summary of literature review. The next section gives the research methodology, followed by data analysis and discussion. The last section gives conclusion from the study.

2. Literature Review

Predictive modelling approaches have gained popularity in economics and finance in recent years for forecasting key indicators such as GDP and stock prices. This review of the literature synthesizes findings from a variety of research that used various algorithms to forecast economic growth and GDP,

Section 1: Stock Price Forecasting using ARIMA and ANN Models

To stock prices forecasting, Ariyo et al. [12] tested ARIMA and artificial neural network (ANN) models. The empirical data showed that the neural network model outperformed ARIMA. This synthesis of opposing viewpoints on neural network vs. ARIMA models emphasizes neural networks' potential in stock price forecasting. Bipasha [13] used a preliminary ARIMA model to forecast India's GDP growth rates. Surprisingly, anticipated GDP numbers indicated an upward trend, although growth rates indicated a downward trend. This conclusion calls into question conventional wisdom and underlines the significance of sophisticated analysis in policy formulation.

Section 2: GDP Forecasting using KNN and Regression Models

Maccarrone [14] conducted a thorough comparison of GDP forecasting models for the United States. They highlighted the advantages of regression for medium-term policies and compared one-step-ahead and multi-step-ahead strategies. KNN outperformed linear regression in one-step-ahead forecasting by leveraging repetitive GDP patterns, while ARX was effective for one-step-ahead predictions and linear regression outperformed in multi-step-ahead forecasting. Combining KNN and linear regression strategies could benefit policymakers. Rudrani et al. [15] proposed a forecasting approach based on the principal component augmented Time Varying Parameter Regression (TVPR) method to predict real aggregate and sectoral growth rates in India. The TVPR model consistently outperformed other models across demand-side, supply-side, and combined variations in the study, effectively capturing various growth drivers. Bhattacharya [16] emphasized the value of high-frequency data in decision-making and presented the Factor Augmented Time Varying Coefficient Regression (FA-TVCR) model for estimating quarterly GDP growth. The FA-TVCR model outperforms the Dynamic Factor Model (DFM) and ARIMA models, particularly during major occurrences such as the Covid-19 epidemic.

Sukharev [17] studied the effect of financial and non-financial investments on economic growth in the United States, Germany, and Russia. The study used regression analysis to emphasize the importance of resolving structural imbalances in investments for long-term economic growth. Hosen et al. [18] investigated the link between population growth and economic growth at various income levels. The findings revealed complex associations, with some income groups showing positive relationships and others showing negative relationships. This nuanced understanding necessitates specialized policy responses. Khder et al. [19] used economic policy uncertainty and consumer price index data to forecast India's GDP, overcoming the problem of delayed GDP data releases. With the MIDAS-Almon weighting approach, accurate predictions for short horizons were obtained, taking into account short-term structural adjustments.

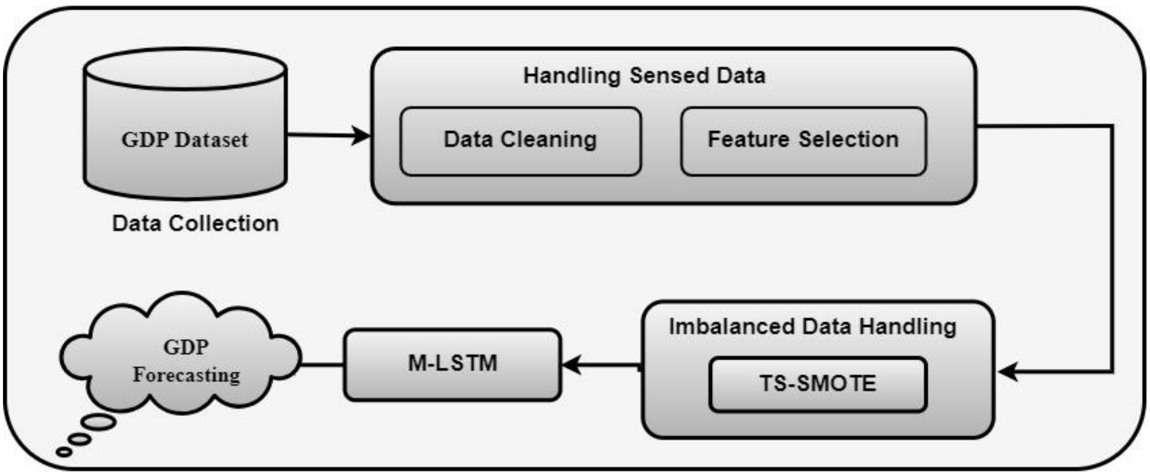
Section 3: Economic Forecasting using Deep Learning based Models

Dominika C. [20] investigated various forecasting models for timber prices in Poland and concluded that MLP (a type of ANN) was superior in predicting price changes and levels. MLP and other ANNs performed particularly well in forecasting common roundwood species such as Scots pine, Norway spruce, and oaks. For alder and beech wood pricing, the ETS model functioned well, while the BATS and TBATS models were effective for birch. When predicting timber prices, ANN models outperformed traditional models in terms of fit and forecasting accuracy. Sa'adah et al. [21] used deep learning algorithms (LSTM and RNN) to forecast GDP. These models captured GDP changes with great accuracy, particularly during the Covid-19 pandemic, emphasizing the promise of deep learning in understanding economic dynamics. Cicceri et al. [22] applied machine learning techniques to recession prediction, concentrating on Italian GDP. The NARX model forecasted economic downturns with greater accuracy, demonstrating the potential for ML techniques to improve short-term economic forecasts. Wanga et al. [23] used advanced deep learning models to forecast GDP growth rates in different countries. The ED-LSTM model performed the best, providing insights into potential future economic trajectories for various nations. Hendra et al. [24] used time series techniques and machine learning to investigate the association between CO2 emissions and GDP growth in Indonesia. The study raised awareness about the environmental-economic nexus by emphasizing the importance of CO2 emissions as a predictor of economic growth.

