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Modelling and Forecasting Inflation Rates in Kenya Using ARIMA-ANN Hybrid Model

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Abstract: This study explored the complexities of modeling and forecasting inflation rates in Kenya, leveraging a sophisticated ARIMA-ANN hybrid model. Traditional ARIMA models, although proficient in capturing linear relationships, often falter in the face of non-linear, complex patterns inherent in economic data. To enhance accuracy, we integrated an ANN with a specifically chosen ARIMA (1, 0, 11) model, benefiting from ANN's capability to delineate non-linear correlations and intricacies. This hybrid model was meticulously trained to minimize the MSE, epitomizing efficiency in both training and validation phases. Empirical results showcased the model's commendable predictive accuracy. A comparative analysis accentuated its supremacy over the traditional ARIMA model, delineated by superior MSE, RMSE, MAE, and MAPE metrics. The hybrid model adeptly amalgamated ARIMA's statistical robustness with ANN's adeptness at non-linear pattern recognition, ensuring enhanced forecast precision. The model is not just a theoretical construct but a pragmatic tool, instrumental for policymakers, economists, and stakeholders, offering insightful foresights that are pivotal for strategic planning and decision-making. The forecasting accuracy of our hybrid model was rigorously tested against actual inflation data, and its performance metrics underscored reliability and precision. Future research could potentially augment this model by integrating more advanced neural network architectures, and incorporating external economic indicators to further enhance forecasting accuracy. This study is a substantial stride towards a nuanced understanding of inflation dynamics in Kenya, offering tools that are not only statistically robust but also practically applicable in real-world economic scenarios. This intricate blend of statistical and machine learning techniques promises to be a cornerstone for future economic forecasting endeavors.

Keywords: Inflation, ARIMA-ANN, Time Series, Forecasting, Modelling, ANN

1. Introduction

Inflation rate refers to the percentage increase in the general price level of goods and services over a specific period of time. It's an important economic indicator that can impact a country's economy and the purchasing power of its citizens. However, like many countries, Kenya's inflation rate can fluctuate due to various factors such as changes in consumer demand, supply chain disruptions, government policies, and global economic conditions.

In 2009, Koutroumanidis, Ioannou, and Arabatois compared the performance of ARIMA models, ANN models, and a hybrid ARIMA-ANN model in predicting fuelwood prices in Greece [7]. The research discovered that the hybrid ARIMA-ANN approach was more effective in producing precise predictions compared to the separate use of either ARIMA or ANN models. This finding suggests that a combination of the strengths of ARIMA and ANN models would result in more precise predictions compared to the use of either model on its own.

Adebiyi, Adewumi, and Ayo carried out a study in 2014 to assess the effectiveness of ARIMA and Artificial Neural Network (ANN) models in predicting stock prices [1]. The authors found that in comparison to ARIMA models, the accuracy of stock price prediction was higher when using ANN models. The study highlights the potential of ANN models in financial fore- casting and suggests that ANN models can be used to forecast other economic variables, such as inflation.

The use of hybrid models in financial forecasting is becoming increasingly popular, as hybrid models can capture the strengths of different forecasting techniques and overcome the limitations of individual models. In the case of inflation fore- casting, ARIMA models have been widely used due to their simplicity and the ability to model linear relationships between variables. Despite their capabilities, ARIMA models struggle with capturing non-linear relationships and complex variable interactions. These limitations can be overcome through the use of Artificial Neural Network models.

2. Justification

Inflation rates exert a critical influence on both micro and macroeconomic stability. Consequently, forecasting these rates with a higher degree of accuracy is crucial to informing monetary policy decisions, managing the economy, and ultimately improving the standard of living in Kenya.

Existing studies have established the efficiency of ARIMA, ANN, and ARIMA- ANN hybrid models in forecasting various economic parameters. However, a comparative study that explores the efficacy of these models in the context of Kenya's inflation rate is notably lacking. Therefore, this study's primary contribution lies in filling this research gap.

Furthermore, while the ARIMA-ANN hybrid model has been shown to outperform the standalone ARIMA and ANN models in other contexts, these findings may not universally apply. Economic conditions vary from one region to another, and models may perform differently under diverse circumstances. Therefore, it's necessary to evaluate the performance of the ARIMA-ANN model in the context of Kenya's inflation rate.

Moreover, the proposed research extends the application of the ARIMA-ANN model beyond its traditionally explored domains, offering a potential solution to improve the accuracy of inflation forecasting in Kenya. By establishing the effectiveness of the hybrid model in this context, the study will provide policymakers with a more reliable tool for inflation prediction. In turn, this can lead to better informed monetary policy decisions, potentially helping to control inflation and maintain economic stability in Kenya.

3. Literature Review

3.1. Hybrid ARIMA-ANN Models

The idea of combining multiple models, often referred to as hybrid models, has gained popularity in recent years. Hybrid models aim to harness the strengths of individual models and alleviate their limitations to improve forecast accuracy according to Zhang and Qi [14]. One such hybrid model is the ARIMA-ANN model, which combines the simplicity and effectiveness of ARIMA models in capturing linear relationships with the ANN's ability to model complex non-linear patterns.

