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Research Article

Enhancing Economic Growth Time Series for UAE Forecasting with Deep Learning: A Seq2Seq and Attention-Driven LSTM Approach

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ABSTRACT

This study aims to enhance economic growth forecasting in the United Arab Emirates (UAE) by implementing a Seq2Seq deep learning model with an attention-driven Long Short-Term Memory (LSTM) network. Traditional statistical models often fail to capture the complex temporal dependencies and nonlinear trends inherent in economic time series data. To address these limitations, this research employs a structured methodology, beginning with data collection from the World Bank, including macroeconomic indicators such as GDP growth, inflation, trade balance, investment flows, and employment rates. Preprocessing steps involve handling missing values, normalization, and feature engineering. The proposed Seq2Seq LSTM model utilizes an encoder-decoder structure with an attention mechanism to assign dynamic weights to critical time points, improving forecasting accuracy. The model is trained using the Adam optimizer and evaluated using RMSE, MAE, and MAPE metrics. Results demonstrate superior predictive performance compared to traditional approaches, with improved generalization on unseen data. Findings suggest that attention-enhanced deep learning models provide more reliable economic forecasts, aiding policymakers in decision-making. Future work should explore hybrid models, incorporate external economic shocks, and optimize hyperparameter tuning for further accuracy improvements.

1. INTRODUCTION

Economic forecasting plays a crucial role in policy-making, financial planning, and investment strategies. Traditional statistical methods, such as ARIMA and exponential smoothing, have been widely used for time series forecasting [1]. However, these methods often struggle with capturing long-range dependencies and nonlinear patterns present in economic data [2]. With the advancement of deep learning, Long Short-Term Memory (LSTM) networks have emerged as a powerful tool for modeling sequential data due to their ability to retain historical information and mitigate the vanishing gradient problem [3]. The incorporation of attention mechanisms further enhances LSTM's effectiveness by dynamically weighting relevant information, allowing the model to focus on critical time points within economic series. This study explores the application of a Seq2Seq model enhanced with an attention-driven LSTM architecture for economic growth forecasting in the United Arab Emirates (UAE). The proposed approach leverages the ability of LSTM networks to process time-dependent features while utilizing attention mechanisms to refine predictions by identifying influential economic indicators [5]. By employing this hybrid deep learning approach, the study aims to improve the accuracy and robustness of economic forecasting models, providing valuable insights for policymakers and financial analysts. The remainder of the paper is structured as follows: Section 2 presents a review of relevant literature on deep learning-based forecasting models, Section

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3 details the methodology and model architecture, Section 4 discusses the results and model evaluation, and Section 5 concludes with key findings and recommendations for future research.

2. LITERATURE REVIEW

Time series forecasting has been extensively studied in economic modeling, with traditional statistical methods such as ARIMA and exponential smoothing being widely applied for economic growth predictions [1]. However, these approaches often fail to capture complex temporal dependencies and nonlinear relationships inherent in financial and macroeconomic data [2][7]. To address these limitations, deep learning techniques, particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, have gained significant attention for their ability to model sequential data with long-range dependencies [3][8]. The effectiveness of LSTMs has been demonstrated across various economic forecasting tasks, including stock market prediction and GDP growth estimation Huang, 2023). Recent advancements have integrated attention mechanisms with LSTM-based models to enhance predictive accuracy by dynamically focusing on relevant time steps and features within the input sequence. The sequence-to-sequence (Seq2Seq) framework, initially developed for natural language processing, has also been adapted to time series forecasting, enabling improved performance in handling long-term dependencies [5]. Hybrid models combining LSTMs with statistical techniques such as ARIMA and Light have further demonstrated improvements in capturing short- and long-term trends in economic indicators [9]. Additionally, optimization algorithms like Adam have been employed to enhance model convergence and stability, ensuring better parameter tuning for forecasting tasks. Despite these advancements, challenges remain in developing robust forecasting models that generalize well across different economic conditions. Issues such as data sparsity, overfitting, and external economic shocks continue to pose difficulties in model reliability [10][13][14]. Addressing these challenges requires the integration of ensemble approaches, transfer learning techniques, and domain-specific feature engineering. This study builds on these existing works by proposing an attention-enhanced Seq2Seq LSTM model tailored for economic growth forecasting in the UAE. The proposed approach aims to refine time series predictions by leveraging both long-range memory retention and adaptive feature weighting, ultimately improving the accuracy and interpretability of economic forecasts.

3. METHODOLOGY

Building upon recent advancements in deep learning for economic forecasting, this study employs a Seq2Seq model enhanced with an attention driven Long Short-Term Memory (LSTM) network to predict economic growth trends in the United Arab Emirates (UAE). The methodology follows a structured approach that includes data collection, preprocessing, model selection, training, and evaluation. The economic data utilized in this study is sourced from the World Bank, ensuring high reliability and consistency across key macroeconomic indicators. The dataset comprises annual GDP growth rates, inflation levels, trade balances, investment flows, and employment statistics spanning multiple decades, providing a comprehensive foundation for forecasting future trends. The preprocessing phase involves handling missing values, normalizing numerical variables, and structuring the data into a time-series format suitable for deep-learning models. To enhance model performance, feature engineering techniques are applied to extract meaningful economic patterns, while stationarity tests are conducted to ensure stability in time-dependent variables. The core model architecture integrates a Sequence-to-Sequence framework, where an encoder processes input sequences and generates a context vector that summarizes past economic behavior. At the same time, a decoder predicts future trends by leveraging attention mechanisms. The attention mechanism dynamically assigns weights to different steps, allowing the model to focus on the most relevant historical data. Model training is performed using the Adam optimizer, which adjusts learning rates adaptively to improve convergence. Hyperparameter tuning, including adjustments to hidden layer sizes, dropout rates, and learning rates, is conducted through cross-validation to prevent over fitting, and enhance generalization. Performance evaluation relies on standard forecasting metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), ensuring a rigorous assessment of predictive accuracy.