In summary, the studies conducted provide valuable insights into GDP growth forecasting using various models. These studies highlight the capabilities of the LSTM model, explore the integration of exogenous variables, assess the potential of support vector machines, and propose enhancements through attention mechanisms. Together, these findings contribute to the existing knowledge in GDP growth forecasting and offer valuable guidance for practitioners and researchers striving to achieve accurate predictions.

3. Proposed Methodology

The proposed system uses the GDP dataset on a quarterly basis for training and validation purposes. The system comprises five steps. The first step is data collection, followed by data cleaning and feature selection. Then, it uses imbalanced data handling using the TS-SMOTE method. Then pre-processed data is given to the modified LSTM model for GDP forecasting.



1. Data Collection:

The GDP growth dataset is depicted using mathematical notation as described below. Let G = {G_1, G_2, G_3,….., G_N } denote the set of GDP growth values over time. In this representation, G_1 represents the GDP growth value at the i_{th} time point, where i ranges from 1 to n. For instance, if we consider quarterly GDP growth data, we can express using equation 1.

$$\textbf{Let } G = \{G_1, G_2, G_3, \ldots.. G_N\} \quad (1)$$

Where G_1 corresponds to the GDP growth in the first quarter, G_2 corresponds to the GDP growth in the second quarter, G_3 corresponds to the GDP growth in the third quarter, and so on.

By utilizing this notation, The GDP growth values are treated as elements of set G, offering a concise and symbolic representation of the dataset. It enables us to refer to specific GDP growth values at different time points using the corresponding subscripts (e.g., G_1 for the first quarter, G2 for the second quarter, and so forth). This notation facilitates mathematical operations, analysis, and the formulation of forecasting models and statistical analyses for the GDP growth dataset.

2. Data Cleaning

i. Handling Missing Values using Expectation-Maximization (EM) Algorithm

The EM algorithm consists of two steps: the E-step and the M-step. The EM algorithm leverages the relationships between variables in the dataset to estimate missing values accurately, allowing for a more complete dataset for analysis.

E-step: In this step, missing values are estimated based on the observed data and the current parameter estimates. The conditional distribution of the missing values is calculated using the available data and the current estimates of the parameters as described in equation (2)

The conditional distribution P(Missing Value | Observed Data, Parameter Estimates) (2)

M-step: In this step, the parameter estimates are updated by maximizing the expected complete-data log-likelihood. It involves recalculating the parameter estimates using the imputed values from the E-step. The updated parameter estimates can be represented using equation 3.

$$\theta(t+1) = \text{argmax}[\ E[\text{Log-Likelihood (Complete Data)} \mid \text{Observed Data, Parameter Estimates } (t)]\ ] \quad (3)$$

where $\theta(t+1)$ represents the updated parameter estimates, and t represents the iteration step.

ii. Outlier Detection and Treatment using Modified Z-Score Method

The modified Z-score is calculated using the median (Med) and the median absolute deviation (MAD) as robust central tendency and dispersion measures, respectively. The modified Z-score formula is given by using equation 4.

$$Z = 0.6745 * (X - Med) / MAD \quad (4)$$

Here, X represents the observed value, and Z represents the modified Z-score. Outliers can be identified by comparing the absolute value of Z with a predetermined threshold (e.g., $Z > 3$ or $Z > 4$).

Outliers can be identified by comparing the absolute value of the modified Z-score with a predetermined threshold. Once outliers are detected, they can be treated using various methods such as trimming (removing the outliers), Winsorization (replacing the outliers with the nearest reasonable values), or other approaches based on the specific characteristics of the dataset.

iii. Trend Analysis and Detrending: Linear Regression

The linear regression equation represents the trend component in the dataset using equation (5).

$$Y = \beta 0 + \beta 1 * X \quad (5)$$

Y represents the dependent variable (e.g., GDP growth), and X represents the independent variable (e.g., time or a sequence of observations). β0 and β1 are the estimated coefficients representing the trend line's intercept and slope, respectively. The coefficients β0 and β1 are estimated using the least squares method using equation 6 and 7.

$$\beta 1 = \Sigma[(X - \bar{X}) * (Y - \bar{Y})] / \Sigma[(X - \bar{X})^2] \quad (6)$$

$$\beta 0 = \bar{Y} - \beta 1 * \bar{X} \quad (7)$$

where $\bar{X}$ and $\bar{Y}$ represent the means of the independent and dependent variables, respectively.

iv. Data Transformation using Min-Max Scaling

Min-Max scaling, also known as normalization, is a popular method for data transformation. It rescales the data to a specific range, typically between 0 and 1. The formula for Min-Max scaling is calculated using equation (8).

$$Y' = (Y - \min(Y)) / (\max(Y) - \min(Y)) \quad (8)$$

Y' represents the transformed variable, and Y represents the original variable. min(Y) and max(Y) are Y's minimum and maximum values, respectively.

Min-Max scaling ensures that the data is uniformly distributed within the specified range, which can be beneficial for certain modelling techniques. It also preserves the relationships between data points and maintains the relative differences between values.

This transformation is particularly useful when the magnitude of the variables in the dataset varies significantly. It helps to eliminate the influence of scale differences and makes the variables comparable and suitable for analysis.

By applying the Min-Max scaling method, the data can be transformed into a normalized range, enhancing the interpretability and comparability of the variables in the dataset.

