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Prediction of Consumer Price Index for Industrial Workers (CPIIW) Using Machine Learning Approaches: Evidence from India

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Abstract

This study fitted the consumer price index for industrial workers (CPIIW) in India using a time series data on Consumer Price Index for Industrial Workers. A comparative evaluation of 28 Machine learning Models for time series data has been carried out. An invariant of Recurrent Neural Network Model viz. Long Short-Term Memory Model (LSTM) was found to be best fit to the CPIIW data. The Performance of the Models were assessed by the four matrices: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percent Error (MAPE) and R Square (R^2). It offered a two-year projection for the anticipated CPIIW. The CPIIW's two-year forecast, which runs from January 2024 to December 2025, was finally made. According to the study, the CPIIW will increase by about 3.4 points during the summer/rainy season (April to September) and stay relatively stable during the winter (October to March).

Keywords: LSTM, CNN, RNN, DEEP LEARNING, RMSR, MAPE, MAE, R^2

Introduction

One of the most significant macroeconomic indicators for assessing inflation is the consumer price index (CPI), and a nation's ability to forecast changes in the CPI is critical to its economic growth. A nation's economic pricing structure is significantly influenced by the consumer price index (CPI). By comparing the relative costs of a group of typical consumer goods and services over a given time period, it illustrates how the cost of a household's purchases of goods and services has changed. Because of this, it is used to monitor how living expenses have changed over time: the average price level increases in tandem with the CPI, and vice versa for industrial workers.

The primary goal of monetary authorities like the Reserve Bank of India is to combat inflation and maintain stable pricing since it is regarded as a significant economic issue in transition economies. The well-known adverse effects of inflation include a decline in the national currency's purchasing power, which exacerbates social conditions and lowers living standards. In addition to creating uncertainty that discourages both domestic and international investors from participating in the economy, high prices also make life miserable for those on fixed incomes. It causes economists and politicians to see things more hazily when they attempt to solve economic problems. Furthermore, since increased prices make domestic commodities more expensive, they impair the nation's terms of trade. A metric called the consumer price index (CPIIW, base 2016 = 100) for industrial workers looks at the weighted average of the prices of a basket of goods and services, including food and drink (39.17%), fuel and light (5.5%), Pan, Supari, tobacco, and intoxicants (2.07). Homeownership (16.87%), apparel and footwear (6.08%), and other miscellaneous expenses such transportation, health care, education, entertainment, and personal hygiene and aftermath (30.31%) Labour Bureau (October 2020). As a guide for the Central Government's twice-yearly declaration of dearness allowance/relief for its employees and retirees in the months of January and July, it is one of the most often cited data for determining periods of inflation or deflation. In light of this, this study aims to fit (a) a number of models to the monthly data on India's CPIIW.

Review of Literature

The set of quantitative observations placed chronologically is called a time series. Over the past three decades, time series analysis has garnered a lot of attention (Kam, Kin Ming, 2014) [6]. In the past, people have typically assumed that time is a continuous or discontinuous variable and that the dependent variables cannot be compared (Hyndman, Rob J., and George Athanasopoulos).

The kind of dataset that is used to train models determines how time series forecasting models are constructed.

Compared to non-stationary datasets, stationary datasets are simpler to train for prediction. In actuality, transforming a non-stationary dataset into a stationary dataset is essential (Manuca, Radu, and Robert Savi, 1996). Models were able to comprehend stationary datasets with ease and extract information from them more effectively.

Python has a wide range of models that are used for value prediction. Deep neural networks and supervised machine learning models are utilised for forecasts. Without being specifically coded, supervised machine learning gives systems the potential to learn from data automatically and improve with experience (Choudhary, Rishabh, and Hemant Kumar Giane, 2017). In a similar vein, deep networks find use in a wide range of domains such as creation, detection, and prediction. When it comes to forecasting, deep neural network models outperform machine learning algorithms.

