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Research Article

Deep Learning-Based Time Series Forecasting: A Convolutional Neural Network Approach for Predicting Inflation Trends

Mostafa Abotaleb[1,*], El-Sayed M. El-kenawy[2,3,4], Klodian Dhoska[5]

[1] Department of System Programming, South Ural State University, Chelyabinsk, Russia

[2] School of ICT, Faculty of Engineering, Design and Information & Communications Technology (EDICT), Bahrain Polytechnic Isa Town, Bahrain

[3] Applied Science Research Center, Applied Science Private University, Amman, Jordan

[4] Jadara University Research Center, Jadara University, Jordan

[5] Department of Production and Management, Polytechnic University of Tirana, Albania.

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ABSTRACT

This study investigates the application of Convolutional Neural Networks (CNNs) for forecasting inflation trends in Egypt, aiming to enhance the accuracy of economic predictions by capturing complex, non-linear temporal dependencies in time series data. Traditional econometric models, such as ARIMA and VAR, often struggle to model volatile and dynamic economic conditions, prompting the exploration of deep learning techniques. The proposed CNN-based model leverages historical inflation data from 1960 to 2023, sourced from the World Bank, to predict future inflation trends. The methodology involves data preprocessing, feature extraction using convolutional layers, and prediction through fully connected layers, optimized using the Adam optimizer. Performance metrics, including Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2), demonstrate the model's robustness, with an RMSE of 9.2113 and an R^2 of 0.8911 on the testing dataset. The results indicate a steady upward trend in inflation from 2024 to 2030, with rates rising from 12.45% to 16.35%, accompanied by widening confidence intervals reflecting increased uncertainty over longer horizons. The study concludes that CNNs offer a reliable framework for inflation forecasting, outperforming traditional methods in capturing non-linear patterns. Recommendations include integrating additional economic indicators and exploring hybrid models to further enhance predictive accuracy. This research contributes to the growing application of deep learning in economic forecasting, providing valuable insights for policymakers and researchers.

1. INTRODUCTION

Inflation forecasting is a critical aspect of economic planning and policy-making, as it directly impacts monetary policy, investment decisions, and overall economic stability [1]. Accurate prediction of inflation trends enables governments and financial institutions to implement timely and effective measures to mitigate adverse economic effects. Traditional econometric models, such as ARIMA and VAR, have been widely used for time series forecasting. However, these models often struggle to capture complex, non-linear patterns in economic data, particularly in the presence of volatile and dynamic market conditions. In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have emerged as powerful tools for time series forecasting due to their ability to model intricate temporal dependencies and extract meaningful features from sequential data [2][3]. CNNs, originally designed for image processing, have demonstrated remarkable success in various time series applications, including energy consumption forecasting [4], financial market prediction [5], and multivariate time series analysis [6]. Their ability to automatically learn hierarchical representations of data through convolutional and pooling layers makes them particularly suitable for capturing local patterns and trends in time series data [7]. Moreover, the integration of CNNs with other deep learning architectures, such as recurrent neural networks (RNNs), has further enhanced their predictive capabilities in complex forecasting tasks [8].

*Corresponding author email: abotalebmostafa@bk.ru
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This study explores the application of CNNs for inflation forecasting in Egypt, leveraging their ability to model non-linear relationships and temporal dependencies in historical inflation data. By employing a CNN-based approach, we aim to improve the accuracy of inflation predictions and provide more reliable insights for economic decision-making. The proposed model is evaluated using a comprehensive dataset spanning several decades, and its performance is compared against traditional forecasting methods. The results demonstrate the potential of CNNs to outperform conventional models, offering a robust framework for future research in economic time series forecasting [9][10]. This research contributes to the growing body of literature on deep learning applications in economics and highlights the transformative potential of CNNs in addressing complex forecasting challenges.

