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# An Extreme Learning Machine Approach for Forecasting the Wholesale Price Index of Food Products in India

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## ABSTRACT

Precise food price forecasting is crucial for any country, and searching for appropriate approach(s) from an assortment of available strategies toward this objective is an open problem. The current Indian Wholesale Price Index (WPI) series contains sixty individual food items in the 'manufacture of food product' category. This work considered the monthly data from April 2011 to June 2022, i.e., one hundred thirty-five months' data of these sixty WPIs. The researchers extracted the linearity, curvature, and autocorrelation features for each WPI. The curvature and linearity-based grouping of these WPIs revealed that the WPIs are heterogeneous. This work proposed an extreme learning machine (ELM) approach for forecasting these WPIs. The present work employed the following twenty-two time-series forecasting techniques: six standard methods (Auto ARIMA, TSLM, SES, DES, TES, and Auto ETS), five neural networks (Auto FFNN, Auto GRNN, Auto MLP, Auto ELM, and proposed ELM), and eleven state-of-art techniques (two ARIMA-ETS based ensembles, an ARIMA-THETAF-TBATS based ensemble, one MLP, and seven LSTM-based models) to identify the best forecasting approach for these WPIs. For the majority of WPIs, the offered ELM attained suitable performance in the case of fifteen months of out-of-sample forecasting. Nearly eighty-seven percent of cases achieved high accuracy (MAPE ≤ ten) and outshined others. Upon accuracy comparison, both forecast-MAPE and forecast-RMSE, between the proposed ELM and others, this paper observed that the proposed ELM's performance is more favorable. This paper's findings imply that the proposed ELM is a promising prospect to offer accurate forecasts of these sixty WPIs.

*Keywords*: Artificial Neural Network, extreme learning machine, feature extraction, time-series forecasting, wholesale price index

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## INTRODUCTION

In the present day, manufactured food products are crucial to daily life, and the food industry delivers various food products to the human population. Price forecasting helps profit maximization (Wibowo & Yasmina, 2021; Gaspar et al., 2021) and risk minimization (Wibowo & Yasmina, 2021; Sabu & Kumar, 2020). Accurate commodity price forecasting assists in effective decision-making (Choong et al., 2021). Food price forecasting adds value to all stakeholders, e.g., policymakers, consumers, and agriculturalists, by providing reliable price projections of the food items (MacLachlan et al., 2022). Researchers applied eclectic time-series forecasting strategies to predict the prices of food items (Menculini et al., 2021; Mgale et al., 2021; Dacha et al., 2021; Sanusi et al., 2022; Mahto et al., 2021). The works of literature exhibited that the researchers utilized an assortment of techniques, e.g., Autoregressive Integrated Moving Average (ARIMA) by Adam (2022), Exponential Smoothing (ES) by Rosyid et al. (2019), 'Error, Trend, Seasonality' (ETS) by Purohit et al. (2021), Regression by Mishra et al. (2019), and Artificial Intelligence (AI) by Sanusi et al. (2022) to predict future prices of food items. Whereas an array of approaches exists for food price forecasting, and none of them is a clear winner, it is imperative that accurate food price forecasting becomes critical for all stakeholders. Therefore, searching for the most appropriate approach for price forecasting of a wide range of food items becomes an open problem.

### Food Price Forecasting Using Several Approaches

The ARIMA (p, d, q), a linear model, has a fixed structure, is more interpretable, and uses historical data to predict future values. It faces difficulty in turning point prediction and involves subjectivity in determining the p, d, and q values. The authors applied the ARIMA techniques to forecast the prices of rice (Adam, 2022; Fernando et al., 2021) and sugar (Şahinli, 2021). The researchers used this technique for forecasting chili (Septiani & Setyowati, 2021), palm oil (Yee & Humaida, 2021), and numerous other items (Zhou, 2021; Astiningrum et al., 2021; Taofik & Tiamiyu-Ibrahim, 2021) prices.

The ES technique is simple, gives a greater emphasis on recent observations, and uses the principle of the weighted sum (linear sum) of lags, where the current data has higher weights and weights reduce exponentially. It ignores the data spikes and is less effective in handling trends. Rosyid et al. (2019) used the following three ES techniques to forecast the prices of rice, chicken, beef, egg, shallot, garlic, red chili, raw chili, oil, and sugar: single exponential smoothing (SES), double exponential smoothing (DES), and triple exponential smoothing (TES). The authors (Dewi & Listiowarni, 2020; Şahinli, 2020) applied Holt-Winters (HW) to forecast various food prices. Some researchers (Lutfi et al., 2019; Fitria, 2018) utilized SES to predict food prices. Talwar and Goyal (2019) employed exponential smoothing techniques, e.g., SES, DES, and HW, to forecast coriander prices. Prakash et al. (2022) applied the HW approach to predict sweet potato prices.

The ETS - a state-space approach, uses exponential smoothing and can model the trend and seasonality components of the data. It combines the error, trend, and seasonality components and offers a family of possible models. An ETS model includes a measurement equation that explains the observations and a few state equations expressing the transition of states. The authors (Purohit et al., 2021; Koblianska et al., 2021) applied it to the potato-price forecast. Other authors utilized the ETS approach for forecasting various food item prices, e.g., onion (Purohit et al., 2021), rice (Wahyuni & Afandi, 2018), and salmon (Tharmarajah & Gjesdal, 2020).

