

# Forecasting the Inflation in India using ARIMA and Deep Learning Techniques

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## ABSTRACT

This Paper Presents forecasting the Inflation of all commodities using Auto Regressive Integrated Moving Average (ARIMA) method, Multi Layer Perceptron (MLP), Recurrent Neural Network (RNN), Convolution Neural Network (CNN), and Long Short – Term Memory (LSTM). The data used for estimating the models for the year Apr 2009 to July 2020. The appropriate best model is computed by comparing the Mean square Error (MSE), Root Mean square Error (RMSE), and Mean Absolute Percentage Error (MAPE). In this Study the Results Shows that CNN is Performing better model than the other traditional models of ARIMA, MLP, RNN, and LSTM.

**KEYWORDS:** WPI, ARIMA, ANN, RNN, CNN, LSTM, MSE, RMSE, MAPE.

## I. INTRODUCTION:

The Wholesale Price Index (WPI) is the price of a representative basket of wholesale goods. use WPI changes as a central measure of inflation. It also influences stock and fixed price markets. The WPI is published by the Economic Adviser in the Ministry of Commerce and Industry. The Wholesale Price Index focuses on the price of goods traded between corporations, rather than the goods bought by consumers, which is measured by the Consumer Price Index. The purpose of the WPI is to monitor price movements that reflect supply and demand in industry, manufacturing and construction. This helps in analyzing the macroeconomic conditions. macro economic indicators like the gross domestic product (GDP). Major components of WPI is the total weight of the Wholesale Price Index involves a number of components of WPI that account for the items included in WPI in India. The total WPI weightage here refers to 100 that demarcates the value of WPI of a base year on the scale. The first component involves **Manufactured Goods**. This category involves goods such as chemical and related products, metal products, raw metals, alloys, machinery, etc. The component of Manufactured Goods accounts for 64.9% of the total weight alone. The second component focuses on the **division of Primary Articles**. Primary Articles account for 20.12% of the total weight. Primary Articles are further divided into Non-Food- Non-Food Primary Articles include minerals, cooking oil, fibers, cotton, and jute. Food- Food Primary Articles involve food materials like pulses, cereals, fruits and vegetables, dairy products, spices, and tea and coffee. The third component focuses on **Fuel and Power**. This category accounts for a total of 14.91%. It accommodates goods such as kerosene, diesel, LPG, coal, and electricity.

## 2. AUTO REGRESSIVE PROCESS AND MOVING AVERAGE PROCESS

In the 2 models which we have considered are containing an infinite number of pairs  $\phi_j$ 's or  $\pi_j$ 's which may not be useful in the analysis of real time series. Hence a method is introduced to restrict an infinite weights to finite in number, such that the representative of the models is retained [1]

### 2.1 AUTO REGRESSIVE PROCESS

Consider the second model or Model-2 with the first  $p$  – number of weights. i.e.,

$$\tilde{z}_t = \phi_1 \tilde{z}_t + \phi_2 \tilde{z}_{t-1} + \dots + \phi_p \tilde{z}_{t-p} + a_t \quad \text{----- (1) } \tilde{z}_{t-p}$$

where  $\phi_j ; j = 1, 2, \dots, p$  represents the finite set of weights parameters.

As  $\tilde{z}_t$  is regressed on its previous values, this model is known as Auto Regressive Process of order( $p$ ) and is represented by AR( $p$ ).  $\phi(B)$  is called the Auto Regressive Operator ;

when  $p=1 \rightarrow$  AR(1)  $\tilde{z}_t = \phi_1 \tilde{z}_{t-1} + a_t$

when  $p=2 \rightarrow$  AR(2)  $\tilde{z}_t = \phi_1 \tilde{z}_{t-1} + \phi_2 \tilde{z}_{t-2} + a_t$   
 $= \phi_2 \tilde{z}_{t-2} + a_t$

In general the AR(P) model is :

$$\tilde{z}_t = \phi_1 \tilde{z}_{t-1} + \phi_2 \tilde{z}_{t-2} + \dots + \phi_p \tilde{z}_{t-p} + a_t$$

### 2.2 MOVING AVERAGE PROCESS MA(Q)

Consider the special case of model 1 with only first  $q$  non-zero  $\phi$  weights .Hence the model can be written as

$$\tilde{z}_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \dots - \theta_q a_{t-q}$$

where  $(-\theta_1, -\theta_2, \dots, -\theta_q)$  represents the first set of weight parameters. The process so defined is called moving average process of order ‘ $q$ ’, and is denoted by MA( $q$ ).