Deep learning architectures are a pretty fresh and modern method for predicting the Consumer Price Index. The effectiveness of artificial intelligence algorithms to forecast the post sample of time series data has previously piqued the interest of scholars. Deep neural network topologies provide the best explanation for the nonlinear data structures. Applications of deep learning algorithms for stock price prediction have been tested in a number of studies (Kwong, 2001; Nygren, 2004; Huang *et al*., 2007) [2, 3]. A small number of researchers have also demonstrated that deep learning algorithms are superior for predicting financial data (Hossain *et al*., 2008; Qian, 2017; Selvin *et al*. 2017) [4, 7, 5]. According to recent research, certain deep learning algorithms (such as CNN-LSTM) should be used for the prediction. The prediction efficiency of three specific machine learning models-Logistic Regression, Support Vector Machine, and Multilayer Perceptron-was compared with the historical time series model ARIMA by Qian *et al*. (2017) [7]. They highlighted that machine learning models, an emerging field of research in recent years, may prove to be superior than traditional models using the S&P 500 as an example. They believe that future researchers should attempt to use long-short term memory networks (LSTM) to anticipate time series data. Kambo b s (2019) [9] in their study on Modeling Consumer Price Index of India for Industrial workers found that the ARIMA (0, 1, 1) X (0, 1, 1) 12 is best fitted to CPI data for industrial workers for the period from January 1990 to January 2019. Kambo b s (2020) [10] *et al* in their paper on forecasting end of Covid 19 in India found that ARIMA (0, 1, 1) and Holt exponential smoothing Models are best fit for active and removed rates respectively. Selvin *et al*. (2017) [5] forecasted the values of three stocks-Infosys, TCS, and Cipla-listed on the National Stock Exchange using a sliding window technique and various deep learning algorithms. Deep learning architectures that are utilized invariantly include Recurrent Neural Network, Convolutional Neural Network. Selected companies from the Dhaka Stock Exchange were selected for analysis using the following prediction methods: Random Forest, Feed Forward Neural Network, Support Vector Machine, and Back-propagation. The outcomes showed that when it comes to stock price prediction, RNN with LSTM performs better than machine learning techniques. The daily trading performance of several equities predicted by six conventional machine learning algorithms and six sophisticated deep neural network algorithms was compared by Lv *et al*. (2019) [13]. Support Vector Machine (SVM), Random Forest (RF), Logistic Regression (LR), Naive Bayes model (NB), Classification and Regression tree (CART), and Extreme Gradient Boosting method (XGB) are some examples of machine learning techniques. Chen *et al*. (2021) explored the application of deep learning algorithms in trading. They used the Long-Short Term Memory (LSTM) neural network architecture and forecasted the stock prices of Intel Corporation (NASDAQ: INTC). The study suggested that various architectures of LSTM could be explored with the different number of neurons and layers. Sen *et al*. (2021) [17] used Long Short-Term Memory neural network architecture for the prediction of stock prices taking daily data (Close price) of 70 Companies listed in National Stock Exchange India. The study revealed that LSTM proved to be highly accurate and prediction of stock prices data. For the purpose of prediction, six long short-term memory neural network algorithms and four convolutional neural network algorithms were employed. A unique method called Multi Step Forecasting with Walk-Forward validation was used to test the models. According to this study, CNN algorithms perform better than LSTM algorithms.

Source of Data

The data on Consumer price index for industrial workers (CPIIW) from January 2006 to December 2023 used in this research work, has been extracted from the Websites: www.lboubureau.gov.in of Labour Bureau Shimla, Ministry of Labour and Employment, Government of India. It is the monthly data with base year 2001.The CPI series with base 2016 was linked to series with base 2016 using linking factor 2.88

Methodology and Modeling

The data was analyzed by fitting 27 models using PYCART (version 3.10) package for time series and LSTM model was also fitted separately.