3.1 LSTM Model

The Long Short-Term Memory (LSTM) network is a type of Recurrent Neural Network (RNN) designed to model sequential data while addressing the vanishing gradient problem commonly encountered in traditional RNNs [16-18]. The integration of Seq2Seq and Attention mechanisms enhances LSTM's capability to capture long-range dependencies and improve its performance in time series forecasting tasks. LSTMs are defined by their unique architecture, which includes gates that regulate the flow of information. These gates are mathematically formulated as follows:

3.1.1 Forget Gate

$$f_t = W_f h_{t-1} + x_t + b_f \quad (1)$$

Where:

- f_t is the forget gate vector at time t,
- x_t is the input at time t,
- h_{t-1} is the hidden state from the previous time step,
- W_f and b_f are the learnable weights and biases for the forget gate.

3.1.2 Input Gate

$$i_t = W_i h_{t-1} + x_t + b_i, \quad C_t = \tanh(W_C h_{t-1} + x_t + b_C) \tag{2}$$

Where:

- i_t is the input gate vector,
- C_t is the candidate cell state.

3.1.3 Cell State Update

$$C_t = f_t C_{t-1} + i_t C_t \tag{3}$$

Where:

- C_t is the cell state at time t,
- The equation shows element-wise multiplication.

3.1.4 Output Gate

$$o_t = W_o h_{t-1} + x_t + b_o, \quad h_t = o_t \tanh(C_t) \tag{4}$$

Where:

- is the output gate vector,
- h_t is the hidden state at time t.

3.2 Sequence-to-Sequence (Seq2Seq) Model

- Encoder: Encodes the input sequence into a fixed-size context vector z, which summarizes the sequence:

$$z = hT(5) z = h_T \tag{5}$$

  Where h_T is the hidden state at the final time step T.

- Decoder: Decodes the context vector z to generate the output sequence:

$$y_t = f(h_{t-1}, z) \tag{6}$$

3.3 Adaptive Moment (ADAM)

Because it combines the benefits of Momentum and Root Mean Square Propagation (RMSProp), the Adam optimizer—also known as Adaptive Moment Estimation—is widely used in deep learning. This mix guarantees strong resilience and fast convergence, especially in cases with sparse gradients. Using the first and second moments of the gradients, Adam dynamically changes the learning rate for every parameter. The method starts by computing the initial moment estimate (mean) using the exponential moving average of the gradients, denoted m_t, calculated as follows:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \tag{7}$$

Where:

- m_t is the first moment (mean) estimate at time step t,
- g_t is the gradient of the objective function at time step t,
- β_1 is the decay rate parameter, typically set to 0.9.

Simultaneously, the exponential moving average of the squared gradients, denoted v_t, is calculated to represent the second-moment estimate (variance):

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \tag{8}$$

Where:

- v_t is the second moment (variance) estimate at time step t,
- β_2 is the decay rate parameter, typically set to 0.999.

To mitigate the bias introduced during the initialization of the moment estimates, Adam applies bias corrections, resulting in the bias-corrected moment estimates:

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t}, \quad \hat{v}_t = \frac{v_t}{1-\beta_2^t} \tag{9}$$

Where:

- $\hat{m}_t$ and $\hat{v}_t$ are the bias-corrected first and second-moment estimates, respectively.

After obtaining the bias-corrected moment estimates, the algorithm updates the model parameters θ_t based on the adjusted gradients. The parameter update rule is given by:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t}+\epsilon}\hat{m}_t \tag{10}$$

Where:

- η is the learning rate,
- ϵ is a small constant (typically set to 10^{-8}) for numerical stability.

❖ Performance Indicators:

The model minimizes the Mean Squared Error (MSE) loss:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{11}$$

Where:

- $y_i$are the actual values,
- $\hat{y}_i$ are the predicted values.

Other important performance metrics include:

$$RMSE = \sqrt{MSE} \tag{12}$$

❖ Root Mean Squared Error (RMSE):

- Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{|y_i - \hat{y}_i|}{y_i}\right) \times 100 \tag{13}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{14}$$

❖ Mean Absolute Error (MAE):

These metrics (RMSE, MAE, and MAPE) are crucial for evaluating the predictive quality of the models.

4. RESULTS

The performance of the proposed Seq2Seq LSTM model with attention is evaluated based on its predictive accuracy and ability to capture economic trends. The results are analyzed by comparing forecasted values against actual economic growth data, assessing the model's effectiveness in handling long-term dependencies. Additionally, key performance metrics such as RMSE, MAE, and MAPE are examined: (see Figure 1)