Regression is a frequently employed quantitative technique and easily adapts to even challenging forecasting assignments. Time series regression, a statistical approach, uses autoregressive dynamics, i.e., response history and dynamics transfer from pertinent predictors to forecast. The authors applied different regression approaches to predict several food item prices, e.g., corn (Ge & Wu, 2020) and potato (Mishra et al., 2019). Asnhari et al. (2019) utilized it for red chili, onion, and garlic price prediction. Volkov et al. (2019) applied it to predict the butter, egg, and bread prices.

The Artificial Neural Network (ANN) is a prominent AI method that processes information inspired by biological-nervous systems and learns via examples. It has an innovative structure for information processing and comprises several intricately linked processing units called neurons that collaborate to address particular issues. ANN is flexible, applies universal approximators, supplies effective forecasting, and can operate on diverse time-series data, both linear and non-linear. The authors applied neural approach-based forecasting techniques to predict the future prices of various items, e.g., white beans (Sanusi et al., 2022), white maize (Sanusi et al., 2022), and soybean (Zhang et al., 2018). Some utilized ANN to forecast potato (Areef & Radha, 2020; Choudhury et al., 2019), coffee (Xu & Zhang, 2022b), and sugar (Xu & Zhang, 2022b) prices. A few employed ANN for price prediction of soybean oil (Xu & Zhang, 2022a; Xu & Zhang, 2022b), rice (Sanusi et al., 2022; Shao & Dai, 2018), and wheat (Shao & Dai, 2018).

## Motivation

To aid the stakeholders in appropriate policymaking, dependable and precise forecasting of food prices plays a vital role. The wholesale price index (WPI) is a macroeconomic indicator. It describes the wholesale pricing of commodities and records the average change in wholesale prices of products. The current WPI-series of India lists sixty individual items in the ‘manufacture of food product’ (food-product) category.

Das and Chakrabarti (2021) developed an MLP model to forecast the WPIs of selected food items in India, considering the data from April 2012 to March 2017, and chose thirty-six items from the food-product category that showed positive linearity and negative curvature features. This MLP [2/1/1] approach proposed by Das and Chakrabarti (2021) exhibited promising results. They had not observed its applicability to other WPIs and have the following gap: evolvement of an efficacious forecasting strategy(s) for all the sixty individual items under the food-product category of the current WPI series of India.

The nonexistence of any work that explored various forecasting techniques on the WPI of all individual items from the food-product category of the current WPI of India and comprehending the significance of forecasting these WPIs, filling this gap thus becomes a stimulus. It motivates the present work to explore the usefulness of several standard time-series forecast approaches and some state-of-the-art techniques offered by others in forecasting all the indices of individual items from the food-product category of the WPI series of India. Further, it motivates this work to deliver a strategy that can provide effective forecasting for all these WPIs.

### Objectives of the Study

- To propose and construct a novel neural approach that is straightforward, easy to use, and capable of delivering effective forecasting for most indices of the individual items from the food-product category of the WPI series of India.
- To predict out-of-sample values for these WPIs using the proposed neural approach.
- To predict out-of-sample values for these WPIs employing several standard time-series forecasting approaches and some state-of-the-art forecasting techniques offered by others.
- To compare the outcomes of the offered technique with others and determine the most acceptable forecasting approach for the WPIs of the individual items from the food-product category of the WPI series of India.

## METHODOLOGY

### Overview of the Research

Figure 1 represents the overview of the present research.

The researchers collected the WPI of sixty items for one hundred thirty-five months, extracted their linearity, curvature, and auto-correlated lag features through feature engineering, obtained the proposed approach's optimized model for them, produced out-of-sample forecasts using the respective optimized models and other techniques, and evaluated the forecast performances of these approaches.

The scope of this work is limited to developing forecast models for the univariate time-series data. Thus, the authors have only considered the univariate time-series forecasting models in this work and have yet to explore the impact of various influencing factors that affect the WPI of food items in model development.

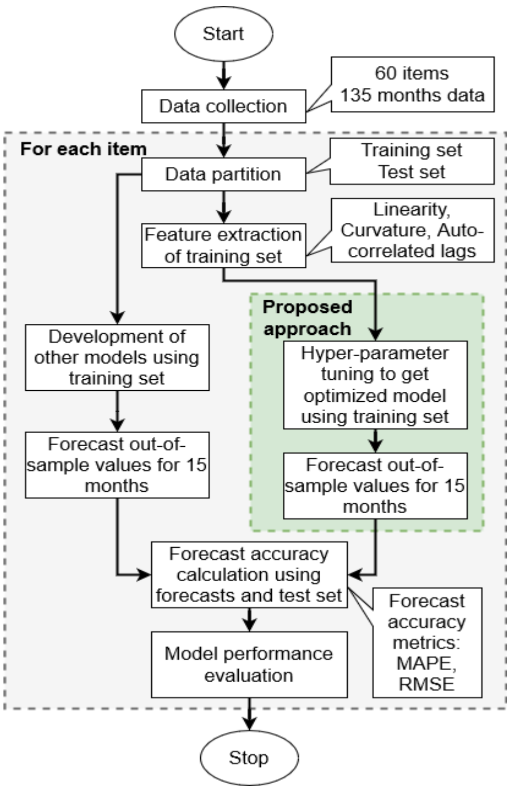


*Figure 1.* Research outline

## Data

This work used the monthly index of sixty individual items from the food-product category of the Indian WPI from April 2011 to June 2022, i.e., one hundred thirty-five months of data (https://data.gov.in/resource/wholesale-price-index-base-year-2011-12-till-last-month).