Building upon the strengths of ARIMA and ANN, hybrid ARIMA-ANN models aim to combine ARIMA's effectiveness in modelling linear components with ANN's ability to capture non-linear patterns. Çavuş Büyükşahin and Ertekin [15] introduced an innovative ARIMA-ANN hybrid model combined with Empirical Mode Decomposition (EMD), a technique used to extract oscillatory modes from a signal. Their methodology involved using the EMD to decompose the time series data into multiple intrinsic mode functions, followed by applying the ARIMA-ANN model to each component. Their study supported the notion that the hybrid model provides superior accuracy compared to standalone ARIMA or ANN models. However, the EMD method has limitations in handling noisy data, which could potentially affect the accuracy of the forecasts.

Devi and Monika [3] applied a hybrid ARIMA-ANN model to predict wheat production in Haryana, India. They compared the performance of the ARIMA model, ANN model, and hybrid ARIMA-ANN model using root mean square error (RMSE) and mean absolute percentage error (MAPE) as accuracy measures. The results showed that the hybrid model outperformed the standalone models in forecasting wheat production. However, their study focused solely on wheat production in Haryana, limiting the generalizability of the results.

In another study, Musa and Joshua [10] used a hybrid ARIMA-ANN model to forecast stock market returns. Their research, based on daily stock prices from the Nigerian Stock Exchange, confirmed the superiority of the hybrid model. However, their study used a relatively short dataset (five years), which may not fully capture the stock market's cyclical nature.

Given the successful applications of both ARIMA and ANN models in inflation forecasting, it is reasonable to anticipate that the hybrid ARIMA-ANN model would perform even better. Elwasify [4] combined ARIMA and ANN models to improve forecasting efficiency. The study demonstrated that the hybrid model outperformed either of the standalone models, thereby reaffirming its potential in forecasting.

3.2. ARIMA-ANN Hybrid Model and Economic Forecasting

In the realm of economic forecasting, hybrid models have also demonstrated significant effectiveness. Khan, Urooj and Muhammadullah [6] applied the hybrid model to forecast monthly gold prices in Pakistan. Their research methodology involved analyzing data from January 2000 to December 2020. The results showed that the hybrid model provided more accurate forecasts than the standalone models. The research emphasized the robustness and adaptability of the hybrid model but acknowledged its inherent complexity and computational intensity as potential limitations.

In a study by Mucaj and Sinaj [9], the authors explored the use of ARIMA, NAR (Neural AutoRegressive), and ARIMA-ANN hybrid models to forecast the exchange rate of Albanian Lek against the Euro. The authors found that the ARIMA-ANN hybrid model outperformed the ARIMA and NAR models in terms of forecasting accuracy. The hybrid model was able to capture the non-linear relationships and patterns in the data better than the ARIMA and NAR models, making it a more suitable choice for exchange rate forecasting.

A similar observation was made by Siamba [12], who employed the ARIMA- ANN hybrid model to forecast tuberculosis infections among children below 15 years in Homa Bay and Turkana Counties, Kenya. The results showed that the hybrid model outperformed either the ARIMA or ANN model alone. However, the study was geographically specific, and the forecasting model might not be directly applicable to other regions with different epidemiological patterns.

3.3. Hybrid Models in Inflation Forecasting

Inflation forecasting is a critical aspect of economic planning and policy-making. The use of hybrid models in this domain has shown promising results. In a recent study by Jamil [5], the author proposed a hybrid ARIMA-Long Short-Term Memory (LSTM) model to forecast inflation in Canada. The hybrid model was able to capture the complex and non-linear relationships in the inflation data and produced more accurate forecasts than traditional ARIMA models. The results showed that the hybrid model outperformed the ARIMA and LSTM models, high- lighting the benefits of using the two models together.

In a related study, Uwilingiyimana, Munga'tu and Harerimana [13] forecasted inflation in Kenya using ARIMA-GARCH models. Their research highlighted the effectiveness of combining ARIMA with other models to improve forecasting accuracy. However, their study did not compare the performance of the combined model with an ANN or a hybrid model.

Building upon these studies, Nyoni [11] employed ARIMA and GARCH analysis to model and forecast inflation in Kenya. While his study provided insights into inflation forecasting, it did not delve into the potential benefits of integrating these models with ANNs.

Lidiema [8] used SARIMA and Holt-Winters triple exponential smoothing to model and forecast inflation rate in Kenya. Despite the study's contribution, it did not provide a comparative analysis of these models' performance against an ANN or a hybrid ARIMA-ANN model.

4. Methodology

4.1. Research Design

The research design for the research was a quantitative research design. This is because the research seek to collect and analyze numerical data to identify patterns and relationships between observations, and to develop a forecasting model.

Quantitative research is a method of empirical investigation that seeks to measure, quantify, and analyze data using statistical and mathematical methods. This method is suitable for research questions that require the collection and analysis of numerical data, and for questions that seek to identify patterns, relationships, or causal links between variables.