where  $q=1$ ; MA (1)  $\rightarrow \tilde{z}_t = a_t - \theta_1 a_{t-1}$

where  $q=2$ ; MA(2)  $\rightarrow \tilde{z}_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2}$

These two processes have the importance in practice. The MA ( $q$ ) process can also be written using backward shift operator ‘ $B$ ’ as

$$\tilde{z}_t = (1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q) a_t$$

Or  $\tilde{z}_t = \theta(B). a_t$

Hence the M.A. process would be appropriate to generate the T.S. Using ‘ $\theta(B)$ ’ the transfer function as the linear filter operator when the input is a white noise.

### 2.3 BOX-JENKINS METHOD

Box-Jenkins Method[2] on time series analysis give the details of this model and the procedure for estimation among others and an autoregressive moving average process of order ( $p,q$ ) of a stationary Gaussian process  $X$ , is given by  $z_t = \sum_{i=1}^p \theta_i z_{t-i} + \sum_{j=0}^q \alpha_j a_{t-j}$  The autoregressive (AR) order and the moving average (MA) order,  $p$  and  $q$ , are respectively determined depending on the partial autocorrelation and autocorrelation of the process[3].

### 3 ARTIFICIAL NEURAL NETWORK

Artificial Neural Network (ANN) ANN approach has become a very valuable tool for solving certain kinds of complex problems. More precisely ANN technology has been successfully applied to problems of i) classification of data, and ii) generalization based on features present in the data. The most important advantage of the approach is that it makes relatively weak assumptions about the dynamics of the system. It relies instead on the data and via a suitable network generates an optimal model.

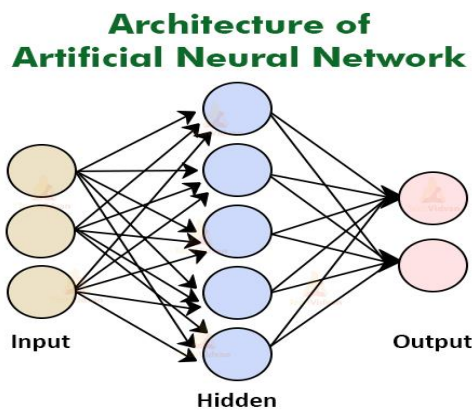


Figure 3.1 Multi Layer Perceptron ( Source: <https://i.postimg.cc/pLgLsJDt/Architecture.jpg> )

### 3.2 RECURRENT NEURAL NETWORK

A Recurrent Neural Network is a type of neural network that contains loops, allowing information to be stored within the network. In short, Recurrent Neural Networks use their reasoning from previous experiences to inform the upcoming events. A common example of Recurrent Neural Networks is machine translation. For example, a neural network may take an input sentence in Spanish and translate it into a sentence in English. The network determines the likelihood of each word in the output sentence based upon the word itself, and the previous output sequence.

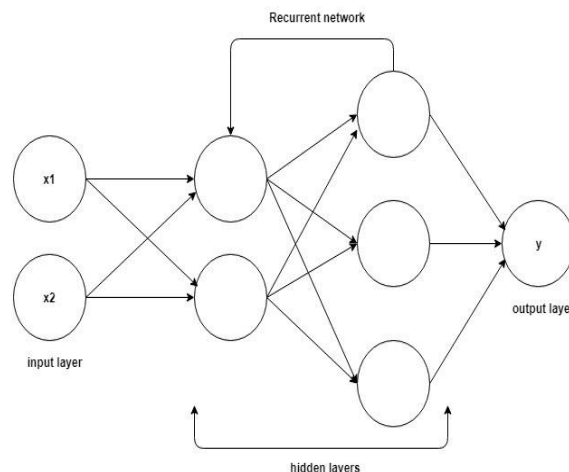


Figure 3.2.1 Recurrent Neural Network ( Source : [https://miro.medium.com/max/651/1\\*6xj691fPWf3S-mWUCbxSJg.jpeg](https://miro.medium.com/max/651/1*6xj691fPWf3S-mWUCbxSJg.jpeg) )