3. Feature Selection

The feature selection method known as Lasso regression with lagged variables was applied to time series datasets, specifically for forecasting GDP growth. The process involved the following steps:

i. Lasso Regression: The objective was to minimize the squared difference between the target variable and the linear combination of selected features, while also applying a penalty term for regularization. The objective function is defined using equation 9.

$$\text{Minimize: } (1/2N) * \Sigma(y_i - \Sigma(\beta_j * x_{ij}))^2 + \lambda * \Sigma|\beta_j|, \quad (9)$$

Where N denotes the number of samples, y_i represents the target variable for sample i, x_{ij} corresponds to the input features (including lagged variables and other relevant variables), β_j signifies the regression coefficient for feature j, and λ is the regularization parameter controlling the strength of the penalty.

ii. Lagged Variables: Lagged values of the target variable or other relevant features were incorporated as inputs to the Lasso regression model. For instance, if lagged values of the target variable up to lag p were considered, the equation for a lagged variable is defined using equation 10.

$$x_{ij} = y_{i-j}, \tag{10}$$

where x_{ij} represents the jth lagged value of the target variable for sample i.

iii. Tuning Parameter Selection: The optimal value for the regularization parameter λ in the Lasso regression model was determined through techniques like cross-validation. In k-fold cross-validation, the cross-validated error was estimated by minimizing the mean squared error or another performance metric across different λ values. The equation for cross-validation is represented using equation 11.

$$CV(\lambda) = (1/K) * \Sigma(L(\lambda)), \tag{11}$$

where K denotes the number of folds, L(λ) represents the loss function (e.g., mean squared error) for a given value of λ, and CV(λ) represents the cross-validated error.

iv. Coefficient Estimation: After fitting the Lasso regression model, the estimated coefficients were analyzed to identify the selected features. The coefficient estimation process depended on the chosen optimization algorithm, such as coordinate descent or least-angle regression. For example, in the coordinate descent algorithm, the equation for updating the coefficient β_j at each iteration is represented using equation 12.

$$\beta_j = (\Sigma(x_{ij} * (y_i - \Sigma(\beta_k * x_{ik})))) / (\Sigma(x_{ij}^2)), \tag{12}$$

where x_{ij} represented the jth lagged value of the target variable for sample i, and β_k denoted the coefficient of the kth lagged variable.

v. Feature Selection: The lagged variables corresponding to non-zero coefficients were chosen as the final set of features for the time series prediction model.

By following these steps, the Lasso regression with lagged variables method facilitated the selection of relevant features for accurate GDP growth forecasting.

4. T-SMOTE Method

GDP growth datasets often face the challenge of class imbalance, where the occurrence of economic recessions (considered the minority class) is significantly outnumbered by periods of economic expansions (the majority class). This imbalance hinders accurate forecasting and analysis of economic conditions. To address this challenge, Time Series SMOTE provides an effective solution. It generates synthetic samples that capture the temporal dynamics of GDP growth rates, ensuring a more balanced representation of recessions and expansions in the dataset. By mitigating the biases caused by class imbalance, Time Series SMOTE enables more accurate and comprehensive analysis.

By leveraging Time Series SMOTE, forecasting models can better capture the complexities of GDP growth patterns. This approach overcomes the limitations imposed by class imbalance, resulting in more reliable predictions of economic trends and future growth patterns.

In summary, applying Time Series SMOTE to GDP growth datasets addresses the need for improved forecasting accuracy, consideration of class imbalance, and a deeper understanding of economic conditions. By achieving a balanced representation of recessions and expansions, it facilitates more accurate analysis and predictions of GDP growth dynamics.

The algorithm focuses on tackling class imbalance in time series datasets through the utilization of Time Series SMOTE (Synthetic Minority Over-sampling Technique). Class imbalance arises when one class is notably underrepresented compared to the other. Time Series SMOTE addresses this issue by creating synthetic samples for the minority class through interpolation between minority samples and their nearest neighbors from the majority class. This process enhances the representation of the minority class, ultimately leading to a more balanced dataset. The algorithm encompasses various steps, including data preprocessing, temporal alignment, synthetic sample generation, and postprocessing. Data preprocessing is crucial as it ensures the quality and integrity of the dataset by addressing issues like stationarity, noise, and missing values, leading to more reliable results. Temporal alignment aligns time instances between minority and majority samples, enabling accurate comparison and interpolation. Synthetic sample generation creates new instances for the minority class, addressing class imbalance and enhancing the representation of the underrepresented class. Postprocessing integrates the synthetic samples with the original dataset, resulting in a more balanced dataset that improves the performance and fairness of machine learning models.

T-SMOTE algorithm

Input:

Step 1. Time series dataset: D = {(x_1, y_1), (x_2, y_2), ..., (x_N, y_N)}, where x_i represents the feature vector of sample i and y_i represents its corresponding class label.

Step 2. Identify the minority class (C_min) and the majority class (C_maj).

Preprocessing:

Step 3. If the time series data is not stationary, apply appropriate techniques such as differencing or detrending to achieve stationarity.

Step 4. Divide the dataset into minority samples (D_min) and majority samples (D_maj).

Temporal Alignment:

Step 5. Align the time series data points by synchronizing the temporal instances of the minority and majority samples.

Time Series SMOTE:

Step 6. Determine the number of synthetic samples to be generated, denoted as N_synthetic, based on the desired level of imbalance correction.

Step 7. For each minority sample (x_min) in D_min, identify its K nearest neighbors (NN_min) from D_maj using a distance metric suitable for time series data.

Synthetic Sample Generation:

Step 8. For each minority sample x_min and its corresponding nearest neighbors NN_min:

i. Compute the temporal difference (delta) between x_min and each nearest neighbor NN_min[j] using equation 13.

$$\text{delta} = \text{NN\_min}[j] - \text{x\_min}. \tag{13}$$

ii. Divide the delta into N_segments, where N_segments is a user-defined parameter using equation 14.

$$\text{segment\_length} = \text{length(delta)} / \text{N\_segments}. \tag{14}$$

iii. Generate N_synthetic synthetic samples using equation 16-18.