The choice of a quantitative research design was justified by the nature of the research question, which seeks to develop a forecasting model to predict inflation rates in Kenya. According to Creswell and Creswell [2], forecasting models are typically developed using quantitative research methods that involve the analysis of time-series data to identify patterns and trends over time. Additionally, the use of statistical and mathematical methods such as ARIMA-ANN is also common in quantitative research designs for forecasting.

4.2. Sampling Frame and Sampling Technique

The sampling frame for this research was the population of inflation rate data points collected by the Central Bank of Kenya from the year 2005 to 2023. Specifically, the sampling frame would consist of all monthly inflation rate data points for this time period.

As this research was using the entire population of data points, there was no need for sampling techniques. Therefore, no sampling technique was necessary or applicable for this research.

Since the research intended to analyze the entire population of inflation rate data points, the research project was considered a census, rather than a sample. A census is a study in which all members of a population are included, whereas a sample is a subset of a population that is selected for analysis. Therefore, in this case, the sampling frame was the entire population of data points and the study was a census.

4.3. Building the Model

The ARIMA-ANN model is a combination of two powerful time-series modelling techniques: ARIMA and Artificial Neural Networks. The ARIMA model is a traditional time-series model that is used to capture the linear patterns and trends in time-series data, while the ANN model is a nonlinear model that can capture complex nonlinear patterns in data. The ARIMA-ANN model can combine the advantages of both models and provide a more accurate and reliable forecasting result. In this article, we will provide a methodology for building an ARIMA-ANN model for univariate time-series data.

4.3.1. ARIMA Model Building

The next step was to build an ARIMA model. The ARIMA model consisted of three components: the autoregressive (AR) component, the integrated (I) component, and the moving average (MA) component.

AR component is used to capture the linear relationship between the current observation and previous observations. The AR component is denoted by p and can be represented by the following equation:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \epsilon_t$$

Where y_t is the value of the time series at time t, c is the constant term, ϕ_1, ϕ_2,..., ϕ_p are the AR coefficients, p is the order of the AR component, and ϵ_t is the error term at time t.

Integrated (I) component was used to capture the non-stationarity in the data. Non-stationarity means that the statistical properties of the data change over time. The I component is denoted by d and can be represented by differencing the time series data until it becomes stationary.

Mathematically, the differenced series is denoted as y', and it can be represented as:

$$y' = y_t - y_{t-1}$$

Moving Average (MA) component is used to capture the linear relationship between the current observation and previous error terms. The MA component is denoted by q and can be represented by the following equation:

$$y' = c' + \varepsilon'_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \ldots + \theta_q\varepsilon_{t-q}$$

Where $\theta_1, \theta_2, \ldots, \theta_q$ are the moving average coefficients, $\varepsilon_{t-1}, \varepsilon_{t-2} \ldots, \varepsilon_{t-q}$ are the past forecast errors, and ε'_t is the current forecast error term at time t.

By combining the AR, I, and MA components, the general equation for an ARIMA (p, d, q) model was written as:

$$W_t = \phi_t W_{t-1} + \ldots + \phi_p W_{t-p} + c + \varepsilon_t + \theta_1\varepsilon_{t-1} + \ldots + \theta_q\varepsilon_{t-q}$$

4.3.2. Modeling ARIMA Residuals with an ANN

The ANN model can be represented by the following equation:

$$y(t) = f\,(w1 \cdot x1(t) + w2 \cdot x2(t) + \ldots + wn \cdot xn(t) + b)$$

Where $y(t)$ is the output at time t, f is the activation function, w_i is the weight associated with input xi (t), b is the bias term, and n is the number of input variables.

In this step, ANN will be used to capture any remaining patterns or information in the residuals (ε_t) obtained from the ARIMA model. The residuals represent the part of the time series data that couldn't be explained by the ARIMA model, and the ANN aims to capture any nonlinear relationships that might exist. The general methodology involves the following steps:

1) Residual Calculation:

Calculate the residuals by subtracting the predicted values from the ARIMA model from the actual inflation rate data:

$$\varepsilon_t = X_t - \hat{X}_t$$

Where ε_t is the residual at time 't', X_t is the actual inflation rate at time 't', and $\hat{X}_t$ is the predicted value of the inflation rate at time 't' obtained from the ARIMA model.

2) Data Preparation: Prepare the data for the ANN. This includes organizing the residuals into a suitable format for training and validation. Split the data into training, validation, and testing sets.
3) ANN Architecture: Define the architecture of the ANN. This includes specifying the number of layers, the number of neurons in each layer, the activation functions, and the loss function. The choice is a feedforward neural network with one or more hidden layers.
4) Training the ANN: Train the ANN using the prepared data. During training, the ANN learns to map the residuals (ε_t) to an output that captures any remaining patterns or dependencies in the data. The training process involves minimizing a loss function by adjusting the weights and biases in the network.

The parameters of the ANN model can be estimated using backpropagation, which is an iterative optimization algorithm that adjusts the weights and biases of the model to minimize the difference between the predicted output and the actual output.