Functioning of the Machine learning Models generally involve the following steps:

i). **Important Libraries:** Down loads necessary Libraries such as Pandas, NumPy, Matplotlib, Seaborn sklearn, and pycaret, karas and tensor flow.

ii). **Data Cleaning:** Data Understanding, handling missing values, removing duplicates, Feature Scaling, Handling categorical variables: Outlier detection and treatment, Feature engineering and Data transformation

iii). **Data Splitting:** we generally split the dataset into training (80%) and testing (20%) sets. The testing set was used to evaluate the performance of the Models.

iv). **Models Selection:** selecting appropriate Models from sk learn and PyCaret library

v). **Model Training:** Train the machine learning models on training data set.

vi). **Model Evaluation:** The model's performance on testing data using appropriate evaluation metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percent Error (MAPE) and R Square (R^2) were employed to estimate the accuracy of the forecast algorithms.

vii). **Model Comparison:** Compared the performance of the models to determine which one provide better results.

LSTM over View

The LSTM model, a type of recurrent neural network (RNN), primarily addresses the issue of gradient disappearance, which is a common occurrence in conventional RNNs, enabling it to analyse longer time series data. The input, output, and forget gates are the three additional memory modules added by the LSTM model in comparison to the RNN. In order to extract beneficial information through the output gate as the final retention layer's state, the LSTM processes the input data at time t, chooses helpful information with a predetermined probability, and then takes part in the subsequent time computation. LSTM is an inbuilt python function that can be imported from Tensor Flow. LSTM is the branch of recurring neural networks. It was seen that there weren't any RNN structures that can do backpropagation of long intervals, so to solve such difficulties LSTM is preferred. It requires the data used to be in a definite shape. The dimension should be equivalent, and the data should be properly cleaned, integrated, and scaled. The commonly used activation functions for LSTM-based regression problems are

Sigmoid and Tanh. Tanh has proven to be very effective in dealing with vanishing gradients.

i). **Memory Cells:** LSTMs have a more complex architecture compared to basic RNNs. They introduce the concept of memory cells, which are capable of storing information for extended periods

ii). **Getting Mechanisms:** LSTMs use gating mechanisms (input, output, and forget gates) to control the flow of information into and out of memory cells. This helps in managing the information flow over long sequences, mitigating the vanishing or exploding gradient problem.

iii). **Long-term Dependencies:** One of the key advantages of LSTMs is their ability to capture long-term dependencies in data. This is crucial for time series analysis, where patterns and dependencies often span across multiple time steps.

LSTM Architecture

i). **Input Gate:** Controls the flow of new information into the memory cell.

ii). **Forget Gate:** Manages the removal of unnecessary information from the memory cell

iii). **Cell State:** The memory cell stores and retrieves information based on input, forget, and output gate decisions.

iv). **Output Gate:** Determines the output based on the current input and the memory content.

Back Propagation through Time (BPTT): LSTMs are trained using BPTT, which helps in learning the temporal dependencies by adjusting the weights during backpropagation.

Hyperparameter Tuning: The architecture of LSTMs, such as the number of layers, hidden units, and dropout rates, can be tuned to enhance performance on specific time series tasks.

Computational Complexity: Training LSTMs can be computationally intensive, especially for large datasets and complex architectures.

Over Fitting: Like any neural network, LSTMs can be prone to overfitting, so regularization techniques and careful model validation are essential.

Thus, LSTMs are powerful tools for time series analysis due to their ability to capture long-term dependencies. Their gating mechanisms and memory cells make them well-suited for understanding and predicting patterns in sequential data.

Empirical Results and Discussions

Statistical Descriptions of data

The various statistic used to test the characteristics such as descriptive statistics, normality, stationarity white noise of CPIIW data are shown in Table 1

Table 1: Showing test deployed on consumer price index for industrial workers time series data