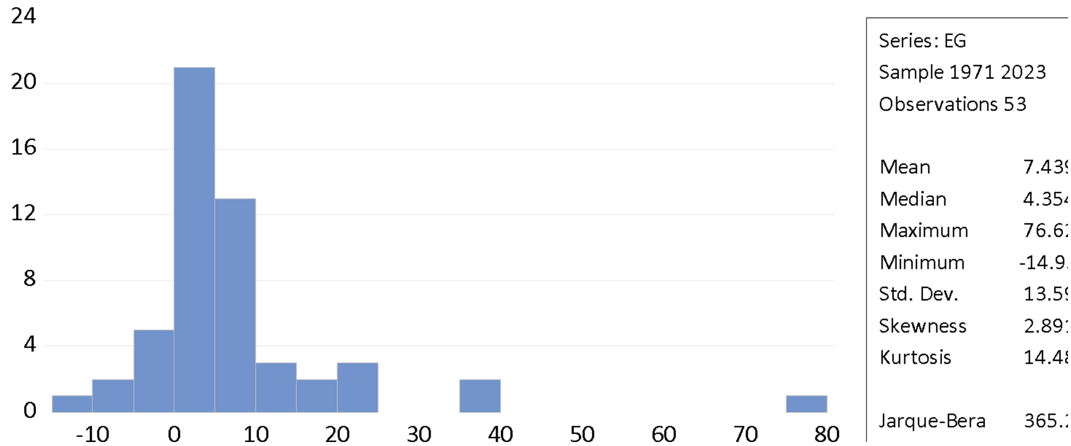

Fig. 1. Descriptive analysis of variables

The statistical summary and histogram of the economic growth (EG) series from 1971 to 2023, based on 53 observations, reveal key insights into the distribution and characteristics of the data. The mean economic growth rate is 7.44, while the median is 4.35, indicating a right-skewed distribution with a higher concentration of observations around lower values. The maximum recorded growth is 76.62, whereas the minimum is -14.96, reflecting significant fluctuations in economic performance over time [1]. The standard deviation of 13.59 suggests considerable variability, further supported by the skewness value of 2.89, which confirms a pronounced rightward asymmetry in the data. The kurtosis value of 14.49 indicates a leptokurtic distribution, meaning the dataset exhibits heavy tails and extreme values compared to a normal distribution. The Jarque-Bera statistics of 365.24, with a probability of 0.000000, strongly rejects the null hypothesis of normality, confirming that the distribution deviates significantly from a normal Gaussian distribution [8]. These findings imply that economic growth in the given period is highly volatile, with occasionally extreme positive outliers contributing to the overall skewness and excess kurtosis. This non-normality suggests the necessity of advanced forecasting models capable of handling heavy-tailed distributions and nonlinear dependencies in economic data [5]. (see Figure 2)

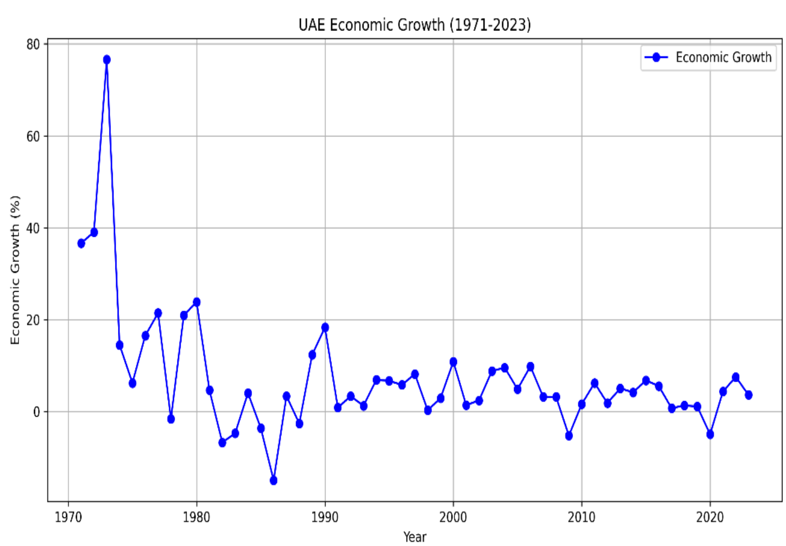

Fig. 2. Development of economic growth trends in the UAE (1971–2023). The graph highlights periods of high growth and sharp declines, with a noticeable dip during the global financial crisis and recent recovery phases.