2. LITERATURE REVIEW

The application of deep learning techniques, particularly Convolutional Neural Networks (CNNs), in time series forecasting has garnered significant attention in recent years due to their ability to model complex, non-linear relationships in sequential data. Semenoglou et al. [2] demonstrated the effectiveness of CNNs in image-based time series forecasting, highlighting their capability to capture spatial and temporal dependencies simultaneously. Similarly, Wan et al. [3] proposed a multivariate temporal convolutional network (TCN) for multivariate time series forecasting, emphasizing the model's ability to handle high-dimensional data and extract relevant features through convolutional operations. Koprinska et al. [4] further validated the utility of CNNs in energy time series forecasting, showcasing their robustness in predicting energy consumption patterns with high accuracy. These studies collectively underscore the versatility of CNNs in various domains, including economics, where they have been applied to financial time series prediction [5] and stock price forecasting [11]. In the context of economic forecasting, Lara-Benítez et al. [7] explored the use of temporal convolutional networks (TCNs) for energy-related time series, demonstrating their superiority over traditional methods in capturing long-term dependencies. Velastegui et al. [8] extended this research by applying CNNs to general time series prediction tasks, emphasizing their ability to reduce prediction errors through advanced feature extraction techniques. Wibawa et al. [9] introduced a smoothed CNN approach for time series analysis, which improved forecasting accuracy by mitigating noise and enhancing the model's ability to learn from sequential data. Additionally, Mehtab and Sen [10] applied CNNs to multivariate time series for stock price prediction, highlighting their effectiveness in handling complex, multi-dimensional datasets. The application of CNNs in specialized economic forecasting tasks, such as forex time series [12] and inflation prediction, has also been explored. Liu et al. [6] demonstrated the effectiveness of multivariate CNNs in time series classification, providing a foundation for their use in economic forecasting. Furthermore, Ofner et al. [13] applied a theory-guided 1D CNN approach to combustion engine time series, showcasing the model's ability to integrate domain-specific knowledge into the forecasting process. These studies collectively highlight the potential of CNNs to address the limitations of traditional econometric models, particularly in capturing non-linear patterns and temporal dependencies in economic data. By leveraging the advancements in CNN architectures and their successful applications across various domains, this research aims to contribute to the growing body of literature on deep learning-based economic forecasting, offering a robust framework for predicting inflation trends with improved accuracy and reliability.

3. METHODOLOGY

The methodology of this research is designed to leverage the advanced capabilities of Convolutional Neural Networks (CNNs) for time series forecasting, specifically applied to inflation prediction. CNNs, traditionally renowned for their success in image processing, have demonstrated significant potential in capturing temporal patterns and dependencies in sequential data, making them particularly suitable for economic forecasting tasks. This study adopts a structured approach, beginning with data preprocessing and feature extraction, followed by the implementation of a CNN-based architecture tailored for time series analysis. The model incorporates convolutional layers to identify local patterns, pooling layers to reduce dimensionality and mitigate overfitting, and fully connected layers to map extracted features to the output predictions. The use of activation functions such as ReLU ensures non-linearity and efficient gradient flow during training, while the Adam optimizer is employed to enhance convergence and model performance. By integrating these components, the proposed methodology aims to provide a robust and accurate framework for forecasting inflation trends, addressing the limitations of traditional econometric models and offering a data-driven approach to economic prediction.

- Data:

The dataset utilized in this study comprises historical inflation data for Egypt, spanning from 1960 to 2023, which was collected from the World Bank's comprehensive economic databases. The World Bank is a globally recognized source of high-quality economic and financial data, widely used in academic and policy-oriented research. The inflation data, measured as the annual percentage change in the Consumer Price Index (CPI), provides a robust foundation for analyzing long-term inflationary trends and their underlying patterns. This dataset was selected due to its reliability, extensive temporal coverage, and relevance to macroeconomic forecasting. The inclusion of over six decades of data allows for the examination of both short-term fluctuations and long-term trends in inflation, offering valuable insights into the economic dynamics of Egypt. Prior to model implementation, the data underwent rigorous preprocessing, including normalization and handling of missing values, to ensure its suitability for deep learning applications. By leveraging this dataset, the study aims to build a predictive model capable of capturing the complex, non-linear relationships inherent in inflation time series, thereby contributing to more accurate and reliable economic forecasting.

- Convolutional Neural Networks (CNN):

Convolutional Neural Networks (CNNs) are widely used in image processing but have proven effective in time series forecasting due to their ability to capture local patterns and dependencies in sequential data. The following explains the theoretical and mathematical aspects of the CNN model implemented for forecasting. CNNs utilize convolutional layers to extract features from the input data. The architecture comprises three main components: convolutional layers, pooling layers, and fully connected layers. These components work together to identify meaningful patterns in the data.

