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A Comparative Analysis of Price Forecasting Models for Black Pepper

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SUMMARY

Black pepper being a perennial crop, the significant fluctuations in prices throughout the year pose a considerable challenge for both farmers and consumers. It is essential to understand the extent to which these price variations can be predicted in the near future to formulate pertinent policy recommendations. Consequently, the modelling and forecasting of time series data related to black pepper price hold paramount significance. Monthly price of garbled black pepper used for forecasting the price using Seasonal Autoregressive Moving Average model (SARIMA) and Time-delay Neural Network (TDNN) models. Comparison of models based on the accuracy measures, revealed **TDNN** as the best model for forecasting monthly price of black pepper.

Keywords: Garbled black pepper; SARIMA; TDNN; Forecasting.

1. INTRODUCTION

Forecasting the prices of agricultural commodities are useful for farmers, governments and agribusiness industries as they assist the policy makers, producers and consumers in taking appropriate decisions. Accurate prediction of agricultural commodity prices would facilitate the reduction of risk caused by price fluctuations (Gu *et al.*, 2022). Several forecast models for time series data are available in literature. Broadly, classified into traditional time series models comprising of linear and non-linear models; and those models developed using machine learning techniques.

Box-Jenkins have introduced Autoregressive Integrated Moving Average (ARIMA) model in times series forecasting and the model was popularized due to its statistical properties and methodology for model building. Price forecasting of agricultural commodities have been done for ages for various crops using traditional time series approaches. However, studies have found that in reality, machine learning techniques have a better predictive power in comparison to the models developed using time series approaches.

A multivariate, non-linear, non-parametric statistical technique that is driven by data and is self-adaptive is called an artificial neural network (ANN). Its advantage being its flexible functional form and it is a universal functional approximator (Zhang *et al.*,1998). In their study on sunflower and soybean price, (Mahato *et al.*2021) concluded that ANN is a better forecasting model for forecasting agriculture commodity price than the ARIMA model. (Paul *et al.* 2021) in their study of market arrival and price data of brinjal in seventeen major markets in Odisha, compared several forecasting models like ARIMA, Support Vector Regression (SVR), Gradient Boosting Machine (GBM), Random Forest (RF) and Generalized Regression Neural Network (GRNN). Their study concluded that GRNN model performed better than other models in majority of the markets studied. Sharma and Burark (2015) conducted an exhaustive comparison of ARIMA and ANN models in order to know the best model for forecasting moth bean. The various forms of ARIMA and ANN were employed to predict the future prices of moth bean in Churu market. Their study revealed that the ARIMA

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(0,1,2) model was the most suitable for forecasting the prices of moth bean.

Naveena (2016) conducted research focused on forecasting the price and export of Indian coffee using different time series models. Within the study, forecasting models, including Exponential Smoothing, ARIMA, GARCH and ANN were constructed for the analysis of both price and export trends. The assessment of the different forecasting models relied on measures such as RMSE and MAPE. Kumari *et al.* (2023) conducted a study to analyse and compare the efficiency of different traditional models like ARIMA, SARIMA, ARCH and GARCH to the deep artificial intelligence techniques like ANN and RNN in forecasting the prices of banana in Gujarat on the time series data from January 2009 to December 2019. Empirical result showed that RNN was the best fitted model among all other models of prediction due to less error accuracy measures.

Black pepper, the 'king of spices' is one of the most popular and widely consumed spices which shares a place on most dinner tables with salt. India is the third largest producer in the world (International Pepper Community, 2023), also a significant consumer and exporter of black pepper, with Kerala and Karnataka producing the majority of the nation's output. Among the states in India, Kerala is ranked second in terms of black pepper acreage (76,160 ha), and production (33290 metric tonnes) but seventh in terms of productivity (0.44 metric tonnes/ha) (GOI, 2023). Historically, the market value of pepper contributed to the development of the city of Kochi as a centre of international commerce. Kochi has the first exclusive pepper exchange in India which was established by the Indian Pepper and Spice Traders Association, IPSTA and the exchange was well regulated by the traditional players here, without any default on supply or delivery of the commodity.

Further, the crop being perennial in nature and the large variation in its price within a year is a major problem faced by farmers as well as consumers. Thus, it is crucial to comprehend the extent to which its price fluctuations can be projected for the foreseeable future in order to draw appropriate policy conclusions. Hence, analysis of time series data of prices of black pepper is of prime importance.