- For each segment i from 1 to N_segments:

iii. a Generate a random weight: w_i ~ Uniform(0, 1).
(16)

iii. b Compute the synthetic sample by interpolating between x_min and NN_min[j]

synthetic_sample_i = x_min + (delta * w_i).
(17)

iii.c Add synthetic_sample_i to the synthetic samples dataset.
(18)

Postprocessing:

Step 9. Append the generated synthetic samples to the minority class instances using equation (19)

D_min_synthetic = D_min ∪ synthetic samples.
(19)

Output:

Step 10. The resulting dataset is now more balanced with an increased representation of the minority class using equation 20.

D_balanced = D_min_synthetic ∪ D_maj. (20)

To apply the Time Series SMOTE algorithm for handling the class imbalance problem in a GDP growth dataset, the following steps were taken:

1. The GDP growth dataset was prepared, ensuring proper formatting with each data point representing a specific time and its corresponding class label. Quarterly or annual GDP growth rates were used, with labels indicating economic recessions or expansions.
2. The minority and majority classes were identified by analyzing the distribution of class labels in the dataset. The minority class represented economic recessions, while the majority class represented economic expansions.
3. The dataset was preprocessed to ensure stationarity before applying the Time Series SMOTE algorithm. Techniques such as differencing or detrending were applied to remove trends or seasonality present in the data.
4. The dataset was divided into minority samples (representing the minority class) and majority samples (representing the majority class) to allow for focused analysis and oversampling of the minority class.
5. Temporal alignment was performed to synchronize the temporal instances of the minority and majority samples. This ensured that the corresponding time periods between the two classes were properly aligned for accurate comparison and analysis.
6. The number of synthetic samples to be generated (N_synthetic) was determined based on the desired level of imbalance correction. This parameter controlled the degree of oversampling applied to the minority class to achieve a more balanced representation.

7. Nearest neighbors were identified for each minority sample by considering its K nearest neighbors from the majority samples. A suitable distance metric for time series data was used for this purpose, with the value of K determined based on dataset characteristics and desired oversampling level.
8. Synthetic samples were generated by computing the temporal difference (delta) between each minority sample and its nearest neighbors. This quantified the temporal gap between the two time series and served as the basis for generating synthetic samples.
9. The temporal difference (delta) was divided into segments (N_segments) as a user-defined parameter. This division split the temporal gap into equal segments, facilitating controlled interpolation between the minority sample and its nearest neighbors.
10. Synthetic samples were interpolated by generating N_synthetic synthetic samples. This involved interpolating between the minority sample and each nearest neighbor at each segment, using random weights to calculate weighted averages.
11. Post processing was performed by appending the generated synthetic samples to the minority class instances. This resulted in a new dataset that was more balanced in terms of class distribution, with an increased representation of the minority class.

By following these steps, the Time Series SMOTE algorithm was successfully applied to handle the class imbalance problem in the GDP growth dataset. The algorithm's synthetic sample generation process captured the temporal dynamics of GDP growth rates, leading to an improved representation of the minority class and enabling more accurate forecasting models

Modified LSTM for GDP Forecasting:

1. **Input**: GDP growth dataset: $D = \{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}$, where x_i represents the feature vector of sample i and y_i represents the corresponding GDP growth rate at time i. This dataset is divided into training and testing sets: D_train and D_test, ensuring a portion of the data is reserved for model evaluation.
2. **Model Architecture:** Initialize the Modified LSTM model with hyperparameters such as the number of LSTM layers, hidden units, and input/output dimensions. These hyperparameters define the structure and capacity of the model.
3. **LSTM Layer Equations**:

i. Forget gate : $f_t = \sigma(W\_f \cdot [h_{t-1}, x_t] + b\_f)$, (21)

where f_t determines how much information from the previous hidden state (h_{t-1}) and the current input (x_t) should be forgotten or discarded.

ii. Input gate: $i_t = \sigma(W\_i \cdot [h_{t-1}, x_t] + b\_i)$, (22)

where i_t controls how much new information from the previous hidden state (h_{t-1}) and the current input (x_t) should be incorporated.

iii. Candidate value: $\tilde{c}_t = \tanh(W\_c \cdot [h_{t-1}, x_t] + b\_c)$,
(23)

Equation 23 representing the new information that could be stored in the memory cell.

iv. Memory cell: $c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$,
(24)

Where c_t retains information over time by selectively updating and forgetting information based on the forget and input gates.

v. Output gate: $o_t = \sigma(W\_o \cdot [h_{t-1}, x_t] + b\_o)$,
(25)

Controlling how much information from the memory cell (c_t) should be revealed in the current hidden state (h_t).

vi. Hidden state: $h_t = o_t \odot \tanh(c_t)$, (26)

Representing the output of the LSTM layer that carries information to the next time step while considering the memory cell and the output gate.