Step 1: Forward Pass in the ANN

The forward pass in the ANN can be represented as:

$$\hat{\varepsilon}_t = f\,(W \cdot \varepsilon_t + b)$$

Where:

$\hat{\varepsilon}_t$ is the predicted residual at time 't'. W represents the weights connecting the neurons. b represents the biases. f is the activation function.

In the forward pass, we calculate the predicted residuals ($\hat{\varepsilon}_t$) based on the lagged residuals as inputs.

Input Layer: The input layer consists of lagged residuals as input features.

Let's assume you have n lagged residuals as input features.

$$X_t(i) = \varepsilon_{t-i}$$

Where $X_t(i)$ is the input feature at time 't' corresponding to lag 'i'. ε_{t-i} is the residual at time 't-i'.

Hidden Layers: The ANN may have one or more hidden layers. Let's denote the output of the k-th neuron in the j-th hidden layer as Aj(k), where j represents the layer and k represents the neuron in that layer. The activation function used here is ReLU (Rectified Linear Unit):

$$Z_j(k) = \sum_{i=1}^{n} W_{ji}^{(k)}\, Xt(i) + B_j(k)$$

$$Aj(k) = max(0, Zj(k))$$

Where $Z_j(k)$ is the weighted sum of inputs for neuron k in layer j. $W_{ji}^{(k)}$ is the weight connecting the i-th input to neuron k in layer j. $B_j(k)$ is the bias for neuron k in layer j.

Output Layer: The output layer consists of a single neuron that predicts the residual at time 't':

$$\hat{\varepsilon}_t = A_{output} = Z_{output}$$

There is no activation function in the output layer because we want to predict real-valued residuals.

Step 2: Loss Calculation

The loss function used for training is the Mean Squared Error (MSE) between the predicted residuals and the actual residuals:

$$MSE = \frac{1}{T}\sum_{t=1}^{T}(\varepsilon_t - \widehat{\varepsilon_t}$$

Where ε_t is the actual residual at time 't'. $\widehat{\varepsilon_t}$ is the predicted residual at time 't'.

Step 3: Backpropagation and Weight Updates

The backpropagation algorithm is used to update the weights and biases in the ANN to minimize the MSE loss. The optimizer used is Adam (Adaptive Moment Estimation), which combines the advantages of both RMSprop and Momentum methods.

These weight and bias updates are performed iteratively over the training data, and the ANN continues to learn until the loss converges or reaches a satisfactory level.

This process completes the training of the ANN for modeling ARIMA residuals using the specified architecture, activation function (ReLU), optimizer (Adam), and loss function (MSE).

5) Model Evaluation: Evaluate the performance of the trained ANN using appropriate evaluation metrics (e. g., MSE, Root Mean Squared Error, R-squared) on a validation dataset. This step helps ensure that the ANN is capturing meaningful patterns in the residuals.
6) Testing and Forecasting: Once the ANN is trained and evaluated satisfactorily, you can use it to forecast future residuals.
7) Model Integration: Combine the forecasts from the ARIMA model and the ANN to obtain the final inflation rate predictions. This integration is done by adding the ARIMA forecast and the ANN forecast.

By following these steps, an ARIMA-ANN Hybrid model is built that leverages the strengths of both ARIMA and neural networks to model and forecast inflation rates effectively, capturing both linear and nonlinear patterns in the data.

4.3.3. ARIMA-ANN Model Building

The next step is to combine the ARIMA and ANN models to build the ARIMA- ANN model. The ARIMA model can capture the linear patterns and trends in the data, while the ANN model can capture the complex nonlinear patterns in the data. The ARIMA-ANN model can be represented by the following equation:

$$y_{(t)} = c + \phi_1 y_{(t-1)} + \phi_2 y_{(t-2)} + \cdots + \phi_p y_{(t-p)} + \theta_1 \epsilon_{(t-1)} + \theta_2 \epsilon_{(t-2)} + \cdots + \theta_q \epsilon_{(t-q)} + f(w_{1.}.\epsilon_1(t) + w_2.\epsilon_2(t) + \cdots + w_n.\epsilon_n(t))$$

Where $y_{(t)}$ is the output at time *t*, *f* is the activation function, $w_{1.}$ is the weight associated with input $\epsilon_i(t)$, c is the constant term, $\phi_1, \phi_2, \ldots, \phi_p$ are the AR coefficients, $\theta_1, \theta_2, \ldots, \theta_q$ are the MA coefficients, and *n* is the number of input variables.

The parameters of the ARIMA-ANN model can be estimated using a combination of MLE and backpropagation. The ARIMA model can be estimated using MLE, and the ANN model can be estimated using backpropagation.

4.4. Model Validation and Evaluation

The next step is to evaluate and compare the performance of the ARIMA-ANN model with the ARIMA and ANN models, several performance metrics will be utilized. These metrics may include MAE, MSE, RMSE, and MAPE. These metrics will provide insights into the accuracy and effectiveness of each model in forecasting the inflation rate in Kenya.