2. MATERIALS AND METHODS

2.1 Source of data

In this study, time series data on monthly average prices of garbled black pepper (252 data points) at Kochi market from January 2000 to December 2020, collected from Spices Board, Kochi was used for evaluating and comparing forecast performance of different individual models. All model building and forecasting have been done by using R software. Unit root tests are statistical procedures used to assess stationarity of time series. Augmented

Dickey Fuller test have been used to test the stationarity of time series.

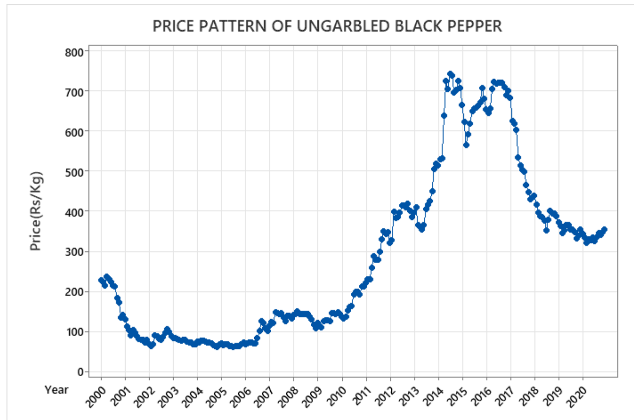

Fig. 1. Price pattern of monthly price of garbled black pepper

Diagnostic test

Augmented Dickey Fuller (ADF) testis the unit root test that is most frequently utilized. ADF test consists of estimating the following regression equation:

$$Y_t' = \phi Y_{t-1} + b_1 Y_{t-1}' + b_2 Y_{t-1}' + \cdots + b_p Y_{t-1}'$$

where, $Y_t' = (Y_t - Y_{t-1})$; where Y_t is the value of the series at time 't' and Y_{t-1} is the value of the series at lag one.

The value of ϕ is estimated from the above regression equation using method of least squares and tested for deviation from unity: $H_0 : \phi = 1$

$$H_1 : \phi < 1$$

$$t_{\phi=1} = \frac{\hat{\phi} - 1}{\mathrm{SE}(\hat{\phi})}$$

where, $\hat{\phi}$ is the least square estimate of ϕ .

If $\hat{\phi}$ is negative and significant, the time series is considered stationary, if $\phi=1$, time series is non-stationary.

2.2 Forecasting Models

2.2.1 Seasonal Autoregressive Integrated Moving Average model (SARIMA)

The SARIMA model is a versatile time series forecasting approach that integrates non-seasonal and seasonal components. Represented as SARIMA (p, d, q) x (P, D, Q)$_S$, the model encompasses non-seasonal autoregressive (AR), differencing (I), and moving average (MA) parameters, along with their seasonal counterparts. The non-seasonal elements (p, d, q) capture patterns over time, while the seasonal elements (P, D, Q) with a seasonality 's' account for recurring seasonal patterns. This multiplicative model provides a comprehensive framework for analysing and forecasting time series data, allowing for an understanding of both short-term and long-term trends.

In the model identification stage of an ARIMA model fitting, the order of the seasonal (p,q) and non-seasonal parameters (P,Q) are determined by using the autocorrelation and partial autocorrelation function plots. One or more models that provide statistically adequate representation of the time series data are identified at this stage.

The subsequent efforts involve determining precise parameter estimates through the least squares method, following the guidelines provided by Box and Jenkins. These parameters are derived using maximum likelihood, which is asymptotically accurate for time series analysis. Estimates generated by the model are typically satisfactory, effective, and reliable when assuming a Gaussian distribution, demonstrating sufficiency and efficiency. Moreover, these estimates approach normality and efficiency in an asymptotic manner when applied to various non-Gaussian distribution families.