Table 1 reveals the divisions of the data set. This work applied the training set for feature extraction, tuning the model hyper-parameters, and estimating the model parameters and model building. The fifteen-month hold-out test set is used for forecast accuracy computation of the models.

## Proposed Neural Approach

An extreme learning machine (ELM) is a feed-forward neural network. It consists primarily of a single hidden layer and exhibits considerably quick convergence than conventional ones (Wang et al., 2022).

Table 1
*Data partition*

| Start | End | Duration (months) | Description |
|---|---|---|---|
| April 2011 | June 2022 | 135 | Full dataset |
| April 2011 | March 2021 | 120 | Training set |
| April 2021 | June 2022 | 15 | Test set |

The ELM uses 'Moore-Penrose generalized inverse' to set the randomly assigned weights instead of backpropagation (Erdem, 2020). Kourentzes (2019b) suggested the following for better modeling of time series with neural approaches: utilizing differences for trend removal as trend modeling is not a strong suit for them and using seasonal dummy(s) to model deterministic seasonality. The ELM is a quick learner, simple, and efficient. ELM approach exhibited promising performances when applied to diverse time-series data (Chakraborty et al., 2022; Feng et al., 2021; Talkhi et al., 2021; Niu et al., 2019).

The structure of the proposed ELM-based neural approach for forecasting the WPIs of the individual items from the food-product category of India is as follows:

- Input (X) = $\{x_1, x_2, ..., x_n, ds_1, ds_2, ..., ds_m\}$ where $x_i$ is autocorrelated lags identified from the ACF plot of the time-series and $ds_j$ is seasonal dummy(s) to model deterministic seasonality. The deterministic seasonality is identified using the Canova-Hansen test.
- Single hidden layer
- No. of neurons in the hidden layer (N) = $N_1$
- Hyper-parameter tuning (Figure 2) of the ELM network to get the optimum $N_1$ value from the search space (S) where S = {100, 200, ...,1200}
- Weights of output layer estimated by lasso regression with CV
- 20 networks trained to deliver ensemble forecasts
- Used median operator to combine forecasts
- Applied first-order differencing for trend removal of the time series

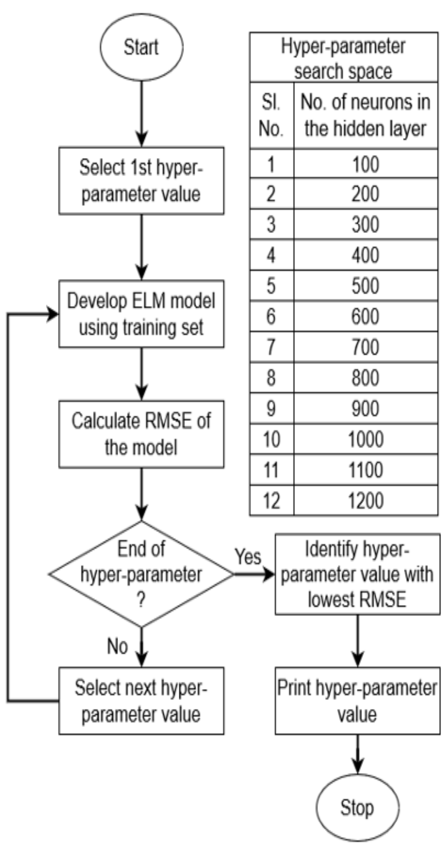


*Figure 2.* Hyper-parameter tuning technique

This work employed the 'nnfor' package of R (Kourentzes, 2019a) to develop the ELM. The proposed ELM, rather than using the offered automatic input selection procedure, employed a tailored strategy for input selection, selected the weight estimation type among the available estimation types (i.e., lasso, ridge, stepwise, and linear regressions), specified the combination operator from the set offered ones (i.e., mean, KDE estimation based mode, and median), selected the number of training networks, applied the number of differencing to detrend the data, designed the hyper-parameter search space to determine the number of hidden nodes for optimization, and tuned the ELM to obtain the optimized ELM from the specified search space.

Chakraborty et al. (2022) offered an ELM with many (6000) hidden nodes. Kourentzes (2019b) suggested using one hundred nodes in the hidden layer by default and adjusting it as required. This work designed the hyper-parameter search space of the proposed ELM using a heuristic approach. It starts from the default 100 and increases in the equal interval (step length 100, i.e., equal to the default value) up to 1200. The authors developed it considering the trade-off between model performance, speed, and computational cost. Expanding the search space may deliver better performance but with much slower performance and increased computational costs.