### 3.3 CONVOLUTIONAL NEURAL NETWORK

Convolutional networks are a specialized type of neural networks that use convolution in place of general matrix multiplication in at least one of their layers or in other words, "A convolutional neural network (CNN) is a type of artificial neural network used in image recognition and processing that is specifically designed to process pixel data." A convolutional neural network consists of an input layer, hidden layers and an output layer. In any feed-forward neural network, any middle layers are called hidden because their inputs and outputs are masked by the activation function and final convolution. In a convolutional neural network, the hidden layers include layers that perform convolutions

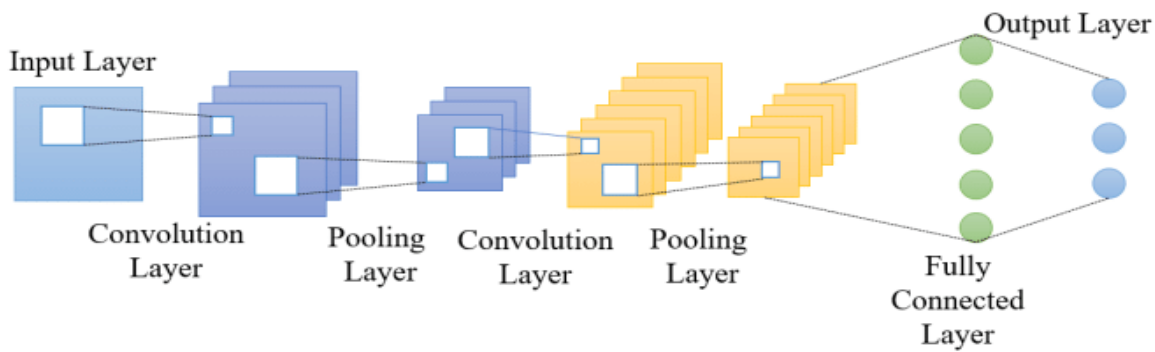


Figure3.3.1 Convolutional Neural Network (Source: <https://www.researchgate.net/publication/335086346/figure/fig3/AS:790156168687616@1565399319399/Basic-architecture-of-CNN.ppm> )

### 3.4 LONG SHORT TERM MEMORY

Long Short Term Memory Network is an advanced RNN, a sequential network, that allows information to persist. It is capable of handling the vanishing gradient problem faced by RNN. A recurrent neural network is also known as RNN is used for persistent memory[4]

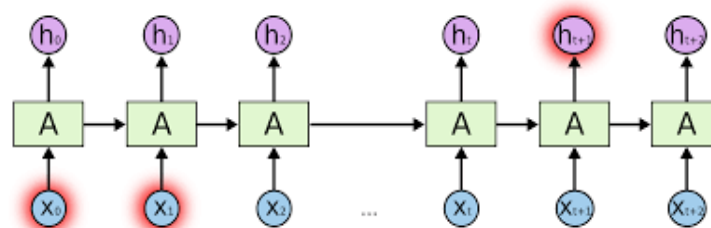


Figure 3.4.1 Long Short – Term Memory ( Source : <https://colah.github.io/posts/2015-08-Understanding-LSTMs/img/RNN-longtermdependencies.png> )

## II REVIEW OF LITERATURE

1. **Anna Almosova, and Niek Andresen (2019):** Nonlinear Inflation Forecasting with Recurrent Neural Networks. This paper conclude that the good performance of the LSTM results from their ability to capture nonlinearities in the data in a combination with their flexible architecture
2. **Subhra Parta (2018):** Time Series Analysis and Forecast of India’s Wholesale Price Index Inflation. In this report the result is monthly inflation of wholesale price index (WPI) for India by using conventional time series forecasting based ARIMA model and machine learning algorithms on the basis of monthly data between January 2005 to March 2017.
3. **Aniruddha Ghosh (2018):** Neural network forecasting for Inflation in India: 2012-2017. In this Paper the results lead way to further such advanced NN methods such as those of deep learning forecasting. Ex. Artificial Neural Network and Extreme Machine learning methods.

4. **Rudra P. Pradhan (2011):** [Forecasting Inflation in India: An Application of ANN Model.](#)  
This result is shows that the multivariate ANN model using WPI, Economic growth (IIP), and (Money supply)MS resulted in better performance than the rest of other models to forecast inflation in India
5. **Kunwar Singh Vaisla (2010) and Dr. Ashutosh Kumar Bhatt(2010):** An Analysis of the Performance of Artificial Neural Network Technique for Stock Market Forecasting.  
In this paper they analysed Neural Networks can be used as an better alternative technique for forecasting the daily stock market prices.