The seasonal components of the SARIMA (Seasonal Autoregressive Integrated Moving Average) model consist of autoregressive (AR) and moving average (MA) expressions, represented as Φ(Bs) and Θ(Bs), respectively, with Bs indicating the seasonal lag. The non-seasonal components are similarly expressed through $\varphi(B)$ and $\theta(B)$. Seasonal differencing, is defined as the difference between value of the series at the current time period (y_t) and its lagged value 's' time periods prior i.e. for monthly data, seasonal differencing is given by $(1-B_{12)})y_t = y_t - y_{t-12}$. This process aims to create a stationary series, making the differences approximately uniform across each month and effectively removing both seasonal trends and non-stationary seasonal random walks. If a trend exists in the data, non-seasonal differencing is also necessary, often achieved through a first non-seasonal difference of the data. The mathematical formulation of the $SARIMA(p,d,q)(P,D,Q)_s$ model in terms of lag polynomials is presented as,

$$\left(1-\sum_{i=1}^{p}\boldsymbol{\varphi}_i\boldsymbol{B}^i\right)\left(1-\sum_{i=1}^{p}\boldsymbol{\varphi}_i\boldsymbol{B}^{is}\right)(1-\boldsymbol{B})^d\left(1-\boldsymbol{B}^s\right)^D\ \boldsymbol{Y}_t$$
$$=\left(1-\sum\nolimits_{j=1}^{q}\boldsymbol{\theta}_j\boldsymbol{B}^{js}\right)\left(1-\sum\nolimits_{j=1}^{Q}\boldsymbol{\Theta}_j\boldsymbol{B}^s\right)\boldsymbol{\varepsilon}_t$$

2.3.2. Time-delayed Neural Network Model (TDNN)

The primary drawback of linear models like ARIMA is their inability to capture the non-linear aspects inherent in time series data, with their effectiveness limited by the constraints imposed by residuals in the case of non-linear time series patterns. In situations where non-linearity is a significant factor, studies have shown that machine learning techniques can offer a more suitable approach. TDNN present an effective alternative for forecasting non-linear time series data, as demonstrated by Zhang *et al.* in 1998. The term "Neural Network" is derived from their capacity to emulate the functioning of the human brain's central nervous system. Machine learning techniques are characterized by their non-linear, nonparametric, and data-driven nature, that provides a more flexible and adaptive framework for capturing complex patterns in time series data.

The architecture of Time Delay Neural Networks (TDNN) includes an input layer for external data, one or more hidden layers introducing non-linearity to the model, and an output layer delivering the desired outcome. TDNN's capability to effectively model non-linear systems, coupled with its elevated forecasting accuracy, has substantially enhanced its attractiveness for time series forecasting applications. A single hidden layer neural network has the capacity to approximate any non-linear function, provided an adequate number of hidden nodes and a sufficient amount of training data points (Jha and Sinha, 2013).

An example of such an architectural design is a Time-Delay Neural Network (TDNN), which is employed in the present research. The incorporation of time delays in neural networks is inspired by neurobiology, as single delays are widely observed in the brain and hold significance in the neurobiological processing of information. In TDNN, the activation function for node *i* at time *t* can be expressed as follows:

$$y_t = (t) = f\left(\sum_{j-1}^{q}\sum_{d-0}^{p} w_{ij}(t-d)\, y_j(t-d)\right)$$

where $y_i(t)$ the output node *i* at time *t*, $w_{ij}(t)$ is the connection weight between node *i* and *j* at time t, *p* is the number of tapped delays, *q* is the number of nodes connected to node *i* from preceding layer, d denotes the time delays and *f* is the activation function, typically the logistic sigmoid**.**

For this study, we specifically focus on the scenario where tapped time delays are present only in the input layer. The TDNN configurations with a single hidden layer can be denoted as I:Hs: Ol, where I is the number of nodes in the input layer, H is the number of nodes in the hidden layer, O is the number of nodes in the output layer, s represents the logistic sigmoid transfer function and l indicates the linear transfer function. Fig. 2 provides a visual representation of a time delay neural network (TDNN).