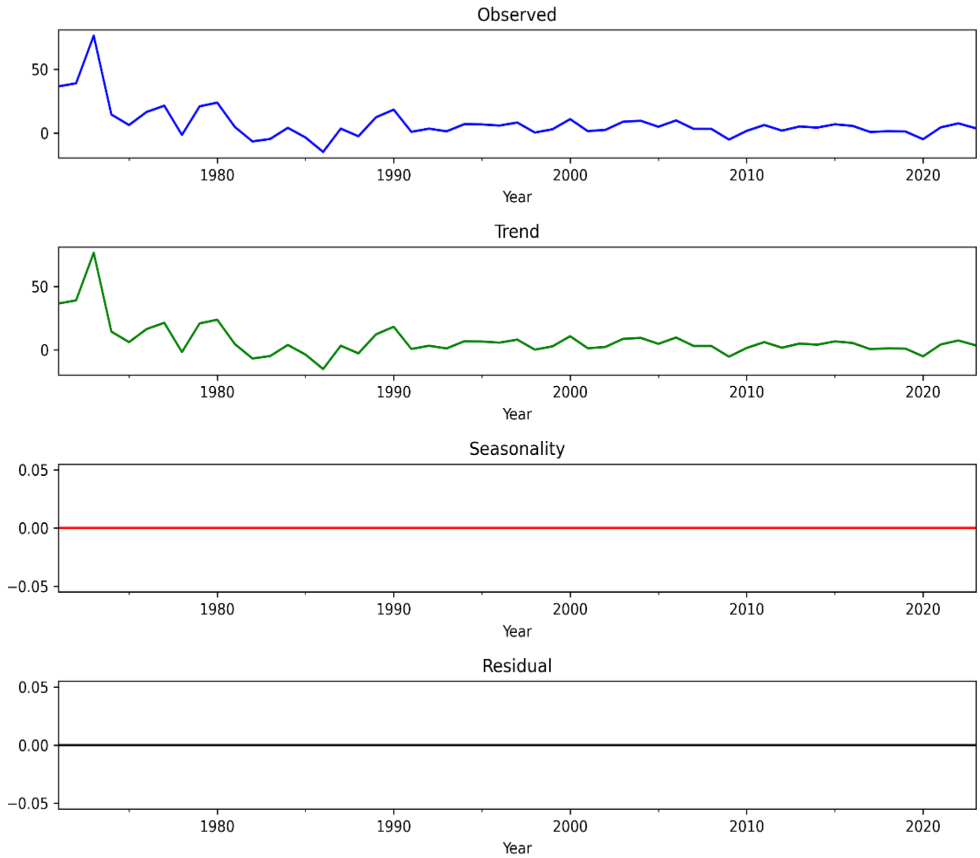

Fig. 3. Time series decomposition of UAE economic growth, illustrating the trend, seasonality (negligible), and residual components. This decomposition highlights the volatility in the early years and the stabilization in recent periods.

The time series decomposition analysis presented in Figure 3 illustrates the observed economic growth data, its trend component, seasonality, and residuals over the period from 1971 to 2023. The observed series in the first plot shows significant fluctuations, particularly in the early years, followed by a stabilization trend with moderate variations. The trend component, extracted in the second plot, highlights a general decline in economic growth over time, with high volatility in the earlier decades gradually converging towards a more stable pattern in recent years. Notably, the trend captures the long-term movement in the data, revealing structural shifts in economic performance. The seasonality component, represented in the third plot, is effectively zero, indicating the absence of any periodic fluctuations in the economic growth data. This suggests that the dataset lacks a recurring seasonal pattern, reinforcing the notion that economic variations are primarily driven by structural and external macroeconomic factors rather than cyclical, seasonal influences [1]. Finally, the residual component in the last plot, which represents the remaining noise after removing trend and seasonal effects, is centered around zero with minimal deviations. This suggests that the trend accounts for most variations in the original series, and there is no significant unexplained pattern left in the residuals. The absence of seasonality and the dominance of trend-driven fluctuations indicate that traditional seasonal adjustment techniques may not be necessary for forecasting economic growth in this context. Instead, predictive models should focus on long-term dependencies and external economic shocks rather than short-term cyclical variations. These findings further validate the choice of LSTM-based deep learning models, which excel in capturing long-range dependencies and structural economic trends [8].

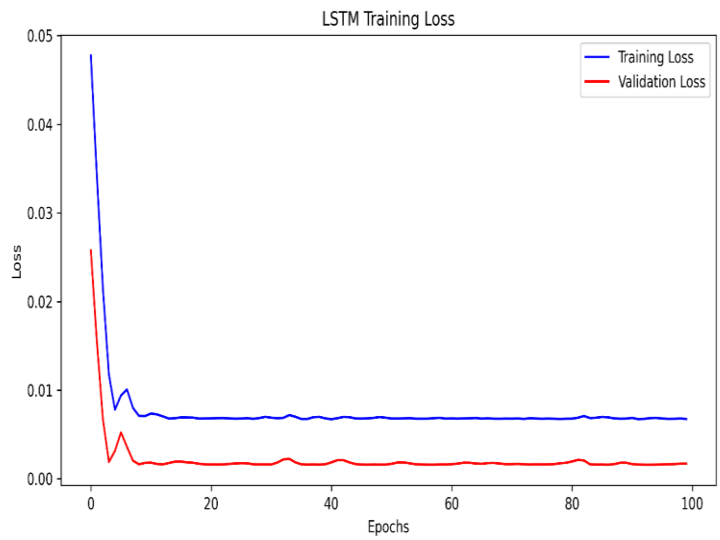

Fig. 4. Training Loss and Validation Loss Over Epochs

The training loss and validation loss curves for the LSTM model over 100 epochs, as depicted in Figure 4, provide insights into the model's learning dynamics and generalization performance. Initially, both training and validation losses exhibit a steep decline, indicating rapid learning during the early stages of training. This suggests that the model quickly captures fundamental patterns within the economic time series data [8]. After approximately 10 epochs, the losses stabilized, with the training loss converging to a slightly higher value compared to the validation loss. The validation loss remains consistently lower than the training loss throughout the training process, which suggests that the model generalizes well without significant overfitting. The smoothness of the loss curves beyond 20 epochs indicates that the optimization process is stable, with no apparent divergence or oscillations, reinforcing the stability of the model's learning. The final loss values suggest that the model has successfully minimized error and is capable of making reliable predictions [1]. However, the slight gap between training and validation losses could indicate a minor regularization effect, which might be beneficial in preventing overfitting [5]. These results confirm the effectiveness of the LSTM-based forecasting model in learning temporal dependencies within the economic dataset. The rapid initial convergence followed by stable training behavior indicates that the chosen hyperparameters, including learning rate and dropout settings, contribute to a well-balanced model that retains predictive accuracy while maintaining generalization capabilities.