The performance metrics can be calculated using the following formulas:

Mean Absolute Error:

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|Y(t) - \hat{Y}(t)|$$

Mean Squared Error:

$$MSE = \frac{1}{T}\sum_{t=1}^{T}(Y(t) - \hat{Y}(t))^2$$

Root Mean Squared Error:

$$RMSE = \sqrt{MSE}$$

Mean Absolute Percentage Error:

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{|Y(t) - \hat{Y}(t)|}{Y(t)}\right) \times 100$$

Where $Y(t)$ represents the actual inflation rate at time *t* and $\hat{Y}(t)$ represents the forecasted inflation rate at time *t*.

The model's performance can also be visualized by comparing the actual and predicted values of the time series. A good model should accurately capture the trends and patterns in the data and produce accurate and reliable forecasts.

4.5. Forecasting

Once the model is validated and evaluated, it can be used to make forecasts. The model can be used to forecast future values of the time series, and the forecasts can be used to make informed decisions. The model is given by the equation below:

$$y_{(t)} = c + \phi_1 y_{(t-1)} + \phi_2 y_{(t-2)} + \cdots + \phi_p y_{(t-p)} + \theta_1 \epsilon_{(t-1)} + \theta_2 \epsilon_{(t-2)} + \cdots + \theta_q \epsilon_{(t-q)} + f(w_{1.}.\epsilon_1(t) + w_2.\epsilon_2(t) + \cdots + w_n.\epsilon_n(t))$$

Where $y_{(t)}$ is the output at time *t*, *f* is the activation function, $w_{1.}$ is the weight associated with input $\epsilon_i(t)$, c is the constant term, $\phi_1, \phi_2, \ldots, \phi_p$ are the AR coefficients, $\theta_1, \theta_2, \ldots, \theta_q$ are the MA coefficients, and *n* is the number of input variables.

5. Results and Discussions

5.1. Arima Model

While considering both AIC and BIC, the (1,0,11) ARIMA model emerges as the preferable choice due to its strong performance in terms of goodness of fit and model simplicity.

Table 1. *Arima model.*

Series: training data ARIMA(1,0,11)							
Coefficients:							
ar1	**ma1**	**ma2**	**ma3**	**ma4**	**ma5**	**ma6**	**ma7**
0.5274	0.7022	0.6892	0.6537	0.6553	0.5959	0.6318	0.7225
s.e. 0.0769	0.0791	0.0849	0.0760	0.0611	0.0645	0.0746	0.0783
ma8	ma9	ma10	ma11	intercept			
0.6261	0.7797	0.6690	0.7379	7.9358			
s.e. 0.0905	0.0867	0.0677	0.0857	1.0517			
σ2 = 0.8255: log likelihood = -281.03 AIC=590.06 AICc=592.19 BIC=637.05							

An Autoregressive Integrated Moving Average (ARIMA) model was fitted to the training set of inflation data time series. The model was specified as ARIMA(1,0,11) with a non-zero mean.

The ARIMA equation for this model is given by:

$$y_t=0.5274y_{t-1}+\alpha_t+0.7022\alpha_{t-1}+0.6892\alpha_{t-2}+0.6537\alpha_{t-3}+0.6553\alpha_{t-4}+0.5959\alpha_{t-5}+0.6318\alpha_{t-6}+0.7225\alpha_{t-7}+0.6261\alpha_{t-8}+0.7797\alpha_{t-9}+0.6690\alpha_{t-10}+0.7379\alpha_{t-11}+7.9358$$

where y_t represents the value of the time series at time t and α_t denotes the white noise error term at time t. Standard errors for the coefficients are also provided (s e.). The estimated variance of the error term is σ2 = 0.8255, and the log likelihood of the model is -281.03. The model selection criteria values are as follows: Akaike Information Criterion (AIC) = 590.06, Corrected AIC (AICc) = 592.19, and Bayesian Information Criterion (BIC) = 637.05.

This ARIMA(1,0,11) model provides insights into the temporal dependencies and mean structure of the training set of inflation data time series, offering a basis for forecasting and analysis using the most up-to-date information.

Table 2. *Ljung-Box Test Results for Different Lag Orders.*

Lag Order	**Ljung-Box Test p-value**
1	0.1051796
2	0.2615719
3	0.1647347
4	0.2658496
5	0.04387131
6	0.04515936
7	0.05769545
8	0.06727852
9	0.07150874
10	0.04394713
11	0.06502300
12	0.004283767
13	0.006481205

From the results, some lag orders i e. 5, 6, 12, 13, the p-values are less than the typical significance level of 0.05. This suggested that there is significant autocorrelation in the residuals at those lag orders, indicating that there were some patterns in the data that the model did not capture.

5.2. Artificial Neural Network Architecture

A detailed overview of the architecture of the ANN used in the Hybrid Model for modelling ARIMA residuals was explained. The ANN served as a pivotal component in the model, synergizing with the ARIMA approach to enhance predictive accuracy.