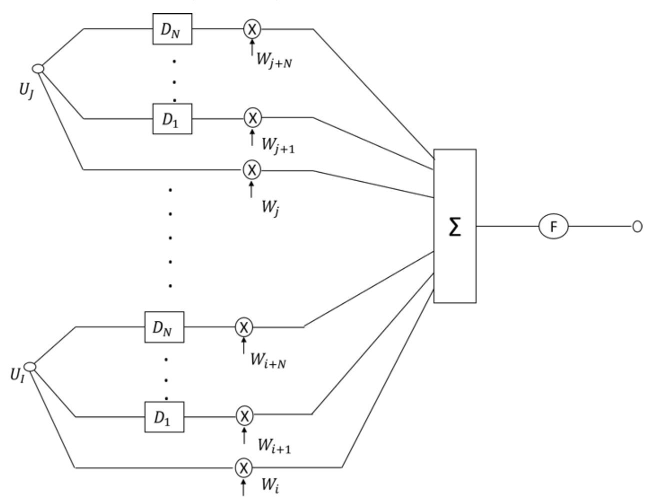

Fig. 2. Architecture of TDNN model

Constructing a TDNN model typically involves the use of training and test samples. The training sample is employed in the development of the TDNN model, while the test sample is utilized to assess the forecasting capabilities of the model. In some cases, a third sample, known as the validation sample, is incorporated to mitigate over fitting issues or determine the stopping point of the training process. It is not uncommon to use a single test set for both validation and testing, especially when dealing with small datasets.

In this study, 80% of the monthly prices of black pepper (data) is used as training set and rest 20% is used as the testing set. The price of years 2021 and 2022 are used for the validation purposes. An accurate TDNN model is developed using 'nnetar' package in R software.

2.3.3 Forecasting

Forecasting is the process of projecting the future values of times series using the fitted model. Accuracy and validity are closely intertwined, although they operate in distinct directions. While results may be valid, they may not necessarily be accurate, as highlighted by Markidakis and Hibbon in 1979. Conversely, an accurate forecast may lack validity. Therefore, accuracy serves as a metric for assessing the appropriateness of the forecast. In the current investigation, the evaluation of models was conducted based on the accuracy of forecasts, and this assessment was subjected to various tests.

2.3.3.1 Forecast Accuracy Measures

The best suitable model among SARIMA and TDNN models are evaluated using lowest MAPE and RMSE values, the forecast accuracy indicators (Prathima, 2018).

MAPE is given by,

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|Y_t - \widehat{Y}_t\right|}{Y_t} * 100$$

where,

Y_t – Actual price at time t

$\widehat{Y}_t$ – Fitted price

n – Number of observations

Root Mean Square Error(RMSE) is given by,

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_t^2}$$

Where,

$e_t = Y_t - \widehat{Y}_t$, e_t is the difference between actual and fitted price

n = Number of observations

4. RESULTS AND DISCUSSION

The descriptive statistics of the dataset have been given in Table 1. Initially, time series data were stationary and first differencing has been applied to make them stationary. Table 2 given below shows that the tests for stationarity of data give significant results for the first differenced level of the garbled black pepper price series used. The datasets underwent decomposition to assess their seasonality, with the Decompose () function of 'stats' package and the stl() function of forecast package in R software being employed for this purpose. The results from these functions confirmed that the datasets exhibit a seasonal nature.

Table 1. Descriptive Statistics of monthly price series of Garbled Black Pepper (2000- 2020)

Statistics	Kochi market
Observations	252
Mean (Rs.)	284.10
Median (Rs.)	214.17
Standard Deviation (Rs.)	13.19
Maximum (Rs.)	742.48
Minimum (Rs.)	60.9
Skewness	0.75
Kurtosis	-0.63

Table 2. Stationarity test for monthly price of garbled black pepper

Garbled Black pepper price	ADF test statistic	Probability(p)	Critical values
Actual	-1.4491	0.8078	0.869
First difference	-9.9902*	0.01	-2.32

* Indicates significant at 5% level ($p<0.05$)

Next, the Brock, Dechert, and Scheinkman (BDS) test was conducted to determine whether the data exhibits non-linearity. This test compares the distribution of nearest neighbour distances in the original data with those in surrogate datasets that assume linear behaviour, allowing for the identification of nonlinearity in time series data. Significant differences between these distributions indicate the presence of nonlinearity. The results presented in Table 3 reject the hypothesis of linearity for all the price series analysed.

Table 3. Brock Dechert Scheinkam Test

	Embedding Dimension= 2		Embedding Dimension=3	
Epsilon	Statistic	p-value	Statistic	p-value
104.71	81.43	0.04	135.41	0.02
209.40	70.00	<0.01	91.96	0.04
314.14	44.52	0.03	47.28	<0.01
418.86	39.68	<0.01	39.09	<0.01

Post determining the nature of the price series, the training data set was used for fitting the ARIMA and TDNN models in this study.