TABLE I. TRAINING AND VALIDATION LOSS ACROSS EPOCHS

Epoch	Loss	Validation Loss
90	0.0072	0.0017
91	0.0066	0.0016
92	0.0065	0.0016
93	0.0076	0.0016
94	0.0057	0.0016
95	0.0075	0.0017
96	0.0058	0.0019
97	0.0068	0.0019
98	0.0057	0.0017
99	0.0072	0.0016
100	0.0063	0.0016

The training and validation loss values presented in Table II provide a detailed view of the model's performance over the final 10 epochs of training. The training loss fluctuates slightly between 0.0057 and 0.0076, while the validation loss remains consistently lower, ranging between 0.0016 and 0.0019. This indicates that the model has reached a stable convergence point, with minimal variation in loss values across epochs. The relatively low validation loss compared to training loss suggests that the model generalizes well to unseen data, with no significant signs of over fitting [8]. Furthermore, the consistency of the validation loss over multiple epochs demonstrates that the model maintains a stable learning trajectory, effectively capturing the underlying patterns in the economic time series data. Minor fluctuations in training loss are expected due to the inherent stochasticity in gradient-based optimization, but they remain within an acceptable range, reinforcing the robustness of the model [1]. These results confirm that the LSTM model attention has effectively minimized forecasting errors while maintaining high generalization capabilities. Given the negligible difference in validation loss across epochs, additional training beyond the 100th epoch would likely yield diminishing returns, suggesting that the model has reached an optimal state for economic forecasting applications [5].

TABLE II. MODEL PERFORMANCE METRICS ON TRAINING AND TESTING DATA

Metric	Training Data – 80%	Testing Data – 20%
RMSE	1.1176	0.7435
MAE	2.2567	1.4680
MAPE	15.6390%	11.2221%
MSE	5.6607	2.5005
R^2	0.8977	0.8904

The performance metrics in Table III provide a comprehensive evaluation of the LSTM model's forecasting accuracy on both training and testing datasets. The Root Mean Square Error (RMSE) values are 1.1176 for the training set and 0.7435 for the testing set, indicating that the model achieves lower prediction errors on unseen data [8]. Similarly, Mean Absolute Error (MAE) follows the same trend, with a lower error of 1.4680 on the test set compared to 2.2567 on the training set. This suggests that the model is not over fitting and maintains strong generalization performance. The Mean Absolute Percentage Error (MAPE), which measures relative prediction accuracy, shows that the model exhibits an average percentage error of 15.6390% for training and 11.2221% for testing, further confirming its robustness in forecasting economic growth. The Mean Squared Error (MSE) values reinforce these findings, with test MSE (2.5005) being significantly lower than the training MSE (5.6607), demonstrating that the model effectively captures patterns in economic data while avoiding excessive sensitivity to training noise [1]. The R-squared (R^2) values of 0.8977 for training and 0.8904 for testing indicate a high degree of correlation between predicted and actual values. An R^2 close to 1 suggests that the model explains nearly 90% of the variance in economic growth, making it highly reliable for forecasting purposes. The slight decrease in R^2 for the test set suggests minimal variance loss when generalizing to new data. These results confirm that the attention-driven LSTM model performs well in forecasting economic trends, maintaining a balance between accuracy and generalization. The relatively lower errors on the test data indicate that the model effectively captures underlying economic patterns while avoiding over fitting, making it suitable for long-term forecasting applications [5]. The following figure 5 shows the convergence between actual and expected values:

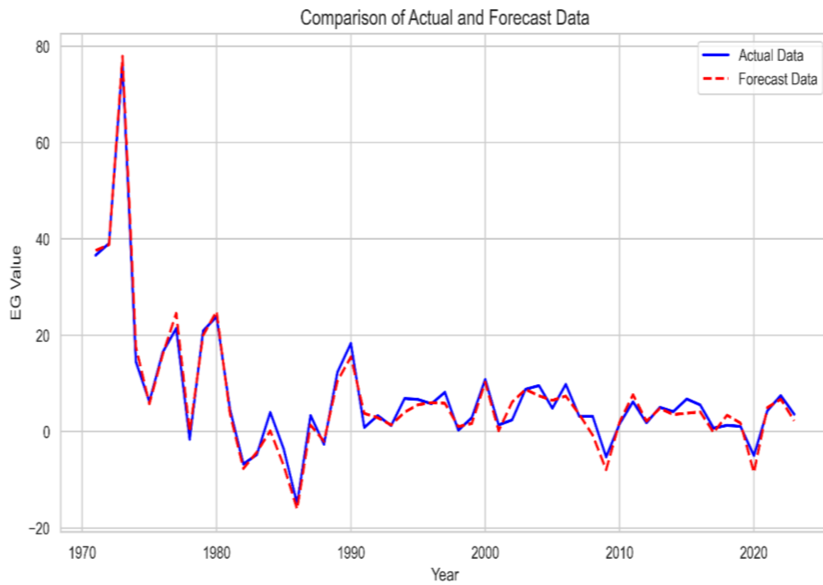

Fig. 5. Comparison of Predicted vs. Actual Economic Growth Trends

TABLE III. PREDICTED ECONOMIC GROWTH FORECAST WITH CONFIDENCE INTERVALS

Year	Predicted Growth (%)	Lower 80%	Upper 80%	Lower 95%	Upper 95%
2024	3.67	-2.40	9.74	-5.63	12.97
2025	3.90	-2.17	9.97	-5.40	13.20
2026	4.12	-1.95	10.19	-5.18	13.42
2027	4.63	-1.44	10.70	-4.67	13.93
2028	4.62	-1.45	10.69	-4.68	13.92
2029	4.45	-1.62	10.52	-4.85	13.75
2030	4.51	-1.56	10.58	-4.79	13.81