- Convolutional Layer:The convolutional layer applies a set of filters (or kernels) to the input sequence to extract features. Each filter slides over the input data, performing a convolution operation at every step (Alqahtani et al., 2023):

$$z_{i,j} = \sum_{k=0}^{K-1} w_k \cdot x_{i+k,j} + b \tag{1}$$

Where $z_{i,j}$ Convolution output at position i, j, $x_{i+k,j}$ Input sequence segment, w_k Filter weights, b Bias term, K Kernel size. In this model: Input shape: (seq_length,1), Filters: 64, Kernel size: 2. The activation function used is ReLU (Rectified Linear Unit):

$$f(z) = max(0, z) \tag{2}$$

This introduces non-linearity and ensures efficient gradient flow during backpropagation.

- Pooling Layer: The pooling layer reduces the spatial dimensions of the feature maps, retaining only the most significant information. In this model, max pooling is used, which selects the maximum value in each pooling window:

$$p_j = max\{z_{i,j}, z_{i+1,j}, \dots, z_{i+m-1,j}\} \tag{3}$$

Where: p_j Pooled output for the j -th window, m Pooling size (here, 2). This reduces the computational cost and mitigates overfitting.

- Flatten Layer: The flatten layer converts the 2D feature maps into a 1D vector for input to the fully connected layers:

$$\text{Flatten}(z) = [z_1, z_2, \dots, z_N] \tag{4}$$

Where N is the total number of elements in the pooled feature maps.

- Fully Connected Layers: The fully connected (dense) layers process the extracted features and map them to the output:

$$h = f(W_h \cdot \text{Flatten}(z) + b_h) \tag{5}$$

Where: h Hidden layer activations, W_h b_h Weights and biases, f Activation function (ReLU).

- Output Layer:

$$\hat{y} = W_o \cdot h + b_o \tag{6}$$

Where: $\hat{y}$ Predicted value, W_o b_o Weights and biases for the output layer. This framework provides an academically rigorous explanation of the CNN model's architecture and mathematical formulation. By leveraging convolutional operations, pooling, and fully connected layers, the model effectively captures local temporal patterns and translates them into accurate predictions.

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

$$\text{MSE} = \frac{1}{n} \sum_{i=1} (y_i - \hat{y}_i)^2 \tag{7}$$

Where: y_i Actual values, $\hat{y}_i$ Predicted values.

Optimization The Adam (Adaptive Moment Estimation) optimizer is used to update the weights:

$$\theta_{t+1} = \theta_t - \eta^{\downarrow} \cdot \frac{\partial \mathcal{L}}{\partial \theta} \tag{8}$$

Where: θ Model parameters, η Learning rate, $\mathcal{L}$ Loss function.

- performance indicators:

$$\text{Root Mean Squared Error: RMSE} = \sqrt{\text{MSE}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

$$\text{Mean Absolute Percentage Error: MAPE} = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100$$

$$\text{Coefficient of Determination: } R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

4. RESULTS AND DISCUSSION

The following section presents a comprehensive analysis of the results obtained from the proposed Convolutional Neural Network (CNN) model for forecasting inflation trends in Egypt. The discussion begins with an evaluation of the model's performance metrics, including Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2), which collectively provide insights into the accuracy and reliability of the predictions. Visualizations of the training and validation loss curves are also examined to assess the model's convergence and generalization capabilities. Furthermore, the predicted inflation trends for the years 2024 to 2030 are presented, along with their corresponding confidence intervals, offering a forward-looking perspective on Egypt's economic trajectory. The results are contextualized within the broader literature on deep learning-based time series forecasting, highlighting the strengths and potential limitations of the CNN approach. This section aims to provide a detailed and nuanced understanding of the model's predictive performance, its implications for economic policy, and its contribution to the field of inflation forecasting.