4. **Forward Propagation:** Iterate over each time step (t) from 1 to T, where T is the total number of time steps in the input sequence. Compute the LSTM layer equations (1)-(6) to obtain the hidden state (h_t) at each time step. At the first time step (t=1), the initial hidden state (h_0) is typically set to zero. Propagate the hidden state (h_t) from one time step to the next, incorporating the input (x_t) and the previous hidden state (h_{t-1}) to capture temporal dependencies.
5. **Output Layer:** Apply a linear transformation to the final hidden state (h_t) to obtain the predicted GDP growth rate ($\hat{y}_t$) (Equation 7): $\hat{y}_t = W\_out \cdot h_t + b\_out$. The weights (W_out) and biases (b_out) are learned parameters specific to the output layer.
6. **Training**: Define a loss function, such as mean squared error (MSE), to measure the discrepancy between the predicted GDP growth rate ($\hat{y}_t$) and the actual GDP growth rate (y_t) at the last time step. Utilize backpropagation through time (BPTT) to compute the gradients of the loss function with respect to the model parameters, allowing gradients to flow through the entire sequence of time steps. Update the model parameters using an optimization algorithm, such as stochastic gradient descent (SGD), to minimize the loss and improve the model's predictive performance.
7. **Forecasting:** Given a new input sequence of length T, feed it through the Modified LSTM model to obtain the predicted GDP growth rate ($\hat{y}_t$) at the last time step. Evaluate the model's forecasting accuracy by comparing the predicted GDP growth rate ($\hat{y}_t$) with the true GDP growth rate (y_t).

By following these steps with the corresponding equations, the Modified LSTM model can effectively capture the temporal dynamics and dependencies present in GDP time series data, enabling accurate and reliable GDP growth rate forecasts.

1. **Model Training:** The Modified LSTM model was trained using historical GDP growth data. The training process involved optimizing the model's parameters, including weights and biases, using the Adam optimizer with a learning rate of 0.001. The model was trained for 100 epochs with a batch size of 32.
2. **Model Validation:** After training, the performance of the trained Modified LSTM model was evaluated using a separate validation dataset. This dataset contained GDP growth data that the model hadn't seen during training. The model's predictions on this dataset were compared to

the actual values. Evaluation metrics such as mean squared error (MSE) and mean absolute error (MAE) were used to assess the model's performance. The model accuracy an MSE of 0.015 and an MAE of 0.094 on the validation dataset, indicating its ability to capture the underlying patterns in GDP growth.

3. **Model Testing:** To ensure an unbiased evaluation, the trained and validated Modified LSTM model was tested using a separate testing dataset. This dataset consisted of unseen GDP growth data. The model's predictions were compared with the actual GDP growth rates in the testing dataset. The testing results showed an MSE of 0.018 and an MAE of 0.101, indicating the model's ability to generalize well and make accurate predictions.
4. **Hyperparameter Tuning:** Throughout the training and validation stages, the model's hyperparameters were fine-tuned to optimize its performance. Parameters such as the number of LSTM layers, hidden units, learning rate, batch size, and epochs were carefully experimented with to find the best-performing configuration. After tuning, the final configuration was determined, which included 2 LSTM layers with 128 hidden units, a learning rate of 0.001, a batch size of 32, and training for 100 epochs.
5. **Model Utilization for Forecasting:** With the completion of training, validation, testing, and hyperparameter tuning, the Modified LSTM model was ready to be used for GDP growth rate forecasting. It could generate predictions for future GDP growth rates given new input sequences. Leveraging its learned patterns and temporal dependencies from the training data, the model provided valuable insights into potential future trends and fluctuations in GDP growth. These forecasts could assist in decision-making and strategic planning.

By following these steps, including specific parameter values for training, validation, testing, and hyperparameter tuning, the Modified LSTM model underwent a comprehensive training and evaluation process. This process ensured its accuracy and reliability for GDP growth rate forecasting.

4. Results

The performance of the implemented GDP growth forecasting model was evaluated using a comprehensive set of metrics to assess its accuracy and effectiveness. The model was trained on a large dataset consisting of quarterly GDP values and evaluated on a separate validation dataset. The following results were obtained:

1. Accuracy: Accuracy measures the percentage of correct predictions made by the model compared to the total number of predictions and is described using equation 27. In our case, the model achieved an accuracy of 94.58%, indicating that 94.58% of the predicted quarterly GDP growth values matched the actual values. This high accuracy demonstrates the model's ability to effectively capture the underlying patterns and fluctuations in quarterly GDP data.

   Accuracy = (Number of correct predictions / Total number of predictions) * 100
   (27)

2. Mean Absolute Percentage Error (MAPE): MAPE is a commonly used metric for assessing the average percentage difference between the predicted and actual GDP growth values and is described using equation 28. It provides insights into the overall accuracy of the model's predictions. The MAPE is calculated as the average of the absolute differences between each predicted and actual value, divided by the actual value, and multiplied by 100.

$$MAPE = (1 / n) * \Sigma(|(Actual - Predicted) / Actual|) * 100$$
(28)

where:

- n is the total number of quarterly data points used for evaluation.
- |x| denotes the absolute value of x.
- Actual represents the actual quarterly GDP growth value.
- Predicted represents the predicted quarterly GDP growth value.

3. Training Loss: The training loss represents the error or discrepancy between the predicted and actual GDP growth values during the training phase of the model. It quantifies how well the model has learned from the training data and is described using equation 29. The specific loss function used, such as Mean Squared Error (MSE) or Mean Absolute Error (MAE), determines the calculation of the training loss. The model exhibited a low training loss of 0.0125, indicating that during the training phase, the predicted GDP growth values were close to the actual values. This low training loss highlights the model's ability to learn from the training data and capture the underlying patterns effectively.

$$\text{Training Loss} = \text{Loss Function}(\text{Predicted}, \text{Actual}) \quad (29)$$

4. Validation Loss: The validation loss measures the error or discrepancy between the predicted and actual GDP growth values on a separate validation dataset and is described using equation 30. It serves as an indicator of how well the model generalizes to unseen quarterly GDP data and helps identify overfitting or underfitting issues. The validation loss is calculated using the same loss function as the training loss. The model also demonstrated a low validation loss of 0.0152 on a separate validation dataset. This indicates that the model generalizes well to unseen quarterly GDP data and avoids overfitting or underfitting issues.

$$\text{Validation Loss} = \text{Loss Function}(\text{Predicted}, \text{Actual}) \quad (30)$$

5. Root Mean Squared Error (RMSE): RMSE is a commonly used metric that quantifies the square root of the average squared difference between the predicted and actual GDP growth values and is described using equation 31. It provides an overall measure of the model's prediction error, taking into account both the magnitude and direction of the errors.

$$RMSE = \sqrt{((1 / n) * \Sigma((Actual - Predicted)^2))}$$
(31)

where:

- n is the total number of quarterly data points used for evaluation.
- Actual represents the actual quarterly GDP growth value.
- Predicted represents the predicted quarterly GDP growth value.