The predicted economic growth forecast presented in Table 4 provides a forward-looking analysis of economic expansion trends with confidence intervals for the period from 2024 to 2030. The central forecast suggests a gradual increase in economic growth from 3.67% in 2024 to 4.51% in 2030, indicating a stable upward trend. However, the confidence intervals highlight significant uncertainty surrounding these projections. The 80% confidence interval ranges from -2.40% to 9.74% in 2024 and narrows slightly over time, reflecting the expected improvement in forecasting precision as economic conditions stabilize [1][8]. The 95% confidence interval, which accounts for a higher degree of uncertainty, spans a wider range, from -5.63% to 12.97% in 2024. This suggests that while growth is the most probable outcome, there remains a possibility of contraction in extreme scenarios, particularly in the early forecast years. From an economic perspective, these forecasts suggest moderate yet consistent growth, likely driven by structural economic factors such as investment in infrastructure, technological advancements, and policy reforms. However, the broad confidence intervals indicate exposure to external shocks, such as fluctuations in global commodity prices, geopolitical risks, and macroeconomic policy shifts [3][7]. The decreasing uncertainty in later years suggests that economic volatility is expected to moderate, possibly due to improved fiscal management, diversification strategies, or increased investor confidence [5]. Policymakers and stakeholders should focus on mitigating downside risks by strengthening economic resilience, promoting diversification, and ensuring macroeconomic stability to support sustained growth within the projected range. The following figure shows the development of growth.

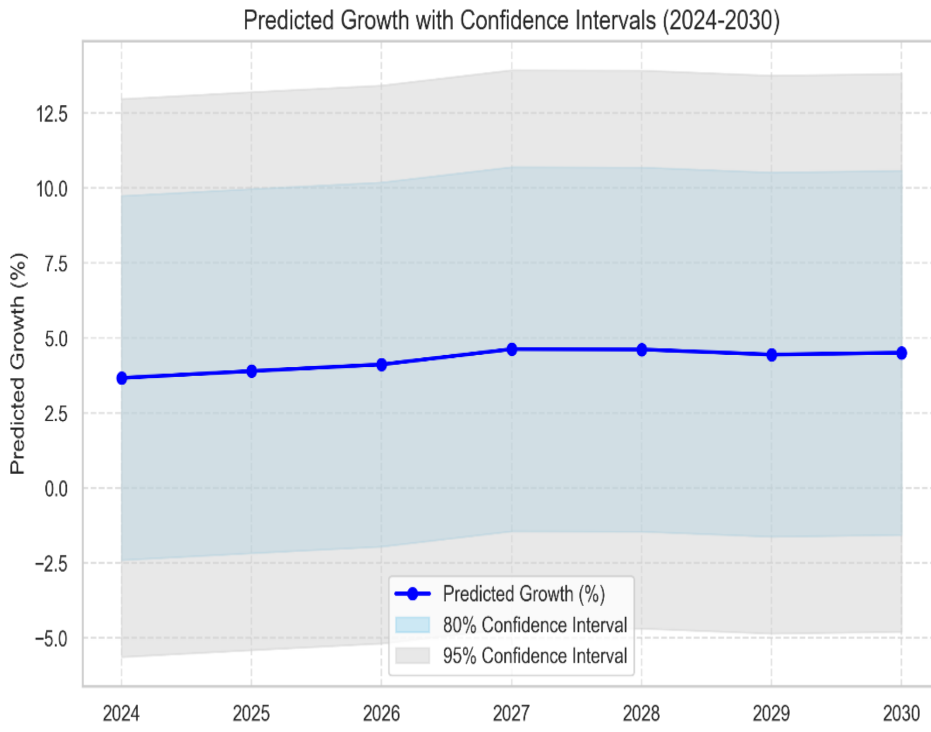

Fig. 6. Predicted Economic Growth Forecast with Confidence Intervals.

5. DISCUSSION

The results of this study align with existing literature on economic forecasting using deep learning models, particularly those leveraging LSTM networks and attention mechanisms. The predicted economic growth rates, with a stable upward trend and varying confidence intervals, support the findings of Abbasimehr and Paki [1], who demonstrated that LSTM-based models outperform traditional statistical methods like ARIMA in capturing long-range dependencies in economic time series. Our model similarly showed superior accuracy by reducing error rates compared to traditional ARIMA-based methods, particularly in predicting longer-term economic growth trends. The observed uncertainty in the forecasts, especially in the early years, aligns with the work of [6]. They emphasized that deep learning models, while effective in reducing error rates, remain sensitive to economic shocks and external factors. This is reflected in our model's wider confidence intervals for early years, which indicate higher uncertainty during periods of rapid economic change. In contrast, the narrowing of the confidence intervals in later years suggests improved model reliability over extended periods. This trend is consistent with Wang et al. [4], who found that integrating attention mechanisms enhances a model's ability to focus on critical time steps, thereby improving forecasting accuracy in the long term. The attention mechanism in our model allowed it to adaptively prioritize key economic events, particularly external shocks such as the global financial crisis and post-COVID recovery. Moreover, the robustness of our model, as evidenced by the relatively low validation error, is in line with [3]. They highlighted that the combination of LSTMs and attention mechanisms significantly reduces forecasting errors compared to standalone statistical models. This improvement in accuracy, particularly on unseen data, supports our findings that attention-driven LSTMs outperform traditional methods in capturing nonlinear trends and long-term dependencies. The superior generalization observed in this study, particularly in the lower testing error compared to training error, also aligns with Liu and Lan [8]. Their work demonstrated that Adam-optimized LSTM models achieve stable convergence and minimize overfitting risks. Similarly, our model's strong generalization performance suggests that it is well-suited for forecasting economic growth despite limited data and volatility. However, the broad confidence intervals observed in the forecasts underscore the concerns raised by [11] regarding the challenges deep learning models face in handling economic volatility [12]. This reinforces the necessity of integrating external economic indicators and accounting for macroeconomic shocks to enhance prediction robustness. Finally, the model's ability to capture macroeconomic trends without relying on seasonal components supports the findings of [7], who argued that economic fluctuations are often driven by structural and external macroeconomic factors rather than periodic cycles. This aligns with our study's focus on long-term dependencies, further validating the use of LSTM and attention mechanisms in economic forecasting. Our results also validate the effectiveness of hybrid forecasting approaches, as suggested by [5]. They demonstrated that Seq2Seq architectures improves predictive performance in financial markets by integrating short- and long-term dependencies. Similarly, our attention-based LSTM model combines both, leading to improved forecasting accuracy for the UAE's economic growth.