### Other Approaches

This work applied several approaches for forecasting fifteen months of out-of-sample values of the sixty WPIs. It employed six standard time-series forecast techniques, which are as follows: linear regression (TSLM), SES, DES, TES, Auto-ARIMA, and Auto-ETS. The work further utilized four automatic neural approaches, namely, feedforward neural network (FFNN), generalized regression neural network (GRNN), Multilayer Perceptron (MLP), and ELM. This work additionally explored four state-of-the-art approaches: an MLP (Das & Chakrabarti, 2021) and three ensembles (Perone, 2022; Shaub, 2020) to evaluate the performance of the proposed ELM. Das and Chakrabarti (2021) developed an MLP to forecast the WPIs of some selected food products from India, whereas Perone (2022) applied the ARIMA-ETS-based ensembles in COVID-19 case prediction. Shaub (2020) used an ARIMA-THETAF-TBATS ensemble approach for quick and precise forecasting of time-series data. It also employed seven LSTM-based models presented by others (Brownlee, 2018; Staffini, 2022; Patel et al., 2018; Jia et al., 2019) to assess the proposed ELM.

### Accuracy Metrics

This work utilized the following forecast accuracy metrics (Saba et al., 2021; https://www.rdocumentation.org/packages/DescTools/versions/0.99.36/topics/Measures%20of%20Accuracy): Root-Mean-Square-Error (RMSE) and Mean-Absolute-Percentage-Error (MAPE). Several authors (Fan et al., 2010; Yadav & Nath, 2019) evaluated the model performance as follows: (a) high accuracy when MAPE $\leq$ 10, (b) good accuracy when 10 $\leq$ MAPE $\leq$ 20, (c) reasonable accuracy when 20 $\leq$ MAPE $\leq$ 50, and (d) inaccurate when MAPE $\geq$ 50.

This work computed the forecast accuracies (i.e., forecast-MAPE and forecast-RMSE) using the forecasts and test set. An in-sample prediction and training set is used to calculate in-sample RMSE.

### Experimental Setup

This paper employed the following packages of R (https://www.r-project.org/):

- Linear, SES, DES, TES, ETS, ARIMA, FFNN models: forecast package (Hyndman, Athanasopoulos, et al., 2022; Hyndman & Khandakar, 2008)

- MLP, ELM models: nnfor package (Kourentzes, 2019a)
- GRNN model: tsfgrnn package (Frias-Bustamante et al., 2022)
- Ensemble models: forecastHybrid package (Shaub & Ellis, 2020)
- Feature extraction: tsfeatures package (Hyndman, Kang, et al., 2022)

## RESULTS

### Features of the WPI

This work extracted the linearity, curvature, and auto-correlated lag features of each WPI. The researchers grouped the WPIs employing the extracted curvature and linearity features (Figure 3). Figure 3 reveals that the WPIs are heterogeneous based on the obtained linearity and curvature groupings.

### Optimized ELM for Each WPI

The current work developed the ELM model for each WPI using the proposed methodology for obtaining the optimized ELM, and Table 2 tabulates the optimized ELM architecture for each of them.

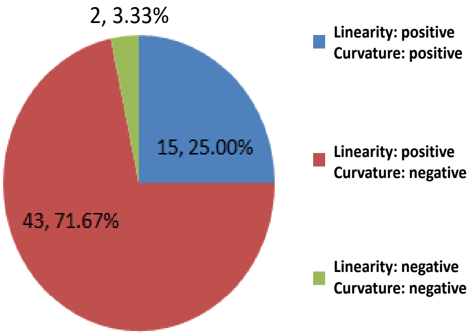


*Figure 3.* Grouping of the WPIs

Table 2
*Optimized ELM*

| Item Code | Item Name | Optimal Inputs | | | Optimized ELM |
|---|---|---|---|---|---|
| | | Auto-correlated lags ($x_i$) | Seasonal dummies ($ds_j$) | Input (X) | |
| WPI1 | 'Buffalo meat, fresh/frozen' | 21 | 11 | 32 | [32-100-1] * |
| WPI2 | 'Meat of goat, fresh or chilled' | 23 | 11 | 34 | [34-100-1] * |
| WPI3 | 'Other meats, preserved/ processed' | 31 | - | 31 | [31-100-1] $ |
| WPI4 | 'Chicken/duck, dressed - fresh/ frozen' | 22 | 11 | 33 | [33-100-1] * |
| WPI5 | 'Shrimps/Prawns - Processed/ Frozen' | 11 | - | 11 | [11-100-1] $ |
| WPI6 | 'Fish frozen/canned/processed' | 29 | 11 | 40 | [40-100-1] * |
| WPI7 | 'Fruit Juice including concentrates' | 12 | 11 | 23 | [23-100-1] * |