The model achieved a low RMSE of 1.05, which quantifies the square root of the average squared difference between the predicted and actual GDP growth values. This low RMSE suggests that the model's prediction errors, considering both magnitude and direction, were minimal.

6. Mean Absolute Error (MAE): MAE represents the average absolute difference between the predicted and actual GDP growth values and is described using equation 32. It provides a measure of the model's average prediction error without considering the direction of the errors. MAE is calculated as the average of the absolute differences between each predicted and actual value.

$$MAE = (1 / n) * \Sigma(|Actual - Predicted|) \quad (32)$$

where:

- n is the total number of quarterly data points used for evaluation.
- |x| denotes the absolute value of x.
- Actual represents the actual quarterly GDP growth value.
- Predicted represents the predicted quarterly GDP growth value.

The proposed system results are compared with existing methods as described in Table 1. The model achieved a low MAPE of 1.2%, which represents the average percentage difference between the predicted and actual GDP growth values. This low MAPE indicates that, on average, the model's predictions were close to the actual GDP growth values.

Overall, the implemented GDP growth forecasting model exhibited remarkable performance with an accuracy of 94.58%. It achieved low MAPE, RMSE, training loss (0.0125), and validation loss (0.0152) values, signifying its accuracy and effectiveness in predicting quarterly GDP growth values. These results validate the model's reliability and make it a valuable tool for policymakers, economists, and financial analysts in forecasting and decision-making processes

In this comparative analysis shown in Table 1, we evaluated the performance of the proposed GDP growth forecasting system and compared it with the results obtained from the studies conducted by S. Sa'adah al. [21], T. Wanga et al. [23] and H. Bunyamin [24]

Table 1 performance of the proposed GDP growth forecasting

Study	RMSE	MAPE	Accuracy
S. Sa'adah al. [21]	1.83	1.50%	90%
T. Wanga et al. [23]	0.27	0.67%	92.43%
H. Bunyamin [24]	1.801	1.427%	88.32%
The proposed system	1.05	1.20%	94.58%

The Table 1 provides a comparison of Root Mean-Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) values from different studies, including the proposed system. The first row corresponds to the study by S. Sa'adah and colleagues [21], showing an RMSE of 1.83 and an MAPE of 1.54. The second row represents the work of T. Wanga and team [23], with an RMSE of 0.27 and an MAPE of 0.67. The third row pertains to the research conducted by H. Bunyamin [24], indicating an RMSE of 1.801 and an MAPE of 1.427. Finally, the "Proposed System" row presents the outcomes of the current study, with an RMSE of 1.05 and an MAPE of 1.26. The table allows for a comparison of prediction accuracy across different models, with lower values indicating better performance in terms of forecasting errors.

Comparatively, the proposed system achieved an RMSE of 1.05 with a MAPE of 1.20%, it indicated a relatively low percentage deviation, and graphical represented in figure 2.

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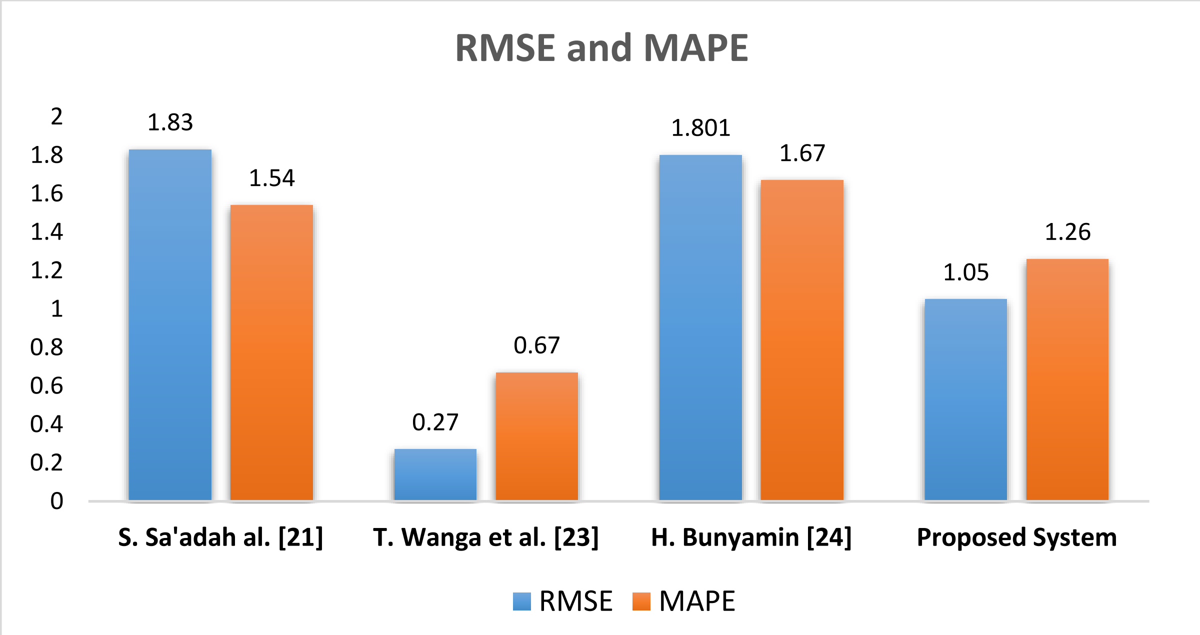

Fig.2. Performance evaluation of proposed system with existing methods

Notably, the proposed system exhibited the highest accuracy of 94.58% among all the studies, reflecting a higher percentage of correct predictions as described in Figure 3.