Test for seasonality

To assess the seasonal variation in data, Kruskal-Wallis Seasonality test was applied. The test statistics value is 19.28 which corresponds to p-value of 0.03 indicating that there is seasonality in the data.

SARIMA Model

Fitting SARIMA Model in R to the price series gave SARIMA$(2,1,2)(3,0,2)_{12}$ as fit to the Kochi market. This model was selected based on the value of MAPE, AIC and RMSE values which is provided in Table 4.

Table 4. SARIMA$(p,d,q)(P,D,Q)_{12}$ model

Selected model	MAPE	AIC	RMSE
SARIMA$(2,1,2)(3,0,2)_{12}$	4.71	2153.46	16.79

The SARIMA $(2,1,2)(3,0,2)_{12}$ model equation is as follows:

$$(1 - 0.503B^2)\ (1\text{-}B)\ (1 + 1.452B^{12} + 0.575B^{24} + 0.165B^{24})\ y_t = (1 - 0.606B^2)\ (1 - 1.538^{12} - 0.828B^{24})\epsilon_t$$

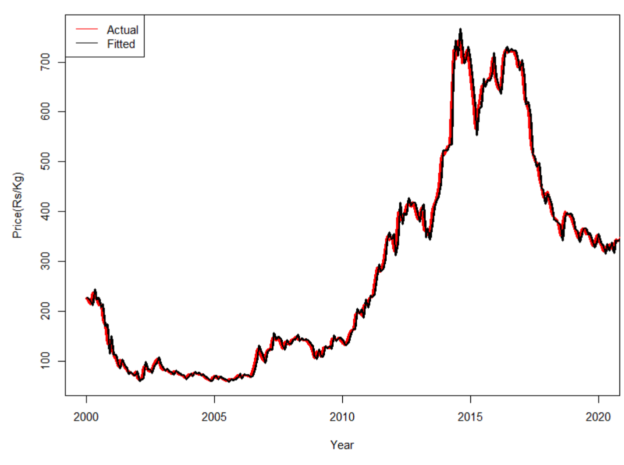

Fig. 3. Actual and fitted values of SARIMA$(2,1,2)\ (3,0,2)_{12}$ for monthly price of garbled black pepper

The plot of actual and fit values for monthly price of garbled black pepperat Kochi market using SARIMA(2,1,2)(3,0,2)$_{12}$ model is given in Fig. 3.

The adequacy of the model was also evaluated using the value of Ljung-Box 'Q' statistic is provided in Table 5 and it was found to be non-significant. So, we can conclude that the SARIMA (2,1,2)(3,0,2)$_{12}$model shows satisfactory result, among different ARIMA models tried.

Table 5. Ljung-Box 'Q' statistic for residuals of SARIMA (2,1,2)(3,0,2)$_{12}$

Statistic	p-value
20.894	0.1403^{NS}

NS: Non-significant

Residual ACF and PACF plots for the fitted SARIMA (2,1,2)(3,0,2)12 model was plotted and it was noticed that majority of the spikes in the ACF and PACF plots fall within the critical values, thus indicating the adequacy of SARIMA (2,1,2)(3,0,2)12 model for forecasting monthly price of garbled black pepper.

In the next step, the Brock, Dechert and Scheinkman (BDS) test was performed to check whether the data are non-linear or not. The BDS test compares the distribution of closest neighbour distances in the original data to those of surrogate data sets reflecting linear behaviour to look for nonlinearity in time series data. There are significant discrepancies between these distributions, which suggests nonlinearity. The results, given in table 4, reject the assumption of linearity for all the price series under study.

TDNN model

Time delayed neural network (TDNN) model was fitted for monthly garbled black pepper price at Kochi market. The best time lagged neural network with single hidden layer was found for each series by conducting experiments with the basic cross validation method. Table 5 summarizes the forecasting performance of various TDNN models for monthly garbled pepper in terms of RMSE and MAPE. Out of a total of 36 neural network structures, a neural network model with six lagged observations as input nodes and two hidden nodes (6:2s:1l) performed better than other competing models in respect of forecasting accuracy measures. This means that most accurate price forecast for the given series is obtained when the price of six preceding months is used as inputs. The selected TDNN model is shown in Table 5 along with the forecasting accuracy measures

Table 6. Model accuracy measures by TDNN model

Model	No. of parameters	MAPE		RMSE	
		Train	Test	Train	Test
6:2s:11	17	5.68	4.29	15.85	13.92

The actual monthly price along with the predicted monthly price of garbled black pepper using TDNN model is provided in Fig. 4.