Table 2 *(Continue)*

| Item Code | Item Name | Optimal Inputs | | | Optimized ELM |
|---|---|---|---|---|---|
| | | Auto-correlated lags ($x_i$) | Seasonal dummies ($ds_j$) | Input (X) | |
| WPI8 | 'Fruit pulp' | 20 | - | 20 | [20-100-1] $ |
| WPI9 | 'Jams, jellies, marmalades and puree' | 35 | 11 | 46 | [46-100-1] * |
| WPI10 | 'Sauces of Vegetables (Tomato, Chilli, Soya & others)' | 16 | - | 16 | [16-100-1] $ |
| WPI11 | 'Vanaspati' | 29 | - | 29 | [29-100-1] $ |
| WPI12 | 'Mustard Oil' | 12 | 11 | 23 | [23-100-1] * |
| WPI13 | 'Soyabean Oil' | 14 | 11 | 25 | [25-1000-1] * |
| WPI14 | 'Sunflower Oil' | 12 | - | 12 | [12-400-1] $ |
| WPI15 | 'Groundnut Oil' | 11 | - | 11 | [11-900-1] $ |
| WPI16 | 'Castor Oil' | 23 | 11 | 34 | [34-100-1] * |
| WPI17 | 'Rice Bran Oil' | 31 | 11 | 42 | [42-100-1] * |
| WPI18 | 'Palm Oil' | 15 | - | 15 | [15-1000-1] $ |
| WPI19 | 'Rapeseed Oil' | 10 | 11 | 21 | [21-100-1] * |
| WPI20 | 'Copra oil' | 24 | 11 | 35 | [35-700-1] * |
| WPI21 | 'Cotton seed Oil' | 18 | - | 18 | [18-1000-1] $ |
| WPI22 | 'Condensed Milk' | 29 | 11 | 40 | [40-100-1] * |
| WPI23 | 'Ghee' | 35 | - | 35 | [35-200-1] $ |
| WPI24 | 'Butter' | 35 | 11 | 46 | [46-100-1] * |
| WPI25 | 'Ice cream' | 31 | - | 31 | [31-100-1] $ |
| WPI26 | 'Powder Milk' | 13 | 11 | 24 | [24-100-1] * |
| WPI27 | 'Maida' | 24 | 11 | 35 | [35-1200-1] * |
| WPI28 | 'Wheat flour (Atta)' | 30 | 11 | 41 | [41-100-1] * |
| WPI29 | 'Wheat Bran' | 29 | 11 | 40 | [40-700-1] * |
| WPI30 | 'Sooji (rawa)' | 26 | 11 | 37 | [37-100-1] * |
| WPI31 | 'Flour of cereals other than rice and wheat' | 26 | 11 | 37 | [37-100-1] * |
| WPI32 | 'Gram powder (besan)' | 15 | 11 | 26 | [26-900-1] * |
| WPI33 | 'Rice, Non-basmati' | 33 | 11 | 44 | [44-100-1] * |
| WPI34 | 'Basmati rice' | 14 | - | 14 | [14-100-1] $ |
| WPI35 | 'Rice products' | 27 | 11 | 38 | [38-700-1] * |
| WPI36 | 'Vegetable starch' | 12 | - | 12 | [12-100-1] $ |
| WPI37 | 'Biscuit, cookies' | 30 | - | 30 | [30-100-1] $ |
| WPI38 | 'Bread, buns & croissant' | 32 | - | 32 | [32-100-1] $ |
| WPI39 | 'Cakes, pastries & muffins' | 29 | 11 | 40 | [40-100-1] * |

Table 2 *(Continue)*

| Item Code | Item Name | Optimal Inputs | | | Optimized ELM |
|---|---|---|---|---|---|
| | | Auto-correlated lags ($x_i$) | Seasonal dummies ($ds_j$) | Input (X) | |
| WPI40 | 'Sugar' | 11 | - | 11 | [11-100-1] $ |
| WPI41 | 'Molasses' | 11 | 11 | 22 | [22-100-1] * |
| WPI42 | 'Bagasse' | 25 | - | 25 | [25-100-1] $ |
| WPI43 | 'Gur' | 15 | 11 | 26 | [26-600-1] * |
| WPI44 | 'Honey' | 26 | - | 26 | [26-100-1] $ |
| WPI45 | 'Chocolate & cocoa powder' | 28 | 11 | 39 | [39-500-1] * |
| WPI46 | 'Sugar confectionary' | 36 | - | 36 | [36-100-1] $ |
| WPI47 | 'Noodles & similar extruded products' | 31 | - | 31 | [31-100-1] $ |
| WPI48 | 'Processed Tea' | 27 | 11 | 38 | [38-1100-1] * |
| WPI49 | 'Instant Coffee' | 11 | 11 | 22 | [22-100-1] * |
| WPI50 | 'Coffee powder with chicory' | 31 | - | 31 | [31-100-1] $ |
| WPI51 | 'Spices (including mixed spices)' | 23 | 11 | 34 | [34-100-1] * |
| WPI52 | 'Salt' | 17 | - | 17 | [17-100-1] $ |
| WPI53 | 'Instant Food/Prepared meals based on vegetables' | 31 | - | 31 | [31-100-1] $ |
| WPI54 | 'Corn Flake' | 33 | 11 | 44 | [44-100-1] * |
| WPI55 | 'Whey powder' | 15 | - | 15 | [15-100-1] $ |
| WPI56 | 'Gola & similar Cattle Feed' | 23 | 11 | 34 | [34-700-1] * |
| WPI57 | 'Rice Bran Extract' | 25 | 11 | 36 | [36-100-1] * |
| WPI58 | 'Soya preparations excluding oil' | 13 | 11 | 24 | [24-100-1] * |
| WPI59 | 'Cotton seed oil cake' | 25 | 11 | 36 | [36-700-1] * |
| WPI60 | 'Mustard oil cake' | 14 | 11 | 25 | [25-100-1] * |