### III OBJECTIVES OF STUDY

1. The objective of this study is to model the monthly Inflation data using the Statistical Technique and the Neural Networks, and then to compare the results of these two techniques.
2. To fit the best model using ARIMA, MLP, RNN, CNN and LSTM using Python coding.
3. To find the values of MSE, RMSE, and MAPE for the models ARIMA, MLP, RNN, CNN and LSTM to decide the best model.
4. To forecast the Inflation for the next 12 months using the best model of this study

### IV RESEARCH METHODOLOGY

To fit an Auto Regressive Integrated Moving Average model, Multilayer Perceptron, Recurrent Neural Network, Long Short Term Memory and Convolution Neural Network models requires big data set. In this study, We collected Secondary data from the official website Reserve Bank of India (RBI) website. Price index data of all commodities data collected monthly for the year Apr 2009 to Mar 2021. In this section, the results of forecasting using these methods are presented. The reported results are then analysed and compared. These traditional methods are compared by Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) which are given by:

Where formulae for the statistics are:

$$MAE = \text{abs}(\text{Actual} - \text{Forecast})/n.$$

$$MSE = 1/n * [\text{Actual} - \text{Forecast}]^2$$

$$RMSE = \text{Sqrt}(MSE).$$

$$MAPE = 1/n * \text{Sum}(\text{Abs}((\text{actual} - \text{forecast})/(\text{forecast}))) * 100$$

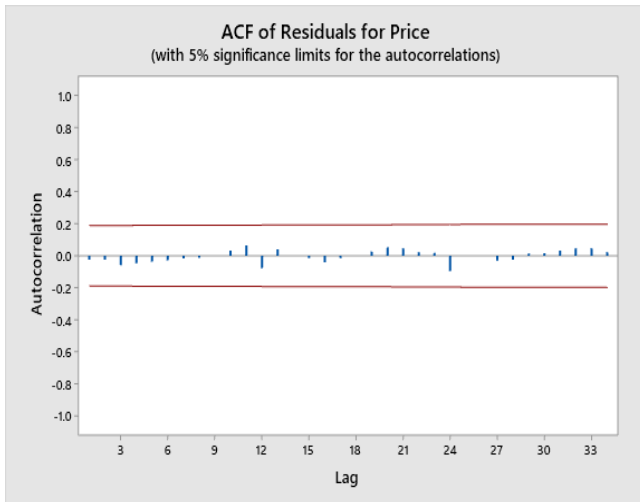


Fig (a)

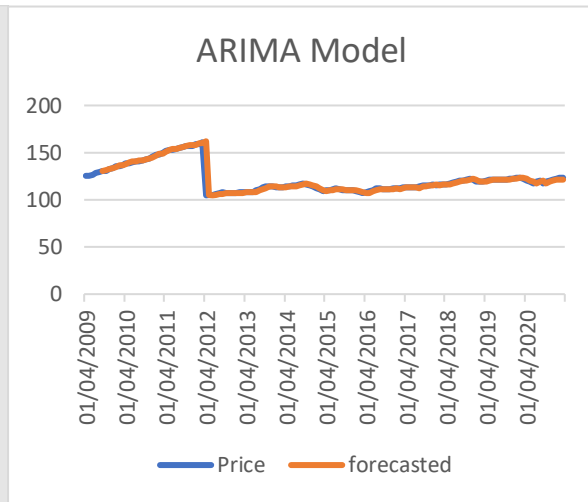


Fig (b)

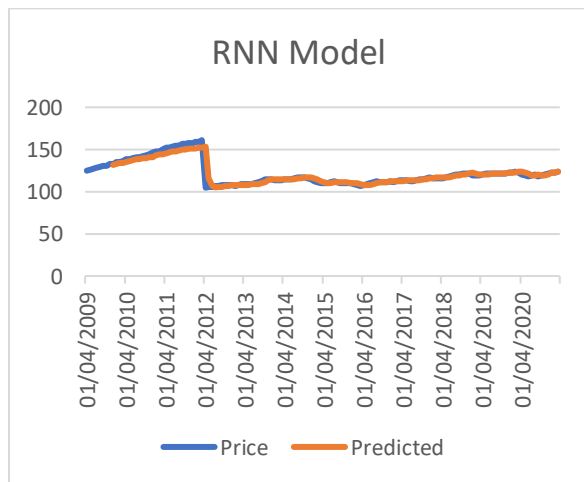


Fig (c)