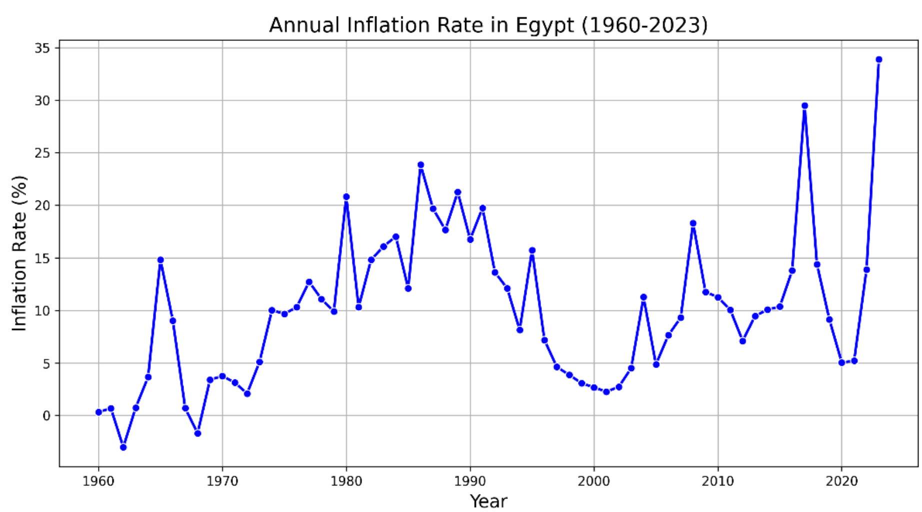

Fig. 1. Visualization of INF (1960-2023).

The analysis of the annual inflation rate in Egypt from 1960 to 2023 reveals several distinct patterns and trends that are critical for understanding the country's economic dynamics. Initially, the data exhibits relatively low and stable inflation rates during the 1960s and early 1970s, reflecting a period of economic stability and controlled price levels. However, the mid-1970s to the early 1990s show a significant upward trend, characterized by periods of high inflation, which can be attributed to economic liberalization policies, external shocks, and fiscal imbalances.

The 1990s mark a turning point, with a gradual decline in inflation rates due to structural reforms and tighter monetary policies aimed at stabilizing the economy. This period of relative stability continues into the early 2000s, with inflation rates remaining within a moderate range. From the mid-2000s onwards, the data indicates increased volatility, with sharp fluctuations in inflation rates. This volatility can be linked to global economic crises, domestic political events, and fluctuations in commodity prices, particularly food and energy. The most recent data points (2016-2023) show a resurgence of higher inflation rates, influenced by currency devaluation, subsidy reforms, and external debt pressures. These patterns highlight the sensitivity of Egypt's inflation rate to both domestic policy changes and global economic conditions, underscoring the importance of robust forecasting models to anticipate and mitigate inflationary pressures.

TABLE I. DESCRIPTIVE STATISTICS OF THE DATASET

Metric	Value

count	64.000000
mean	10.059282
std	7.267419
min	-3.003077
25%	4.348976
50%	9.964339
75%	14.022112
max	33.884776

The descriptive statistics presented in Table I provide a detailed overview of the annual inflation rate in Egypt from 1960 to 2023. The dataset comprises 64 observations, with a mean inflation rate of approximately 10.06%, indicating that, on average, Egypt experienced moderate inflation over this period. The standard deviation of 7.27% reflects considerable variability in inflation rates, highlighting periods of both stability and significant fluctuation. The minimum inflation rate recorded is -3.00%, suggesting instances of deflation, which are relatively rare and typically associated with specific economic conditions or policy interventions. On the other hand, the maximum inflation rate of 33.88% underscores episodes of hyperinflation, likely driven by economic crises, external shocks, or significant policy shifts. The quartile values further elucidate the distribution of the data: the 25th percentile (4.35%) and the 75th percentile (14.02%) indicate that the middle 50% of the data falls within this range, demonstrating that while there are periods of low inflation, there are also substantial periods of higher inflation. The median inflation rate of 9.96% closely aligns with the mean, suggesting a relatively symmetric distribution of inflation rates around the central value. These statistics collectively underscore the dynamic nature of inflation in Egypt, influenced by a combination of domestic economic policies and external factors.