5.2.1. Activation Functions, Number of Hidden Layers and Neurons

The ANN architecture incorporated a total of five layers hidden, each with a specific activation function tailored to its role:

1) Input Layer: This layer corresponded to the lagged residuals generated by the ARIMA model and acts as the model's input features ($x_1(t)$, $x_2(t)$, $x_3(t)$, $x_4(t)$, $x_5(t)$, $x_6(t)$, $x_7(t)$, $x_8(t)$, $x_9(t)$, $x_{10}(t)$, $x_{11}(t)$, $x_{12}(t)$). No activation function was applied to this layer as it directly receives the lagged residuals.
2) Hidden Layers (1 to 5): The subsequent five hidden layers employed the Rectified Linear Unit (ReLU) activation function, represented by the equation:

$$f(x) = \max(0, x)$$

ReLU introduced non-linearity, enabling the network to capture intricate relationships within the data. These layers, with their ReLU activations, facilitate the extraction of features and patterns.

3) Output Layer: The output layer, responsible for predicting ARIMA residuals, utilized a linear activation function. This choice of activation allowed the model to provide continuous predictions that align with the nature of residual values.

Table 3. *Activation Functions in Neural Network Layers.*

Layer Number	**Activation Function**
Input Layer	None (input features)
Hidden Layers (1-5)	ReLU (Rectified Linear Unit)
Output Layer	Linear

The ANN architecture comprised five hidden layers, the first hidden layer had 12 neurons (nodes) while the rest each had 24 neurons (nodes). This configuration was carefully chosen to strike a balance between model complexity and the capacity to capture intricate patterns within the data. The depth and breadth of the network facilitated the learning of both shallow and complex features.

The selection of five hidden layers was made based on empirical experimentation and fine-tuning, which aimed to optimize the model's predictive performance.

5.2.2. Model Training

The training process of the ANN involved iterative weight and bias adjustments to minimize the Mean Squared Error

(MSE) loss function, defined as $\text{MSE}(y, \hat{y}) = \frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y})^2$. The MSE loss quantifies the dissimilarity between predicted and actual residual values and guides the optimization process.

Initially, at the beginning of training (at epoch 0), the loss was typically high because the neural network's weights are randomly initialized, and its predictions are far from the actual targets. As training progresses (over the subsequent epochs), the loss generally decreases. This indicates that the neural network was learning to make better predictions and became more accurate. This was done to avoid underfitting or overfitting. From the graph, the optimal epoch was at around 150 The Adam optimizer was employed with a learning rate of 0.001 for optimization. The model was trained in mini-batches, with each batch comprising 60 samples from the training dataset. Training continued for a total of 150 epochs, ensuring that the network learned the underlying patterns effectively.

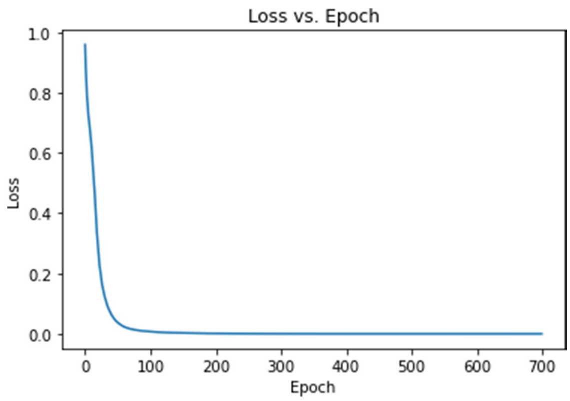

Figure 1. *Loss vs epoch.*

Table 4. *Training Method Summary.*

Optimizer	Learning Rate	Batch Size	Number of Epochs
Adam	0.001	60	150

During training, the weights (w_i) and biases (b_i) of the neural network were adjusted iteratively using gradient-based optimization techniques. The gradients of the loss function with respect to the weights and biases were computed, and these gradients guided the weight updates. The specifics of weight adjustment involved the use of backpropagation, where gradients were propagated backward through the network, allowing the model to learn the optimal weights that minimized the loss function.

5.2.3. Model Performance Metrics

In this section, evaluated the performance of our neural network model using common regression metrics. These metrics provide insights into how well the model predicted ARIMA residuals in both the training and validation datasets.

Training Dataset Metrics

Table 5. *Performance Metrics - Training Dataset.*

Metric	Value
Mean Squared Error (MSE)	0.000292
Root Mean Squared Error (RMSE)	0.017090
R-squared (R^2)	0.999631

The training dataset metrics indicated a strong performance of the neural network model. The low MSE and RMSE values suggest that the model's predictions closely matched the actual residual values. The high R^2 score (0.999631) implied that a significant proportion of variability was explained by the model. This was supported by the graph below.