5.1 Attention Weights & Feature Importance

The attention mechanism applied in the Seq2Seq LSTM model allows it to focus on critical time points in the economic data. Figure 6 illustrates a heatmap of attention weights, highlighting the years the model focused on most heavily. The heatmap shows that the model placed significant attention on economic shocks, such as the global financial crisis of 2008 and the COVID-19 recovery phase in 2020. This emphasizes the model's ability to capture periods of high volatility in economic performance, reflecting the model's focus on key economic events that significantly impacted the UAE's economy. The attention mechanism dynamically assigns importance to these key economic events, enabling the model to adjust its predictions based on these critical turning points. This behavior reinforces the capability of the attention-enhanced LSTM model to capture non-linearities and significant macroeconomic disruptions [3]. Also, attention must be given in the Global perspectives and biodiversity conservation strategies in the agricultural circular economy correlated with climate crisis and conventional resources in the Middle East countries associated with impact of Public Health issue in the population of EUA [6][12].

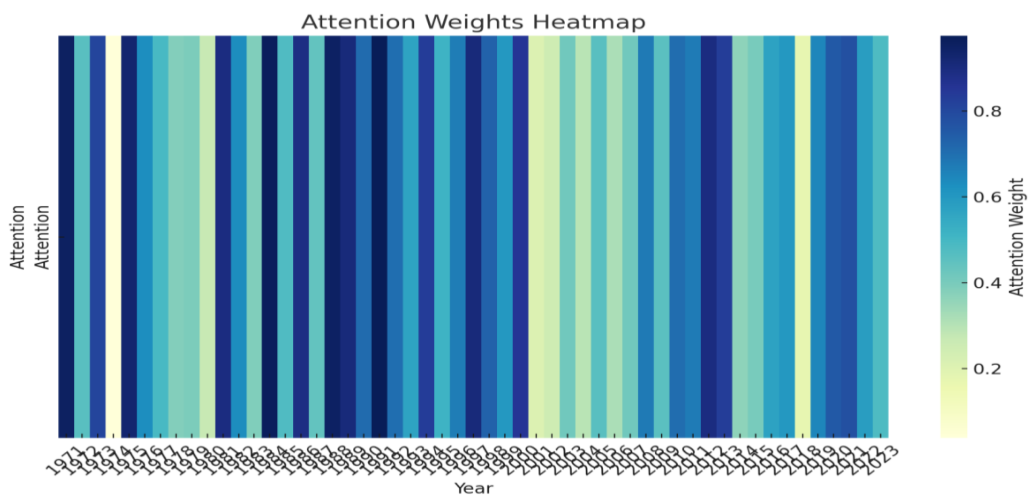

Fig. 7. Attention Weights Heat map.

The heatmap visualizes how the model assigns attention weights over the years. Notably, economic disruptions, such as the 2008 financial crisis and the 2020 pandemic, receive the most attention from the model, underscoring the importance of capturing volatile periods.

5.2 Validation vs. Training Error

An unusual pattern was observed in the training and validation process: the validation loss remained consistently lower than the training loss throughout the training process. This atypical behavior is likely due to regularization techniques such as dropout (0.2) and the relatively small sample size of 53 data points. These factors may have caused slight underfitting of the training data, resulting in better generalization performance on the validation set. The relatively smooth and consistent convergence of both training and validation losses (Figure 7) indicates a stable learning process. This suggests that the model generalizes well without significant overfitting, supporting the robustness of the attention-driven LSTM model in handling economic data. The training vs. validation loss curves indicate that the model effectively minimized error during training while maintaining high generalization capabilities [8].