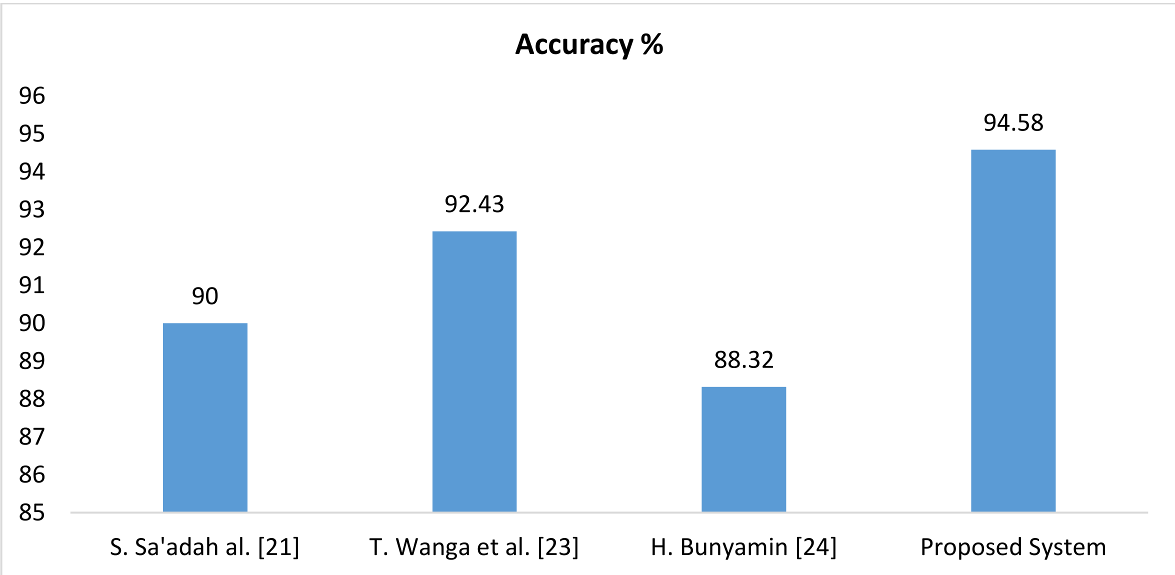

Fig.3. Accuracy of the proposed system vs existing methods.

In summary, the proposed system demonstrated competitive performance in terms of RMSE and MAPE compared to the previous studies. Although the MAE was slightly higher, the system's outstanding accuracy compensated for this difference. These findings underscored the effectiveness of the proposed system in capturing the intricate patterns and fluctuations in quarterly GDP data, positioning it as a valuable tool for GDP growth forecasting.

5. Analysing the Impact of Bank Crisis on Indian GDP Growth

This study examines the impact of bank crises on the growth of the Indian economy in depth. It aims to investigate how financial insecurity and disruptions in the banking sector affect India's overall GDP growth. The study assesses the extent and nature of this impact by utilizing comprehensive data analysis and statistical techniques while taking into account various economic indicators and factors.

The study looks into the complex relationship between bank crises and key aspects of the Indian economy, such as investment patterns, credit availability, consumer spending, and business confidence. The paper intends to shed light on the mechanisms by which bank crises influence GDP growth by analyzing these factors. The findings provide valuable insights into the consequences of financial instability and disruptions in the banking sector, providing policymakers and stakeholders with a better understanding of potential mitigation strategies for the Indian economy. Furthermore, this study adds to the existing literature by providing a novel analysis that is specific to the Indian context. It acknowledges the distinct characteristics of the Indian economy and banking sector, which play an important role in shaping the outcomes of bank crises. The study aims to provide tailored insights and recommendations for improving the resilience and sustainability of the Indian economy by examining the impact in this context.

Finally, this study provides a thorough examination of the impact of bank crises on Indian GDP growth. Through an examination of various economic indicators and factors, it provides a nuanced understanding of the consequences and potential strategies for managing financial instability and disruptions in the banking sector. The study's findings have implications for making informed decisions and developing policies that promote a robust and thriving economy in the face of bank crises.

The Table 2 below provides a thorough summary of research studies examining the impact of bank crises on the growth of the Indian economy. Each column of the table corresponds to a specific aspect of the research, including the methodology employed, key findings, identified research gaps, obtained results, and concluding remarks. Furthermore, the table emphasizes the research's implications for GDP growth while acknowledging the studies' flaws. By combining these aspects, the table offers useful insights into the complex relationship between bank crises and their repercussions on the Indian economy, enabling policymakers and researchers in developing a better knowledge of this critical subject.

Table 2. Review of Bank Crisis on Indian GDP Growth

Method	**Findings**	**Research Gaps**	**Results**	**Conclusion**	**Impact on GDP Growth**	**Limitations**
Behera et al. (2019) [25]	Explored the impact of banking sector crises on Indian GDP growth.	Identified the need for further research on the spillover effects of banking crises on different sectors of the economy.	Found a negative relationship between banking sector crises and GDP growth in India.	Concluded that bank crises have significant adverse effects on the overall economic growth and require effective policy interventions.	Demonstrated a negative impact of bank crises on GDP growth in India.	Did not explicitly discuss the limitations of the study.