*Note.* * Input nodes of the optimized ELM are auto-correlated lags and seasonal dummies.
$Input nodes of the optimized ELM are auto-correlated lags

## Forecast Performance of the Proposed ELM

For forecasting the future values (forecast horizon of fifteen months) of each WPI, this work applied the optimized ELM obtained for each. The proposed ELM exhibited outstanding results, with nearly eighty-six-point-seven percent of cases, i.e., fifty-two out of sixty indices achieved high forecast accuracy. It attained good forecast accuracy for approximately eleven-point seven percent indices, i.e., seven out of sixty. Figure 4 exhibits the forecast performance of the proposed ELM.

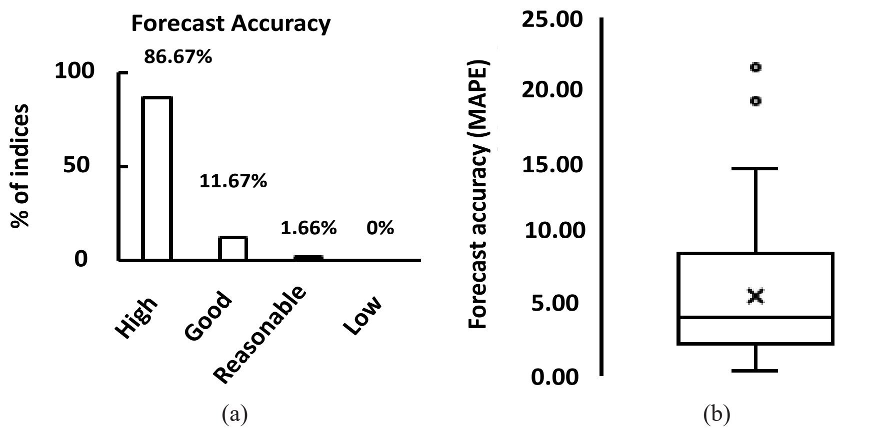


*Figure 4.* Forecast performance of the proposed ELM

Table 3 details the group-wise performance of the proposed ELM. The proposed ELM performed satisfactorily for group 1. It achieved high percentages of high accuracies for the WPIs with negative curvature.

Table 3
*Group-wise performance of the proposed ELM*

| Group No. | Group Description | WPI with MAPE ≤ 10 |
|---|---|---|
| 1 | Linearity: positive, Curvature: positive | 73.33% |
| 2 | Linearity: positive, Curvature: negative | 90.70% |
| 3 | Linearity: negative, Curvature: negative | 100.00% |

**Forecast Accuracy Comparison of the Proposed ELM with Others**

The current work applied six statistical, namely Auto-ARIMA, Auto-ETS, SES, DES, TES, and TSLM, and four neural approaches, namely Auto-FFNN, Auto-GRNN, Auto-MLP, and Auto-ELM, to make a forecast of fifteen months ahead of values for each of the sixty WPIs. This work counted the cases when each approach achieved high accuracy and compared the results. The proposed ELM topped the list with the highest count, i.e., nearly eighty-six-point seven percent high accuracy cases. Further, the work compared the proposed ELM's forecast-MAPE and forecast-RMSE with others and observed that the proposed ELM outperformed all in the maximum events. Figures 5, 6, and 7 demonstrate the determinations.