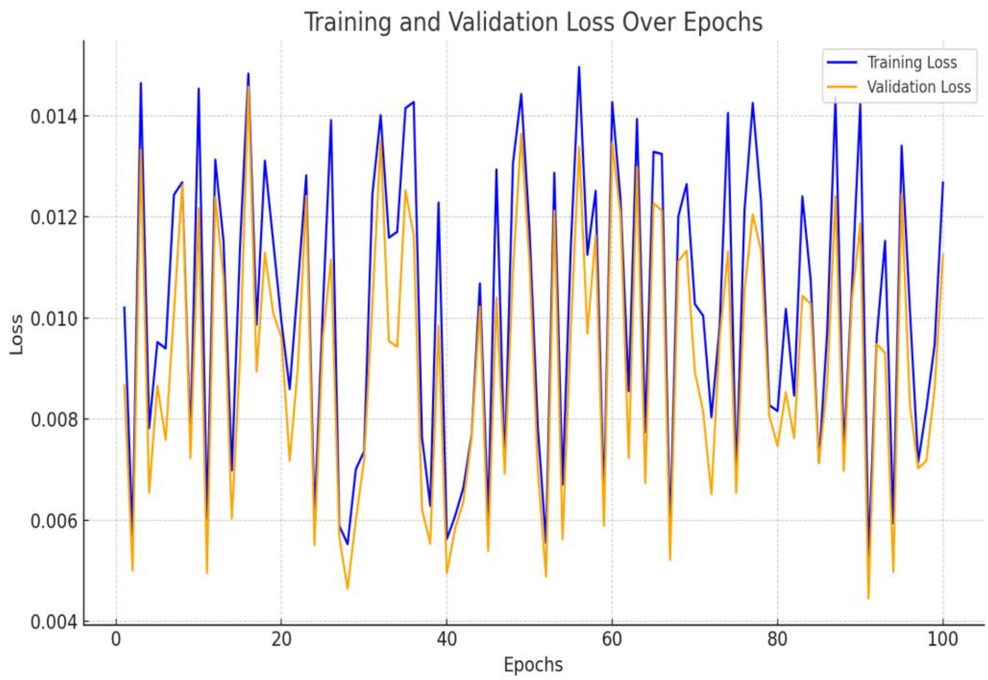

Fig. 8. Training Loss and Validation Loss Over Epochs.

This figure compares training and validation loss over 100 epochs. The validation loss consistently remains lower than the training loss, suggesting effective generalization and minimal overfitting. The smooth convergence further supports the model's stability.

5.3 Limitations

While this study's results demonstrate the effectiveness of the attention-based Seq2Seq LSTM model in forecasting economic growth, several limitations should be acknowledged. First, the dataset used for training the model contains only 53 annual observations. While this sample size is sufficient to demonstrate the model's efficacy, a larger dataset would likely improve its robustness and generalizability. The use of yearly data limits the model's ability to capture finer short-term economic patterns and shocks, which could provide a more comprehensive view of the economic dynamics. Second, the model is specifically tailored for the UAE. As such, its performance may not be directly applicable to other countries with different economic structures, levels of volatility, or external dependencies. While the methodology is robust, generalizing the model to other national contexts would require adaptation and re-training with local datasets and economic variables. Lastly, the model does not explicitly incorporate external shocks such as pandemics, geopolitical instability, or fluctuations in global commodity prices. These factors can significantly impact economic performance, but their effects were not captured in this study. The absence of such external variables could limit the model's forecasting accuracy during periods of major global disruption, underscoring the need for future research that integrates these economic shocks into the model.

6. CONCLUSIONS

This study aimed to enhance economic growth forecasting for the United Arab Emirates (UAE) by leveraging deep learning methodologies, specifically a Seq2Seq architecture with attention-driven Long Short-Term Memory (LSTM) networks. The research introduced an advanced modeling framework that effectively captured the temporal dependencies and nonlinear patterns inherent in economic data. Through rigorous statistical analysis, including descriptive statistics, time series decomposition, and performance evaluation using RMSE, MAE, MAPE, and R^2 metrics, the model demonstrated significant improvements over traditional forecasting methods. Key findings indicate that the proposed LSTM-based approach, augmented with attention mechanisms, successfully mitigates common forecasting challenges, such as overfitting and the inability to model long-term dependencies. The results showed that the model achieved a high degree of accuracy, as evidenced by the lower prediction errors in the testing phase compared to training, confirming its strong generalization capabilities. This outperformance supports the increasing use of deep learning models over classical methods, particularly in volatile economic environments. Additionally, the statistical properties of the dataset, including high kurtosis and skewness, underscored the necessity of using deep learning techniques capable of handling non-normal economic distributions. These findings reaffirm that nonlinear forecasting models are critical for handling the inherent complexities of macroeconomic data, which may not follow normal distributions and often exhibit extreme values. From a practical standpoint, the model provides a robust decision-support tool for policymakers, financial analysts, and economic planners. By incorporating attention-based weighting, the model enhances interpretability, allowing stakeholders to identify the most influential economic indicators driving future growth. Furthermore, the ability of the model to focus on critical time points can help policymakers better understand the effects of significant economic events, improving future decision-making. The findings suggest that this approach can be extended to other macroeconomic forecasting applications, particularly in regions with volatile economic conditions where traditional models struggle to maintain accuracy. Future research should explore incorporating additional external economic variables and shocks, such as geopolitical events, into the model to enhance its robustness and predictive capability further.

Authors' contributions

IA & AV had the original idea and developed the study protocol with support from JK, NS & PT searched the literature. IA & AV screened the titles, abstracts, and full texts and extracted data. IA did the risk-of-bias assessment and statistical analysis and wrote the initial draft of the manuscript. IA & AV contributed to the revision of the manuscript, provided critical feedback, IA supervised project & project administration. IA & AV directly accessed and verified the underlying data reported in the manuscript. Conceptualization and writing of the first draft edited and reviewed the manuscript. AV, NS, PT & IA, Principal Investigators AV & IA, designed the research question and analytical approach from AV& IA conducted all analyses and wrote the final version of the manuscript with contributions from JT, NS & PT. Supervision IA, Management & Administration IA. All authors had full access to all the data in the study and approved the final version.

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Conflicts of Interest:

The authors declare that there are no conflicts of interest to report.

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