SI No.	Test	Test Name	Data	Property	Setting	Value
1	Summary	Statistics	Transformed	Length		216.00
2	Summary	Statistics	Transformed	# Missing Values		0.00
3	Summary	Statistics	Transformed	Mean		86.60
4	Summary	Statistics	Transformed	Median		87.80
5	Summary	Statistics	Transformed	Standard Deviation		28.83
6	Summary	Statistics	Transformed	Variance		831.16
7	Summary	Statistics	Transformed	Kurtosis		-1.14
8	Summary	Statistics	Transformed	Skewness		0.06
9	Summary	Statistics	Transformed	# Distinct Values		156.00
10	White Noise	Ljung-Box	Transformed	Test Statictic	{'alpha':0.05, 'K':24}	3799.40
11	White Noise	Ljung-Box	Transformed	Test Statictic	{'alpha':0.05, 'K':48}	5353.98
12	White Noise	Ljung-Box	Transformed	p-value	{'alpha':0.05, 'K':24}	0.00
13	White Noise	Ljung-Box	Transformed	p-value	{'alpha':0.05, 'K':48}	0.00
14	White Noise	Ljung-Box	Transformed	White Noise	{'alpha':0.05, 'K':24}	0.00
15	White Noise	Ljung-Box	Transformed	White Noise	{'alpha':0.05, 'K':48}	0.00
16	Stationarity	ADF	Transformed	Stationarity	{'alpha':0.05}	False
17	Stationarity	ADF	Transformed	p-value	{'alpha':0.05}	0.98
18	Stationarity	ADF	Transformed	Test Statistic	{'alpha':0.05}	0.35
19	Stationarity	ADF	Transformed	Critical Value 1%	{'alpha':0.05}	-3.46
20	Stationarity	ADF	Transformed	Critical Value 5%	{'alpha':0.05}	-2.88
21	Stationarity	ADF	Transformed	Critical Value 10%	{'alpha':0.05}	-2.57
22	Stationarity	KPSS	Transformed	Trend Stationarity	{'alpha':0.05}	False
23	Stationarity	KPSS	Transformed	p-value	{'alpha':0.05}	0.05
24	Stationarity	KPSS	Transformed	Test Statistic	{'alpha':0.05}	0.15
25	Stationarity	KPSS	Transformed	Critical Value 10%	{'alpha':0.05}	0.12
26	Stationarity	KPSS	Transformed	Critical Value 5%	{'alpha':0.05}	0.15
27	Stationarity	KPSS	Transformed	Critical Value 2.5%	{'alpha':0.05}	0.18
28	Stationarity	KPSS	Transformed	Critical Value 1%	{'alpha':0.05}	0.22
29	Normality	Shapiro	Transformed	Normality	{'alpha':0.05}	False
30	Normality	Shapiro	Transformed	p-value	{'alpha':0.05}	0.00

It is clear from the table 1 that a significant auto correlation that cannot be attributed to chance we can say with 99 percent confidence that the CPIIW data is not pure white noise as value for Ljung test for white noise is zero less than 0.01

Normality Shapiro Transformed Normality {'alpha': 0.05} False implies that data is not normal because Shapiro Transformed p-value 0.00 which is less than .01