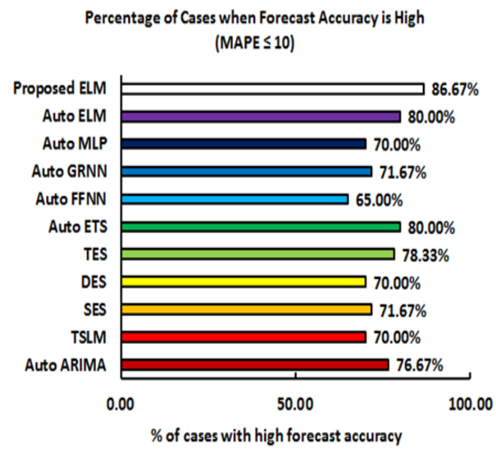


*Figure 5*. High accuracy: proposed ELM vs. others

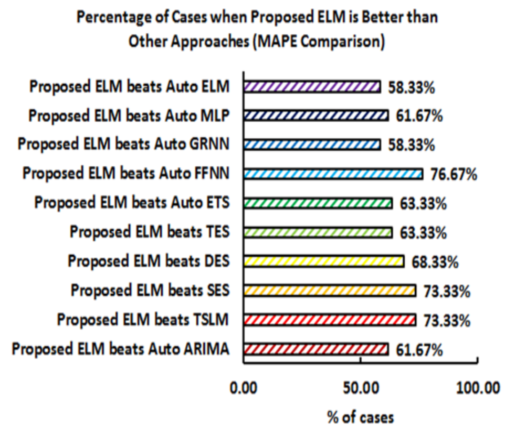


*Figure 6*. Forecast-MAPE comparison: proposed ELM vs. others

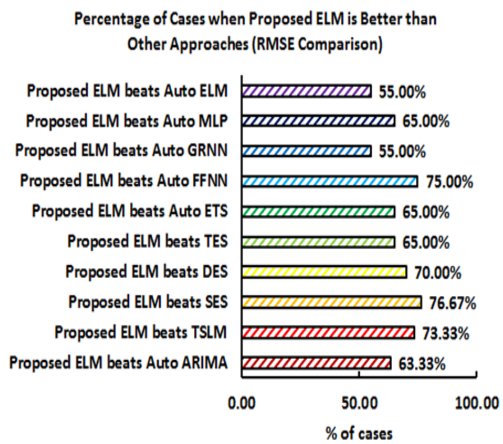


*Figure 7*. Forecast-RMSE comparison: proposed ELM vs. others

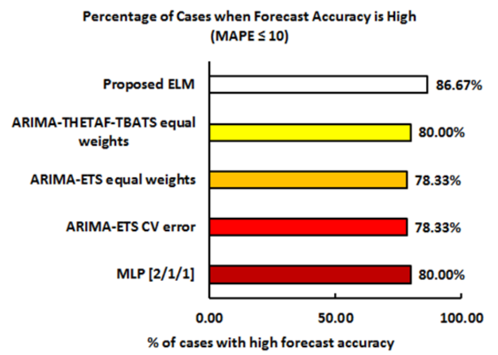


*Figure 8*. High forecast accuracy of proposed ELM, MLP, and ensemble approaches

The current work contrasted the proposed ELM with the following approaches and represents the findings in Figures 8 and 9:

- MLP [2/1/1] (Das & Chakrabarti, 2021)
- ARIMA-ETS equal weights (Perone, 2022)
- ARIMA-ETS CV error (Perone, 2022)
- ARIMA-THETAF-TBATS equal weights (Shaub, 2020)

The proposed ELM outperformed others as regards the counts of high accuracy and the number of cases when the proposed approach's accuracy is better.

Table 4 compares the proposed ELM with these models (i.e., an MLP and three ensemble models presented by others). The proposed ELM approach obtained lower maximum, mean, and median MAPE values than the others and surpassed them.

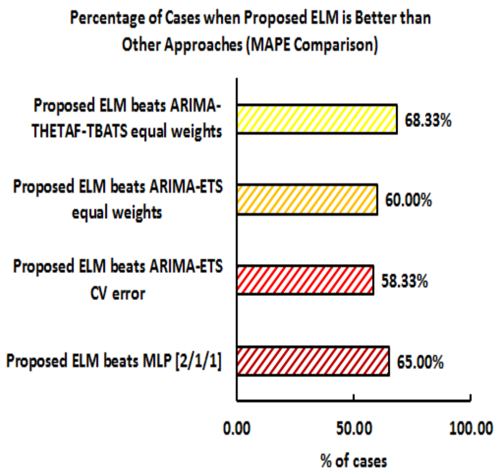


*Figure 9*. Forecast-MAPE comparison of proposed ELM with others

Further, to evaluate the proposed ELM's usefulness in forecasting the WPIs compared to the deep-learning approaches, this work analyzed the performance of the proposed ELM with the deep-learning models offered by other researchers (Brownlee, 2018; Staffini, 2022; Patel et al., 2018; Jia et al., 2019). This work employed the WPI data used in this paper for the purpose. Table 5 lists the findings. The proposed ELM's performance is better than others.

Table 4
*Comparison of the proposed ELM with others*

| Author | Model | Forecast horizon | Maximum MAPE | Mean MAPE | Median MAPE |
|---|---|---|---|---|---|
| Das and Chakrabarti (2021) | MLP [2/1/1] | | 22.26 | 6.51 | 4.36 |
| Perone (2022) | ARIMA-ETS equal weights | | 26.32 | 6.80 | 4.53 |
| Perone (2022) | ARIMA-ETS CV error | 15 months | 26.42 | 6.80 | 4.49 |
| Shaub (2020) | ARIMA-THETAF-TBATS equal weights | | 25.12 | 6.75 | 5.06 |
| Our work | Optimized ELM | | 21.46 | 5.63 | 4.12 |

Table 5
*Comparison of the proposed ELM with deep learning models*

| Author | Model | Forecast Horizon | Maximum MAPE | Mean MAPE | Median MAPE |
|---|---|---|---|---|---|
| Brownlee (2018) | LSTM | 15 months | 33.37 | 8.78 | 6.05 |