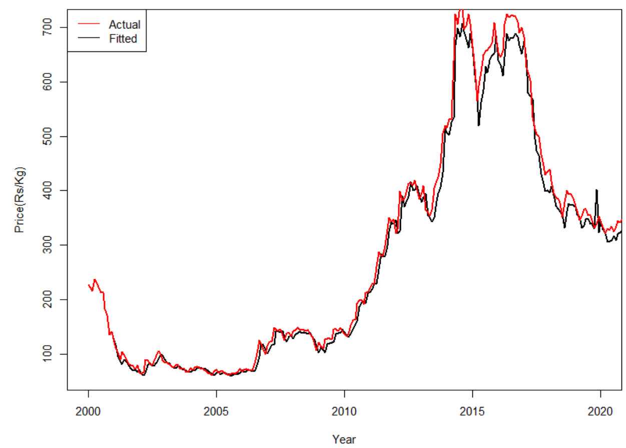

Fig. 4. Actual and fitted plot of TDNN model for monthly price of garbled black pepper

Comparison of models

In the present study, a comparison of different models has been done in order to know the best model for forecasting monthly price of garbled black pepper in Kochi market. According to the Table 7, the TDNN model with least test MAPE and RMSE values was considered to be best among all the models considered.

For checking the predictive accuracy of the fitted models Diebold-Mariano (DM) test is performed and the test results indicate the superiority of TDNN model over ARIMA model in terms of predictive accuracy as the DM statistic was .0045 < 0.05 showing significant difference between the two forecast.

Table 7. Comparison of time series forecasting models

Model	MAPE	RMSE
SARIMA(2,1,2)(3,0,2)$_{12}$	4.71	16.19
TDNN(6:2s:1l)	**4.29**	**13.92**

Monthly price for 2021 and 2022 was predicted using the models fitted and it showed that the price exhibited an increasing trend with MAPE of 4.19 and 4.86 respectively. Forecast based on TDNN model were in more agreement with the actual price for next two years, which is shown in Fig. 5.

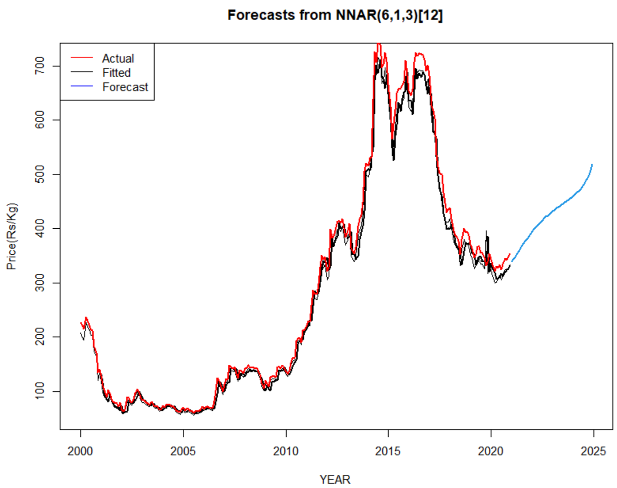

Fig. 5. Actual, predicted and forecasted plot from TDNN model of monthly price of garbled black pepper

3. CONCLUSION

The present study was undertaken to evaluate different time series models for prices of black pepper and to suggest suitable forecast models for Kochi market. Analysis of price pattern revealed that wide fluctuation exists in the prices of black pepper in Kochi market which is shown in Fig. 1. SARIMA $(2,1,2)(3,0,2)_{12}$ was obtained as the best suitable model for monthly price of garbled black pepper in Kochi market. Comparison of SARIMA with TDNN model revealed that TDNN (6:2s:1l) was more appropriate than SARIMA model to forecast prices as per the accuracy measures obtained. The analysis suggested that the TDNN model proves to be a reliable forecasting tool for predicting prices of black pepper in the Kochi market. The robustness of the TDNN model offers a plethora of opportunities for understanding the future price pattern of black pepper which enables, various stakeholders such as producers and traders to adapt with the price fluctuations and for policymakers to ensure market stability. The reliability of TDNN model in forecasting black pepper prices not only enhances market transparency but also attracts investors, fostering overall market efficiency in India.

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