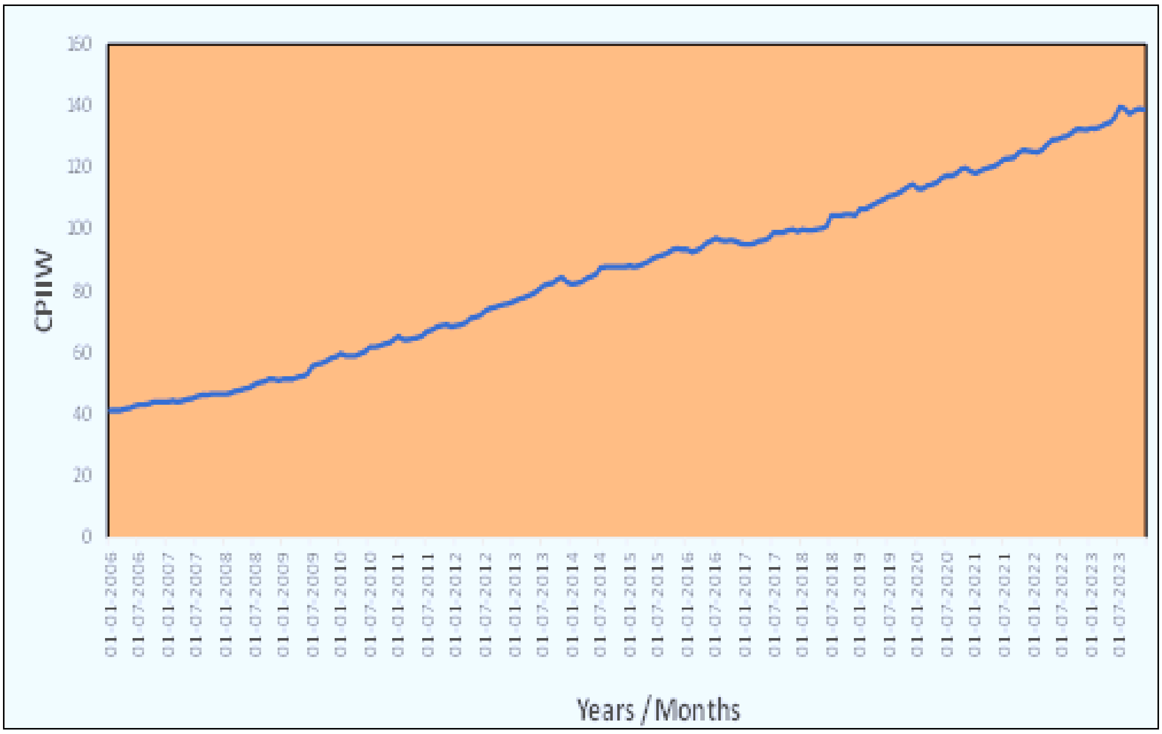

Fig 1: Mostly consumer price index for industrial workers from January 2006 to 2023

Monthly Consumer price index for the industrial workers from January 2006 to December 2023 (base 2016 = 100) are shown in the (figure 1). The increasing trend of CPIIW clearly indicates that CPIIW time series data is not stationary.

It is further confirmed by as the p value for ADF test for stationary is 0.98 which is greater than 0.01.

The CPIIW data is transformed by taking non-seasonal difference (d =1). Plot the transformed series (figure 2) which clearly shows that the time series is now stationary.