Table 5 *(Continue)*

| Author | Model | Forecast Horizon | Maximum MAPE | Mean MAPE | Median MAPE |
|---|---|---|---|---|---|
| Brownlee (2018) | Stacked LSTM | 15 months | 34.03 | 9.04 | 6.18 |
| | Bi-LSTM | | 33.89 | 8.63 | 5.96 |
| Staffini (2022) | Stacked LSTM | | 33.74 | 8.42 | 6.70 |
| Patel et al. (2018) | Stacked LSTM | | 34.69 | 8.77 | 6.25 |
| Jia et al. (2019) | LSTM | | 27.69 | 8.09 | 5.75 |
| | Bi-LSTM | | 33.97 | 8.24 | 5.91 |
| Our work | Optimized ELM | | 21.46 | 5.63 | 4.12 |

## DISCUSSION

This research employed the monthly WPI of sixty items from the Indian WPI's food-product category for one hundred thirty-five months, from April 2011 to June 2022, and divided the data into training (one hundred twenty months) and test (out-of-sample fifteen months) sets. For each WPI, this work applied the training set for feature extraction (linearity, curvature, and auto-correlated lags), developed the forecast models using the proposed ELM and twenty-one others, performed fifteen months of out-of-sample predictions operating the developed models, and utilized the test set to compute the forecast accuracies of the models. This paper grouped the WPIs using the extracted curvature and linearity features. Three groups categorized all the indices and revealed the heterogeneity of the WPIs. The positive linearity and negative curvature group contained the majority of WPIs. The proposed ELM exhibited high accuracy for the majority (nearly eighty-seven percent of the WPIs) and outperformed others. It outperformed others as regards the maximum number of cases with high accuracy (MAPE $\leq$ 10). The proposed ELM also exhibited better performance regarding forecast-MAPE and forecast-RMSE comparisons.

### Novelties

The following are the novelties of the current work:

- Feature extraction (linearity, curvature, and auto-correlated lags) of the WPIs of all sixty individual items from the food-product category of the WPI-series of India for one hundred twenty months (April 2011 to June 2022)
- Grouping of the WPIs based on the extracted curvature and linearity features

- Devising a novel ELM strategy for the WPIs that is straightforward, easy to use, and capable of delivering effective forecasting
    - A simple yet effective way of selecting the inputs and specifying optimum hidden neurons by hyper-parameter adjustment from its predefined search space to obtain an ELM model for each WPI.
    - The proposed ELM approach incorporates the following to enhance the performance of the models obtained from the ELM strategy offered by Kourentzes (2019a): using a bespoke procedure for selecting the inputs rather than automated ones; noise and trend removal of data; selection of the weight estimation type and combination operator from the offered sets; set the number of training networks; hyperparameter tuning using the custom-designed search space to obtain the optimized model for each WPI. The proposed ELM outperformed the automated ELM.
- This work compared the proposed ELM with twenty-one established and state-of-the-art techniques: six automatic time-series forecasting approaches, five ANNs, three ensemble methods presented by others, and seven deep-learning models of the other researchers. For the forecast horizon of fifteen months, the proposed ELM achieved high forecast accuracies in nearly eighty-seven percent of the items and outperformed all.
- To the extent of our knowledge, it marks the initial endeavor toward ELM model development to forecast the WPIs of sixty food items using these one hundred thirty-five months of data.
- Analyzing twenty-two diverse time series forecast approaches (the proposed ELM, six automatic time-series forecasting approaches, four automated ANNs, three ensemble methods presented by others, one MLP proposed by other researchers, and seven deep-learning models of the other authors) in furnishing fifteen months of out-of-sample forecasts of the WPIs.

## LIMITATIONS

This work applied the proposed ELM to the indices of sixty individual items from the food-product category of the Indian WPI series. This work obtained the optimum ELM by applying hyper-parameter tuning using its predefined search space. It employed other preset conditions, such as the weight estimation technique, the number of training networks, and combining operators, to develop the model. This paper has not experimented with the proposed approach using different model settings and on other univariate time-series data.

## CONCLUSION AND FUTURE WORK

This research focuses on the WPIs of all sixty individual items from the food-product category of the current Indian WPI. It aimed to analyze these WPIs and present a suitable forecasting strategy for these indices. The WPIs behaved heterogeneously per their extracted feature (i.e., curvature and linearity) based grouping. The grouping of WPIs revealed that these sixty WPIs have different trends and patterns, and their characteristics have varying natures. Therefore, this work exhibited that the design and performance of the proposed ELM approach are not confined to a particular type of univariate series but are suitable for a wide variety of time-series data. The Auto-ETS, a standard time-series forecast technique, performed best with eighty percent high accuracy cases. As per the number of high-accuracy cases, attaining the Auto-ELM, a neural approach is at par with it. Both exhibited high accuracy for a considerable quantity of WPIs. The offered ELM attained the maximum number of high-accuracy cases (nearly eighty-seven percent) among all the employed approaches. It also outshined others for the maximum number of indices concerning forecast-MAPE and forecast-RMSE comparisons. In conclusion, this research suggests that the proposed ELM is a well-suited prospect for providing effective forecasts of these sixty indices.

The future work includes attempting the proposed ELM on additional WPIs to test its pertinence. Endeavoring different combinations of model settings with an expanded hyper-parameter search space is another approach toward future research.

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