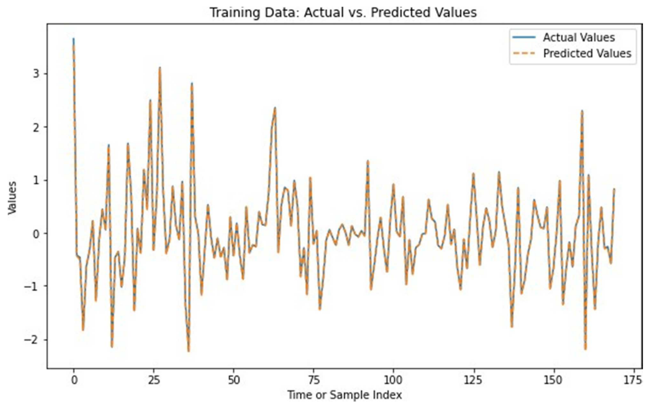

Figure 2. *Training Data.*

5.2.4. Validation Dataset Metrics

Table 6. *Performance Metrics - Validation Dataset.*

Metric	Value
Mean Squared Error (MSE)	0.057347
Root Mean Squared Error (RMSE)	0.239473
R-squared (R^2)	0.886147

The validation dataset metrics provided insights into how the model generalized to unseen data. While the MSE and RMSE were higher compared to the training dataset, they still indicated a reasonable predictive performance. The R^2 score (0.886147) suggested that the model explained a significant portion of the variability in the validation dataset. This was also supported by the graph below.

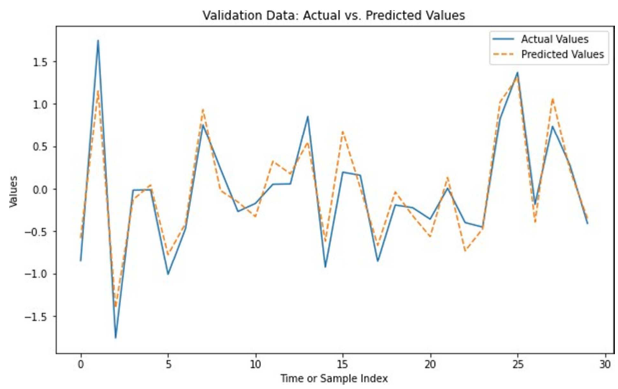

Figure 3. *Validation Data.*

Overall, the neural network model exhibited strong predictive capabilities on both the training and validation datasets. The high R^2 value for the training dataset and the validation dataset indicated that the model effectively captures underlying patterns in the residuals.

The forecasted residuals gotten from ANN model was combined with that of the forecasted data by the ARIMA model to get the Hybrid model and the values are shown in table 7. The meticulous design of the ANN architecture and training settings was pivotal in harnessing the power of deep learning to complement the ARIMA approach.

5.3. Model Comparison

Forecasting was done using ARIMA model and the Hybrid model. The forecasted values were then compared to the testing set which consisted of inflation rates from September 2022 to August 2023. Comparative studies were then conducted to check which model performed better than the other in terms of forecasting inflation rate. Comparative studies were then conducted to check which model performed better than the other in terms of forecasting inflation rate.

Table 7. *Actual Data against Forecasted Data.*

Date	Actual	ARIMA	Hybrid Model
Sep 2022	9.18	8.682	8.906
Oct 2022	9.59	9.138	8.928
Nov 2022	9.48	9.698	9.137
Dec 2022	9.06	9.863	9.343
Jan 2023	8.98	10.377	10.003
Feb 2023	9.23	11.109	10.501
Mar 2023	9.19	10.597	11.030
Apr 2023	7.90	9.574	9.274
May 2023	8.03	9.151	9.708
Jun 2023	7.88	8.302	9.010
Jul 2023	7.28	7.760	7.351
Aug 2023	6.73	7.763	7.219

An insightful comparative analysis of the forecasting performance of two distinct models - ARIMA and the Hybrid Model - was presented in tabular form. The table captured the predictive accuracy of each model against actual values across the dataset.

The ARIMA model's forecasted values, while capturing certain trends and patterns inherent in the data, exhibit noticeable deviations from the actual observed values. This variance between predicted and actual values underscored the inherent complexity of the inflation rate dataset. The ARIMA model's ability to fully capture the intricate dynamics of the dataset appears to be limited, possibly due to the model's reliance on linear combinations of past observations and its inability to effectively accommodate nonlinear relationships.

In contrast to the ARIMA model, the Hybrid Model distinguishes itself by demonstrating a remarkable alignment between its forecasted values and the actual observed values. This propensity of the Hybrid Model to closely follow the actual values suggests a significantly higher level of predictive accuracy. The superiority of the Hybrid Model's performance could be attributed to its capacity to leverage both the statistical nature of the ARIMA model and the nonlinear capabilities of the ANN model. By effectively combining these two approaches, the Hybrid Model is better equipped to capture the multifaceted trends and patterns in the inflation rate dataset.