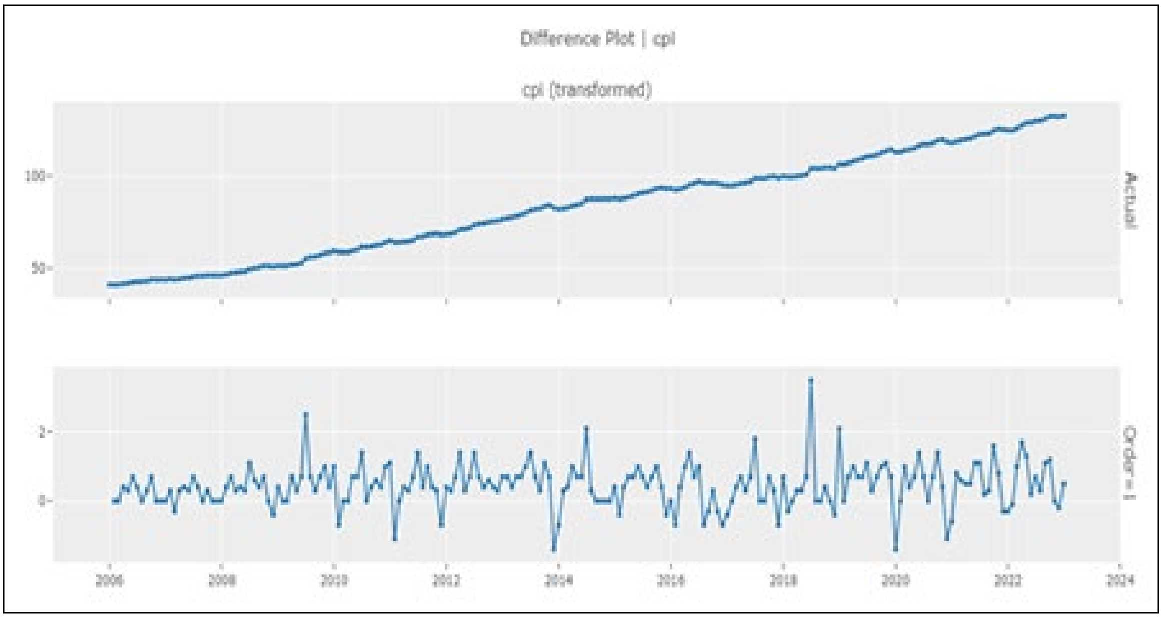

Fig 2: Shows that the time series is now stationary

Table 2: Comparision of Performance of machine learning Models for Consumer Price index for Industrial Workers in India models

S. No.	Model	MAE	RMSE	MAPE	R^2
1.	LSMT	0.638	0.823	0.518	0.992
2.	Huber w/Cond. Deseasonalize & Detrending	0.519	0.673	0.004	0.893
3.	Linear w/Cond. Deseasonalize & Detrending	0.566	0.739	0.005	0.870
4.	ETS	0.611	0.740	0.005	0.867
5.	Exponential Smoothing	0.612	0.741	0.005	0.867
6.	Ridge w/Cond. Deseasonalize & Detrending	0.587	0.760	0.005	0.863
7.	Bayesian Ridge w/Cond. Deseasonalize & Detrending	0.593	0.768	0.005	0.860
8..	Extra Trees w/Cond. Deseasonalize & Detrending	0.738	0.909	0.006	0.781
9.	AdaBoost w/Cond. Deseasonalize & Detrending	0.827	0.982	0.007	0.770
10.	Random Forest w/Cond. Deseasonalize & Detrending	0.825	0.987	0.007	0.757
11.	Decision Tree w/Cond. Deseasonalize & Detrending	0.837	1.015	0.007	0.755
12.	Orthogonal Matching Pursuit w/Cond. Deseasonalize & Detrending	0.851	1.019	0.007	0.749
13.	Auto ARIMA	0.822	1.032	0.007	0.731
14.	Elastic Net w/Cond. Deseasonalize & Detrending	0.945	1.099	0.008	0.707
15.	ARIMA	0.823	1.057	0.007	0.690
16.	Lasso Least Angular Regressor w/Cond. Deseasonalize & Detrending	0.940	1.104	0.008	0.687
17.	Lasso w/Cond. Deseasonalize & Detrending	0.940	1.104	0.008	0.687
18.	Gradient Boosting w/Cond. Deseasonalize & Detrending	1.002	1.139	0.009	0.672
19.	Polynomial Trend Forecaster	0.925	1.173	0.008	0.650
20.	Extreme Gradient Boosting w/Cond. Deseasonalize & Detrending	1.258	1.409	0.011	0.505
21.	STLF	1.087	1.234	0.010	0.503
22.	Light Gradient Boosting w/Cond. Deseasonalize & Detrending	1.239	1.458	0.011	0.435
23.	K Neighbors w/Cond. Deseasonalize & Detrending	1.451	1.693	0.012	0.246
24.	Theta Forecaster Naive	1.669	1.971	0.014	0.070
25.	Forecaster Seasonal	4.344	4.805	0.037	-4.564
26.	Naive Forecaster	6.533	6.586	0.056	9.462
27.	Croston	8.129	8.472	0.070	-16.396
28.	Grand Means Forecaster	41.486	41.538	0.353	-424.660

The comparative Performance of the 28 machine learning algorithms on training data (Table 2) were assessed by the Four matrices viz. Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percent Error (MAPE) and R Square (R^2). The most important measure of goodness of fit of models is R^2 which estimate the proportion of total variation in the series explained by the model. It has been observed that LSTM model explains 99.2 percent of variation in CPIIW time series data of CPIIW

Table 3: Evaluations metrics for LSTM model on training and testing data.