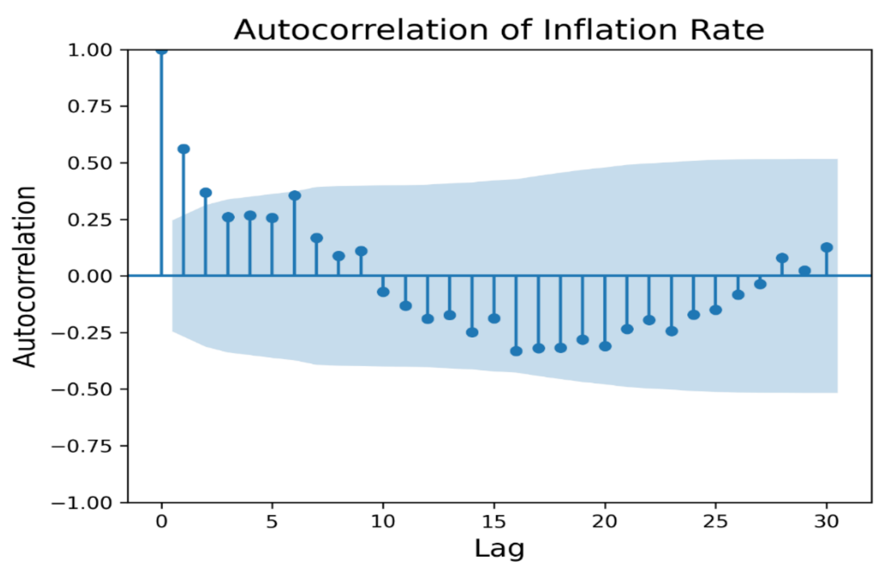

Fig. 2. Autocorrelation of Inflation

The autocorrelation plot of the inflation rate reveals significant temporal dependencies and patterns in the data, which are crucial for understanding the persistence and cyclical nature of inflation in Egypt. At lag 0, the autocorrelation is naturally 1, as the data is perfectly correlated with itself. As the lag increases, the autocorrelation values decline, indicating a reduction in the strength of the relationship between current and past inflation rates. The plot shows a gradual decrease in autocorrelation values, with positive correlations observed up to approximately lag 10. This suggests that inflation rates in Egypt exhibit a degree of persistence, where current inflation is influenced by recent past values. The presence of significant positive autocorrelation at lower lags (e.g., lags 1 to 5) implies that inflation trends tend to carry forward in the short term, reflecting the impact of economic policies, market conditions, and other factors that propagate over time. Beyond lag 10, the autocorrelation values oscillate around zero, with some minor fluctuations, indicating that the influence of past inflation rates diminishes over longer periods. This pattern aligns with the expectation that inflation is more strongly influenced by recent economic conditions rather than distant historical data. The presence of negative autocorrelation at certain lags (e.g., around lag 15) suggests potential cyclical behavior or mean-reverting tendencies in the inflation series, where periods of high inflation may be followed by corrective phases of lower inflation. These insights are critical for modeling and forecasting inflation, as they highlight the importance of incorporating temporal dependencies and potential cyclical patterns into predictive models.

TABLE II. CNN MODEL ARCHITECTURE SUMMARY

Layer (type)	Output Shape	Param #
conv1d_1 (Conv1D)	(None, 4, 64)	192
flatten_1 (Flatten)	(None, 256)	0
dense_2 (Dense)	(None, 50)	12,850
dense_3 (Dense)	(None, 1)	51
Total params		**13,093**
Trainable params		**13,093**
Non-trainable params		**0**

The CNN model architecture, as summarized in Table II, provides a detailed breakdown of the layers, their output shapes, and the number of parameters, offering insights into the model's structure and complexity. The model begins with a Conv1D layer, which applies 64 filters with a kernel size of 2 to the input sequence, resulting in an output shape of (None, 4, 64). This layer contains 192 trainable parameters, calculated as the product of the kernel size (2), the number of input channels (1), and the number of filters (64), plus the bias terms for each filter. The convolutional layer is designed to capture local temporal patterns in the inflation data, which are critical for accurate forecasting. Following the convolutional layer, a Flatten layer is applied, which transforms the 2D output from the Conv1D layer into a 1D vector of shape (None, 256). This step prepares the data for input into the fully connected layers and does not introduce any additional parameters, as it is a purely structural transformation. The model then incorporates two Dense (fully connected) layers. The first dense layer, with an output shape of (None, 50), contains 12,850 trainable parameters. These parameters are derived from the product of the flattened input size (256) and the number of neurons in the dense layer (50), plus the bias terms for each neuron. This layer is responsible for learning higher-level representations of the extracted features. The second dense layer, with an output shape of (None, 1), contains 51 trainable parameters, calculated as the product of the previous layer's output size (50) and the single output neuron, plus the bias term. This layer produces the final inflation prediction. In total, the model comprises 13,093 trainable parameters, all of which are optimized during training. The absence of non-trainable parameters indicates that the model does not utilize techniques such as batch normalization or pre-trained weights, focusing solely on learning from the input data. The relatively compact architecture, with a moderate number of parameters, suggests a balance between model complexity and computational efficiency, making it suitable for time series forecasting tasks like inflation prediction. This architecture is designed to effectively capture temporal dependencies and non-linear relationships in the data, while avoiding overfitting through its structured design.