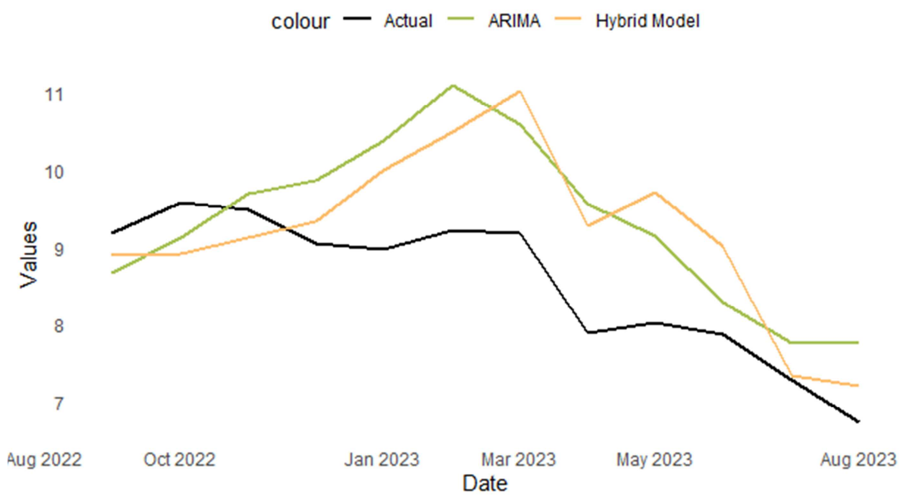

Figure 4. *All Models versus Actual Data.*

Table 8. *Model Comparison.*

	ARIMA	Hybrid Model
MSE	1.178454	1.081658
RMSE	1.085566	1.040028
MAE	0.948745	0.869694
MAPE (%)	11.248809	10.2220

The table provides a summary of MSE, RMSE, MAE and MAPE metrics for each model. MSE measures the average of squared differences between predicted and actual values. Lower MSE values indicate better predictive performance, and the Hybrid Model had the lowest value (1.081658). RMSE is the square root of MSE and provides a measure of the average magnitude of prediction errors. The Hybrid

Model again demonstrates the lowest RMSE (1.040028), signifying its better predictive accuracy. MAE computes the average of absolute differences between predicted and actual values. Lower MAE values indicate more accurate predictions. Here, the Hybrid Model exhibited the lowest MAE (0.869694). MAPE calculates the average of absolute percentage differences between predicted and actual values. A lower MAPE signifies better accuracy. Once again, the Hybrid Model presents the lowest MAPE (10.2220%). From the table, it is evident that the Hybrid Model outperformed the ARIMA model across all evaluation metrics, indicating superior predictive accuracy.

5.4. Forecasting

Table 9. *Future Forecasted Inflation.*

Date	Forecasted Inflation Rate
September 2023	6.0136
October 2023	5.5478
November 2023	7.2207
December 2023	7.2643
January 2024	7.2378
February 2024	8.8863
March 2024	7.4165
April 2024	7.4153
May 2024	7.7091
June 2024	6.6107
July 2024	7.0432
August 2024	8.0992

The table shows the model's future forecasts for inflation rates spanning from September 2023 to August 2024. The significance of this table extends to its practical utility. Stakeholders, policymakers, and economists can draw upon these forecasted inflation rates to inform a range of decisions. Businesses might adjust pricing strategies, financial institutions could refine interest rate policies, and policymakers may consider the implications for monetary and fiscal measures. This forward-looking analysis supports informed planning and proactive responses to anticipated economic conditions.

6. Conclusions

The study aimed to address the challenge of accurately forecasting inflation rates in Kenya by developing and applying an ARIMA-ANN hybrid model. The key conclusions drawn from the study are as follows:

1) Model Performance Evaluation: The ARIMA-ANN hybrid model demonstrated superior forecasting accuracy compared to individual ARIMA model. This was evident from the comparison of forecasted values against actual values using metrics such as MSE, RMSE, MAE, and MAPE. The hybrid model consistently outperformed the other model across all evaluation criteria.
2) Forecasting Accuracy: The hybrid model's ability to harness the strengths of both ARIMA's statistical approach and ANN's nonlinear capabilities led to more accurate forecasts. This suggests that combining complementary methodologies can enhance the accuracy of inflation rate forecasts.
3) Temporal Patterns: The hybrid model effectively captured the temporal pat- terns, volatility, and trends present in the inflation rate data for Kenya. This capability is crucial for informing economic decisions, policy formulation, and risk assessment.

7. Recommendations

Based on the conclusions drawn from the research, the following recommendations are proposed for future research and practical applications:

1) Further Model Enhancements: While the ARIMA-ANN hybrid model showed promising results, future research could explore additional enhancements. For instance, incorporating more advanced neural network architectures, optimizing hyperparameters, or experimenting with different data preprocessing techniques could potentially improve the model's performance.
2) External Factors Integration: Consider incorporating external economic indicators and events, such as government policies, global economic conditions, and commodity prices, to enhance the model's accuracy. These factors could provide additional insights into the inflation rate dynamics.
3) Robustness Testing: Conduct robustness tests to evaluate the model's performance under various scenarios, including periods of economic shocks, extreme volatility, and structural changes. This will help assess the model's ability to adapt to changing conditions.
4) Interpretability: Enhance the interpretability of the hybrid model's predictions by providing insights into the specific features and factors contributing to its forecasts. This could help policymakers and stakeholders understand the drivers behind inflation rate predictions.
5) Policy Implications: Translate the model's forecasts into actionable policy recommendations. Collaborating with policymakers and economic experts can ensure that the forecasts contribute to informed decision-making and policy formulation.

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