Data	RMSE	MAE	R2	MAPE
Training	0.8321	0.6384	0.9921	0.5188
Testing	0.7874	0.6234	0.9918	0.4989

The value of the four metrics viz. RMSE, MAE, MAPE and R^2 are very close to each other (Table 4) on test as well as on training data indicating there is no overfitting.

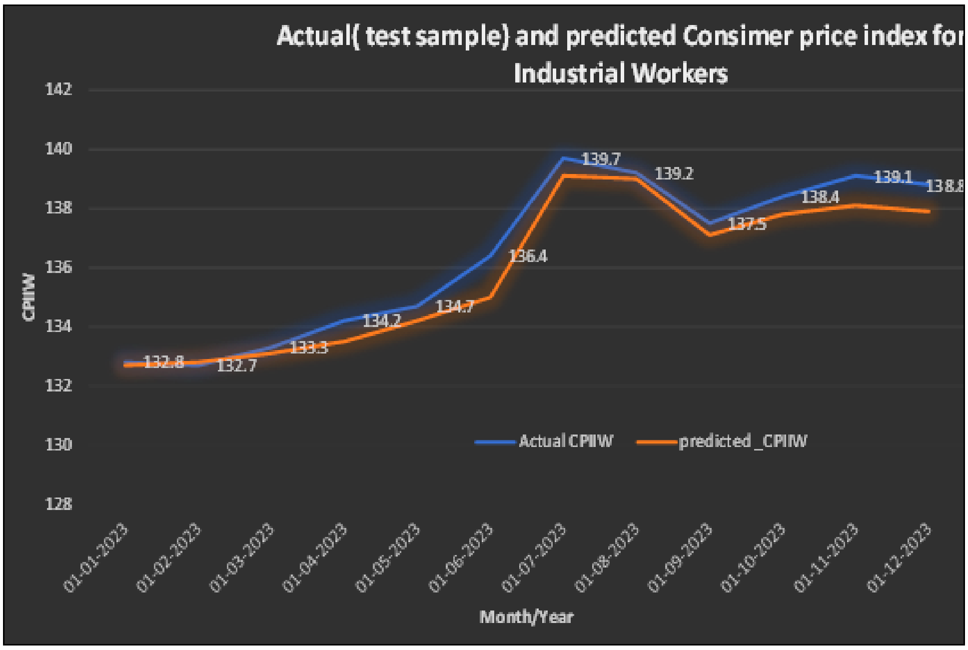

Fig 3: Actual (test sample) and predicted consumer price index for industrial workers

From the above discussion it is inferred that LSTM model is best and can be deployed to predict the Consumers Price index for Industrial workers.

The two years forecasting from January 2024 to December 2025 are shown in the table 4

Table 4: Predicted Consumer Price Index for Industrial Workers ((CPIW)) from January 2024 to December 2025

Month	CPIW	
	2024	**2025**
January	138.9	144.5
February	138.9	144.5
March	139.3	144.9
April	140.0	145.6
May	140.6	146.2
June	141.3	146.9
July	142.7	148.3
August	143.0	148.6
September	143.4	148.9
October	144.2	149.7
November	144.4	150.0
December	144.3	149.8

The predicted CPIIW for January 2024 is 138.9 which exactly matches with the index released by Labour Bureau Shimla India. It has been observed that CPIIW increasing steadily during the period from January 2024 to June 2024 and reached to 141.3 in June 2024. Thereafter it jumps by 2.4 point and reached to 144.3 in the month of December 2024. It remains more or less stable during the period from October 2024 to March 2025 (Winter season). It has been found that CPIIW remained almost stable during the winter season (October to March) and jumped to approximately 3.4 points during summer/monsoon season (April to September). This may be due to the fact that price of Food, Beverages & Tabaco (48.47 Percent weight) remains more or less stable during winter season whereas during summer or monsoon season the prices of food related items shoot up at faster rate due to lack or excess of rainfall which often hits India's food production.

Trend in CPI-IW attracts the interest of Central Government Employees and Pensioners as their Dearness Allowance/Relief given as compensation for inflation, is fixed based this index. On the basis of forecasted CPIIW, the Dearness allowances for central government employees as per 7th pay Commission recommended formula have been computed (Fig 4).