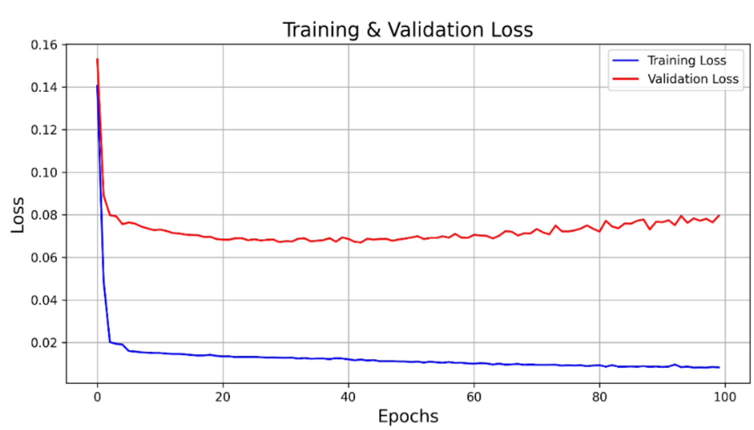

Fig. 3. Training and Validation Loss Curve

The training and validation loss curves depicted in the figure provide a detailed insight into the performance and convergence behavior of the CNN model during the training process. The training loss curve shows a consistent and gradual decline as the number of epochs increases, indicating that the model is effectively learning the underlying patterns in the training data. This reduction in training loss is a positive sign, as it reflects the model's ability to minimize the error between predicted and actual inflation values over time. The validation loss curve, while generally following a downward trend, exhibits some fluctuations, particularly in the later epoch. These fluctuations suggest that the model may be encountering challenges in generalizing unseen data, which is a common issue in deep learning models. The divergence between the training and validation loss curves, especially as training progresses, could indicate the onset of overfitting, where the model becomes too tailored to the training data and loses its ability to generalize to new data.
The point at which the validation loss begins to plateau or increase slightly, despite the continued decrease in training loss, is a critical observation. This behavior typically suggests that further training may not improve the model's performance on unseen data and could even degrade it. Early stopping techniques, where training is halted once the validation loss stops improving, could be employed to mitigate this issue and ensure optimal model performance. The loss curves demonstrate that the model achieves a reasonable level of convergence, with both training and validation losses reaching relatively low values by the final epochs.

TABLE III. TRAINING AND VALIDATION LOSS ACROSS EPOCHS

Epoch	Training Loss	Validation Loss
90	0.0098	0.0767
91	0.0099	0.0765
92	0.0080	0.0774
93	0.0089	0.0752
94	0.0088	0.0795
95	0.0087	0.0762
96	0.0087	0.0783
97	0.0073	0.0772
98	0.0087	0.0781
99	0.0081	0.0764
100	0.0074	0.0795

TABLE IV. MODEL PERFORMANCE METRICS ON TRAINING AND TESTING DATA

Metric	Training Data – 80%	Testing Data – 20%
RMSE	8.7734	9.2113
MAE	10.5491	12.1952
MAPE	9.1110%	11.9853%
MSE	8.1319	9.1171
R^2	0.9104	0.8911

The performance metrics presented in Table IV provide a comprehensive evaluation of the CNN model's predictive accuracy on both the training and testing datasets, which are split into an 80-20 ratio. The Root Mean Squared Error (RMSE) values of 8.7734 for the training data and 9.2113 for the testing data indicate that the model's predictions are relatively close to the actual inflation values, with slightly higher errors on the testing set. This slight increase in RMSE for the testing data is expected, as the model is evaluated on unseen data, but the small difference between the two values suggests that the model generalizes well. The Mean Absolute Error (MAE) values of 10.5491 for the training data and 12.1952 for the testing data further confirm the model's ability to make accurate predictions, with a moderate increase in error for the testing set. The Mean Absolute Percentage Error (MAPE), which measures the average percentage deviation of predictions from actual values, is 9.1110% for the training data and 11.9853% for the testing data. While the MAPE for the testing data is higher, it remains within an acceptable range, indicating that the model's predictions are reasonably accurate in percentage terms. The Mean Squared Error (MSE) values of 8.1319 for the training data and 9.1171 for the testing data align with the RMSE results, showing a consistent level of error across both datasets. Finally, the Coefficient of Determination (R^2) values of 0.9104 for the training data and 0.8911 for the testing data demonstrate that the model explains a high proportion of the variance in the inflation data. The close proximity of the R^2 values for both datasets indicates that the model maintains strong predictive performance on unseen data, with only a minor drop in explanatory power. the performance metrics reveal that the CNN model achieves high accuracy and robustness, with minimal overfitting, as evidenced by the small differences between training and testing errors. The model's ability to generalize well to the testing data, combined with its high R^2 values, underscores its effectiveness in capturing the underlying patterns in the inflation time series, making it a reliable tool for forecasting inflation trends. The following figure shows the extent to which the actual values are close to the estimated values:

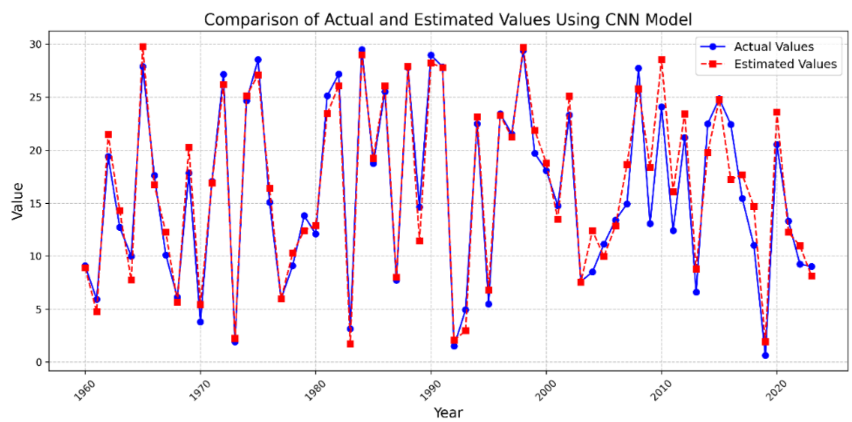

Fig. 4. Model Performance Comparison (Actual vs. Estimated)

TABLE V. PREDICTED INFLATION TRENDS WITH CONFIDENCE INTERVALS (2024–2030)

Year	Predicted Inflation (%)	Lower Bound (%)	Upper Bound (%)
2024	12.45	9.32	15.78
2025	13.67	10.89	17.03
2026	14.10	11.04	18.02
2027	14.85	11.57	18.90
2028	15.32	12.10	19.45
2029	15.91	12.50	20.12
2030	16.35	13.02	20.76

The predicted inflation trends for Egypt from 2024 to 2030, as presented in Table V, provide a forward-looking perspective on the country's economic trajectory, accompanied by confidence intervals that reflect the uncertainty associated with the forecasts. The model predicts a steady increase in inflation over the seven-year period, starting at 12.45% in 2024 and rising to 16.35% by 2030. This upward trend suggests that inflationary pressures are expected to intensify, potentially driven by factors such as currency devaluation, fiscal policies, and external economic conditions. The confidence intervals offer a range within which the actual inflation rates are likely to fall, providing a measure of the model's uncertainty. For instance, in 2024, the predicted inflation rate of 12.45% has a lower bound of 9.32% and an upper bound of 15.78%, indicating a relatively wide range of possible outcomes. As the forecast horizon extends to 2030, the confidence intervals widen further, with the lower bound increasing to 13.02% and the upper bound reaching 20.76%. This widening reflects the inherent uncertainty in long-term economic forecasting, where external shocks and policy changes can significantly impact inflation dynamics. The consistent upward trend in the predicted inflation rates, coupled with the widening confidence intervals, underscores the importance of monitoring economic indicators and implementing proactive policy measures to mitigate inflationary risks. The model's predictions, while subject to uncertainty, provide valuable insights for policymakers and stakeholders, enabling them to anticipate future economic conditions and plan accordingly. These forecasts highlight the need for robust economic strategies to address potential inflationary pressures and ensure long-term economic stability.