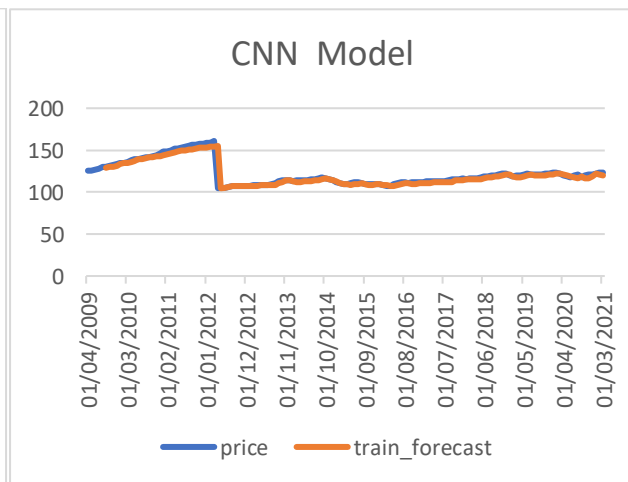


Fig (d)

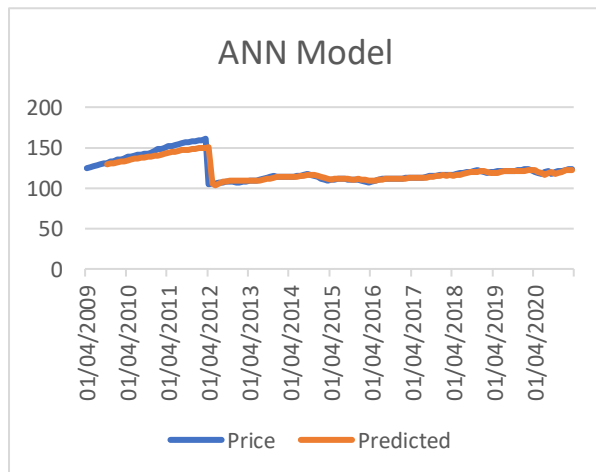


Fig (e)

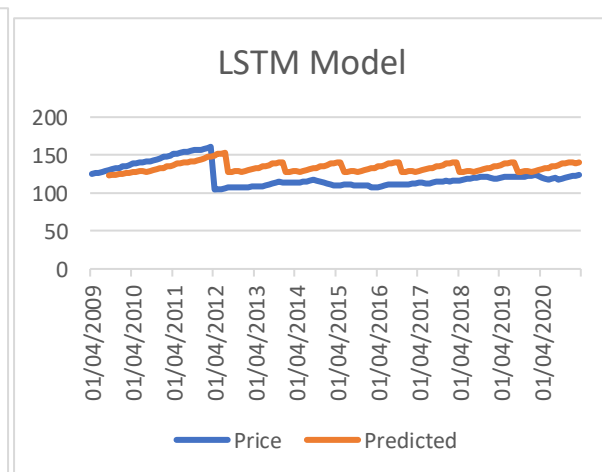


Fig (f)

## V. CONCLUSION

### Test Accuracy

	RMSE	MAPE
ARIMA(0,2,2)	1.54123	1.17405
MLP(ANN)	3.12720	0.02135
RNN	6.39177	0.14087
CNN	1.40215	0.01243
LSTM	4.39721	0.02135

From the above table, we observe that CNN is showing with least RMSE and MAPE as compared to ARIMA(0,2,2), MLP, RNN, CNN, and LSTM. Hence CNN performs better for forecasting monthly inflation of all commodities.

Hence the Whole Sale Price Index forecasted values for the next 12 months using CNN

Date	Forecast
01/08/2020	109.726
01/09/2020	109.549
01/10/2020	109.372
01/11/2020	109.195
01/12/2020	109.018
01/01/2021	108.840
01/02/2021	108.663
01/03/2021	108.486
01/05/2021	108.309
01/06/2021	108.132
01/07/2021	107.955
01/08/2021	107.778

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