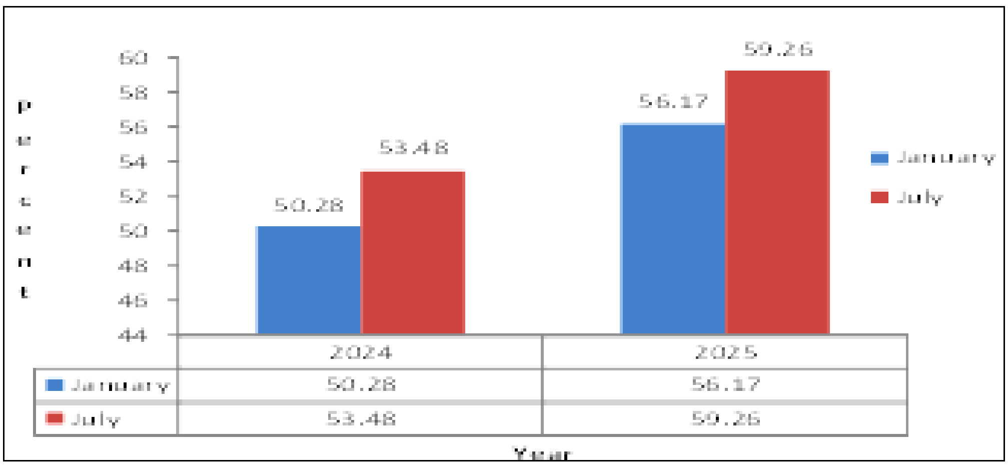

Fig 4: Dearness/Relief allowance (%) for central government Employees/Pensioners

The dearness allowance/relieve to the Central Government Employee/pensioners shall be of the order of 53.48 percent in July 2024 which may rise to 59.26 percent in January 2025. DA will be 56.17 percent and in January 2025 it stands at 59.26 percent July 2025. The percent hike in Dearness allowance/relief in January and July in each of the years from 2024 to 2025 will be at the most 3 percent.

Conclusions

The consumer price index for industrial worker (CPI IW) has been studied using Artificial Intelligence Machine Learning approach. The monthly data of CPI for industrial workers for the period from January 2006 to December 2023 was extracted from the website (www.lboubureau.gov.in) of Labour Bureau Shimla, Ministry of Labour and Employment, Government of India and has been used to develop and test the models. The paper examined the appropriate model that fits the Consumer price index for industrial workers between January 2006 and December 2023. It was discovered that the LSTM model was found to be best fit to the CPIIW time series data among the 28 models trained. The study revealed that CPIIW will remains more or less stable during the winter season (October to March) and jumped approximately 3 points during summer/rainy season (April to September) for each of the year from 2024 and 2025. This may be due to the fact that price of Food, Beverages & Tabaco (48.47 Percent weight) remains more or less stable during winter season whereas during summer or monsoon season the prices of related items shoot up at faster rate due to lack or excess of rainfall which often hits India's food production.

The dearness allowance/relieve to the Central Government Employee/pensioners shall be of the order of 53.48 percent in July 2024 which may rise to 59.26 percent in January 2025. DA will be 56.17 percent and in January 2025 it stands at 59.26 percent July 2025. The forecasted CPIIW showed very good agreement with the actual recorded data. This gave an increasing confidence of the selected LSTM models. The study reveals that the Long Short-Term Memory (LSTM) model could be used as an appropriate model to forecast the monthly CPIIW two years (January 2024-December 2025). Since high gasoline or food price often corresponding to political chaos. Therefore, results achieved for CPIIW forecasting will help the traders, politicians, and analyst and policy makers for analyzing price movements, market trends and determine the indexing of dearness allowances/relief to the industrial workers in the country. The forecasted numbers may also help the finance departments of the central and state governments to allocate funds for release of dearness allowances/relief to their employees/pensioners in their coming two years annual budget.

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