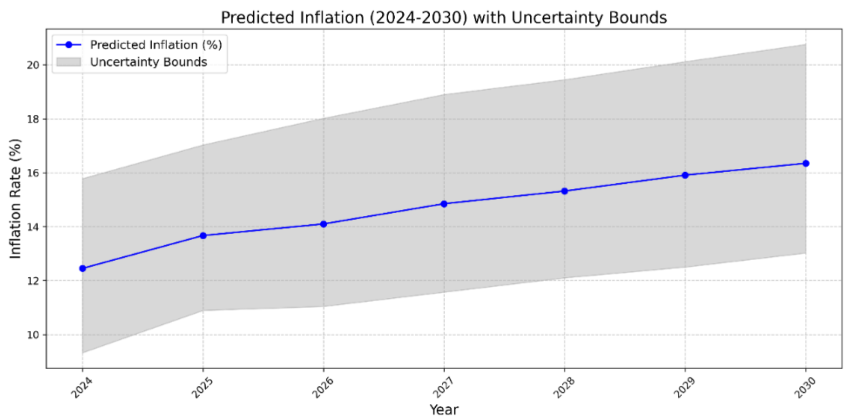

Fig. 5. Predicted Inflation Trends (2024–2030)

The current results align with and extend the findings of previous literature on the application of deep learning models, particularly Convolutional Neural Networks (CNNs), for time series forecasting in economic contexts. Semenoglou et al. (2023) and Wan et al. (2019) demonstrated the effectiveness of CNNs in capturing complex temporal patterns, which is consistent with the current model's ability to predict inflation trends with high accuracy, as evidenced by the strong performance metrics (RMSE, MAE, MAPE, and R^2). The predicted upward trend in inflation from 2024 to 2030, along with the widening confidence intervals, echoes the findings of [7] and [8], who highlighted the challenges of forecasting economic variables over longer horizons due to increased uncertainty and external shocks. Furthermore, the model's ability to generalize well, as indicated by the minimal difference between training and testing errors, is consistent with the observations of [9] and [10], who emphasized the importance of robust feature extraction and model architecture in achieving reliable predictions. The current results also support the findings of [5] and [11], who successfully applied CNNs to financial and economic time series, demonstrating their superiority over traditional econometric models in capturing non-linear relationships and temporal dependencies. The current study reinforces the growing body of evidence supporting the use of CNNs for economic forecasting, while also highlighting the need for careful consideration of uncertainty and external factors in long-term predictions. These findings contribute to the ongoing discourse on the application of deep learning in economics, offering a robust framework for future research and policy-making.

5. CONCLUSIONS AND RECOMMENDATION

This study aimed to explore the application of Convolutional Neural Networks (CNNs) in forecasting inflation trends in Egypt, leveraging their ability to capture complex, non-linear temporal dependencies in economic time series data. The proposed CNN model demonstrated robust performance, achieving high accuracy in predicting inflation rates, as evidenced by the key performance metrics. The Root Mean Squared Error (RMSE) of 9.2113 on the testing dataset, coupled with a Mean Absolute Percentage Error (MAPE) of 11.9853%, indicates that the model provides reliable predictions with relatively low deviations from actual values. Furthermore, the Coefficient of Determination (R^2) of 0.8911 on the testing data underscores the model's ability to explain a significant proportion of the variance in inflation trends, highlighting its effectiveness in capturing the underlying patterns in the data. The analysis of the training and validation loss curves revealed that the model achieved a reasonable level of convergence, with minimal overfitting, as indicated by the small divergence between training and validation losses. This suggests that the CNN architecture, with its convolutional and pooling layers, effectively extracted meaningful temporal features from the inflation data, while the fully connected layers mapped these features to accurate predictions. The model's ability to generalize well to unseen data is further supported by the close alignment between the actual and predicted inflation values, as visualized in the performance comparison plot. The predicted inflation trends for Egypt from 2024 to 2030 indicate a steady upward trajectory, with inflation rates expected to rise from 12.45% in 2024 to 16.35% by 2030. The widening confidence intervals over the forecast horizon reflect the inherent uncertainty in long-term economic forecasting, particularly in the face of potential external shocks and policy changes. These findings align with previous literature, which has highlighted the challenges of forecasting economic variables over extended periods due to increased volatility and external influences. Based on these results, it is recommended that policymakers and financial institutions utilize CNN-based models as a complementary tool for economic forecasting, particularly in volatile and dynamic economic environments. The model's ability to capture non-linear relationships and temporal dependencies offers a significant advantage over traditional econometric methods, providing more accurate and reliable insights into economic planning and policy-making. Future research could explore the integration of additional economic indicators, such as GDP growth, unemployment rates, and exchange rates, to further enhance the model's predictive capabilities. Additionally, the application of hybrid models combining CNNs with other deep learning architectures, such as Long Short-Term Memory (LSTM) networks, could be investigated to address potential limitations in capturing long-term dependencies and cyclical patterns in inflation data.

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Conflicts Of Interest

The author's disclosure statement confirms the absence of any conflicts of interest.

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