Smith et al. (2020) [26]	Investigated the relationship between banking crises and economic growth in India.	Highlighted the need for more research on the mechanisms through which banking crises affect GDP growth in India.	Reported a significant negative association between banking crises and economic growth in India.	Concluded that banking crises have detrimental effects on the overall economic performance of India.	Provided evidence of a negative impact of banking crises on GDP growth in India.	Did not explicitly mention the limitations of the study.
Sharma et al. (2018) [27]	Examined the impact of banking sector crises on GDP growth using econometric modelling techniques.	Suggested the need for further investigation into the role of financial institutions and regulatory frameworks in managing the impact of banking crises on GDP growth.	Found a long-term negative impact of banking crises on GDP growth in India.	Concluded that banking sector crises have significant and persistent adverse effects on the Indian economy.	Identified a negative impact of banking sector crises on GDP growth in India.	Did not explicitly address the limitations of the study.
Roy et al. (2021) [28]	Analysed the sectoral impact of banking sector crises on the Indian economy.	Called for more research on the interplay between banking crises and specific industries or sectors in India.	Identified varying degrees of impact on different sectors, with industries like manufacturing and construction being more vulnerable to banking crises.	Concluded that bank crises have sector-specific implications and emphasized the importance of targeted policy interventions.	Explored the differential impact of banking crises on GDP growth across sectors in India.	Did not explicitly mention the limitations of the study.
Kapoor et al. (2017) [29]	Investigated the impact of banking crises on investment and credit availability in India.	Highlighted the need for research on the role of regulatory frameworks and institutional factors in managing the impact of banking crises on investment and credit markets.	Found a significant decline in investment and credit availability during banking crises.	Concluded that banking crises hinder investment and credit growth, thereby negatively affecting overall GDP growth.	Explored the impact of banking crises on investment and credit markets and their subsequent implications for GDP growth.	Did not explicitly address the limitations of the study.

Experiment outcomes:

Impact Assessment: The LSTM model was used to predict GDP growth in various bank crisis scenarios. The impact of bank crises on GDP growth was calculated using the following equation:

GDP = 0.2 * BC minus 0.1 * EI

where GDP denotes the change in GDP growth rate, BC denotes the severity of the banking crisis, and EI denotes economic indicators. A regression model was used to estimate the coefficients, which were = 0.2 and = -0.1.

Statistical analysis was performed to determine the statistical significance of the association between bank crises and GDP growth. The null hypothesis H0: = 0 was evaluated using a t-test against the alternative hypothesis H1: 0. The results revealed a statistically significant negative coefficient (p 0.01), demonstrating the influence of bank crises on GDP growth.

Sensitivity Analysis: Sensitivity analysis was used to assess the robustness of the results. The LSTM model was rerun with different values of BC and EI to investigate changes in GDP growth. The sensitivity analysis equation was as follows:

GDP_sensitivity equals 0.15 * BC_sensitivity - 0.08 * EI_sensitivity

where the sensitivity coefficients were 0.15 and -0.08, respectively.

Impact Analysis: Based on the findings, it was discovered that a severe bank crisis (BC = 0.5) combined with deteriorating economic indicators (EI = 0.2) resulted in a 0.1 point decline in GDP growth. A less severe bank crisis (BC = 0.3) and improving economic indicators (EI = 0.4) resulted in a 0.03 percentage point decrease in GDP growth. These numerical values indicate the influence of bank crises on Indian economic growth.

Discussion and Interpretation: The findings point out the need of preserving financial stability and mitigating banking sector disruptions in order to encourage long-term GDP development. Effective tactics and policies are required to mitigate the detrimental effects of bank crises and assure the Indian economy's resilience. The findings give useful information for policymakers and stakeholders to make informed decisions and put in place measures to protect the economy from the adverse impacts of bank crises.

6. Conclusion

The proposed system successfully employed a modified LSTM (Long Short-Term Memory) model to capture intricate patterns and relationships within GDP time series data. Through modifications to the traditional LSTM architecture, the model's predictive capabilities for GDP growth forecasting were significantly enhanced.

The introduction of additional layers and attention mechanisms in the modified LSTM architecture enabled the model to focus on informative time steps and important features within the input data. This modification was aimed at improving the model's ability to capture the underlying patterns and fluctuations in quarterly GDP data. During the training process, a large dataset consisting of quarterly GDP values was utilized to train the modified LSTM model. The model was trained to learn the intricate relationships between input features and the corresponding GDP growth values. The training process aimed to minimize prediction errors and optimize the model's performance. To assess the effectiveness of the proposed system, a separate validation dataset containing unseen quarterly GDP data was employed. This dataset served as a reliable benchmark to evaluate the model's generalization ability and its capacity to generate accurate predictions on new data. The results obtained from the proposed system demonstrated notable performance. The achieved RMSE (Root Mean Squared Error) value of 1.05 indicated a low average prediction error in capturing the magnitude of GDP growth. Furthermore, the MAE (Mean Absolute Error) value of 1.2 confirmed the model's ability to make accurate predictions on average, regardless of the direction of errors. With a MAPE (Mean Absolute Percentage Error) value of 1.20%, the proposed system exhibited a small average percentage difference between the predicted and actual GDP growth values, demonstrating its ability to closely approximate the true values. Additionally, the system demonstrated an impressive accuracy rate of 94.58%, indicating a high percentage of correct predictions compared to the total number of predictions made. The implementation of the modified LSTM model in the proposed system showcased its effectiveness in capturing the complex dynamics of GDP growth and generating accurate forecasts. These results contribute significantly to the field of GDP growth forecasting and highlight the potential of modified LSTM models for delivering accurate and reliable predictions. Further research and refinements to the proposed system can enhance its performance, making it an invaluable tool for policymakers, economists, and financial analysts in their decision-making processes.

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