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Hybrid Time Series Models for Forecasting Banana Production in Karnataka State, India

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SUMMARY

Autoregressive integrated moving average (ARIMA) technique has been widely used for forecasting in divergent domains for several decades. One of the main drawbacks of this model is the presumption of linearity. As many time series phenomenon in real word are nonlinear hence, it is required to enhance the prediction ability of ARIMA models by amalgamating it with other nonlinear models. One of the sound techniques to achieve this goal is to combine linear and nonlinear time series models so that forecasting efficacy of the models can be improved. In the present research paper, an attempt is made to combine the ARIMA model with Time delay neural network (TDNN) and also with nonlinear support vector regression (NLSVR) model. As a case study, banana production in Karnataka has been considered to evaluate the forecasting performance of the hybrid models under study. Empirical results clearly reveal that the forecasting accuracy of the hybrid models are better as compared to the ARIMA model.

Keywords: Banana production, ARIMA, TDNN, NLSVR, Hybrid methodology.

1. INTRODUCTION

Fruit crops play a significant role in the economic development, nutritional security, employment generation and overall growth of a country. Among the major fruit crops, banana (*Musa sp.*) is one of the important tropical fruit crop and plays a key role in the economy of many developing countries like India. Banana is world's fourth most important food commodity after rice, wheat and maize. As a staple food, banana contribute to the food security of millions of people in majority of the developing countries and when traded in local markets it provides income and employment to the rural population. It is a good source of vitamin A, B and C. The optimum temperature suitable for banana ranges between 25-30^{o}C. Almost all the agricultural soils are suitable, provided they are deep well drained. Black loams and sandy loam uplands soils or deep and well drained soils are most suited soils for this crop. Average yields of its dwarf and tall varieties are 300-400 quintals per ha and 150-200 quintals per ha respectively (Hand Book of Horticulture 2011)**.** India leads the world in banana production which accounts to about 39.8 % among all other fruit crops by occupying about 8.30 lakh hectares of area and 29.78 million tonnes of production. Karnataka occupies 1.12 lakh hectares of area and production of 2.28 million tonnes in Karnataka (NHB 2013-14).

Forecasting is used to provide an aid to decision-making and in planning for the future effectively and efficiently. It is important aspect for a developing economy so that adequate planning is undertaken for sustainable growth, overall development and poverty alleviation. Statistical forecasting models are used to develop an appropriate forecast methodology by using the past data to predict the future with the help of identifying the trends and patterns within the data. In other words, Statistical forecasting is the likelihood estimation of an event taking place the future based on available data.

One of the most important and widely used time series models is the autoregressive integrated

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moving average (ARIMA) model. The popularity of the ARIMA model is due to its statistical properties as well as the well-known Box–Jenkins methodology (Box and Jenkins 1970) in the model building process. Sarika *et al.* (2011) used, ARIMA model for modeling and forecasting India's pigeon-pea production. Suresh *et al.* (2011) applied this model for forecasting sugarcane area, production and productivity in Tamil Nadu state of India. Kumari *et al.* (2014c) applied ARIMA model for prediction of rice yield of India. Naveena *et al.* (2014) forecasted coconut production of India using ARIMA methodology.

The major drawback of ARIMA model is presumption of linearity, hence, no nonlinear patterns can be recognized by ARIMA model. Sometimes, the time series often contain both linear and nonlinear components, under such condition neither ARIMA nor artificial neural network (ANN) and nonlinear support vector regression (NLSVR) are adequate in modeling and forecasting. To overcome this difficulty, hybrid methods were evolved. It has been observed that hybrid methods (Zhang 2003, Jha and Sinha 2014, Chen and Wang 2007, Kumar and Prajneshu 2015, Ray *et al.* 2016) are effective and more efficient ways to improve forecast ability of the model.

The major advantage of time delay neural network (TDNN) is their flexible nonlinear modeling capability and no need to specify a particular model form. Rather, the model is adaptively formed based on the data pattern (Kumari *et al.* 2013, 2014a, 2014b, Mishra and Singh 2013). By introducing the ε-insensitive error loss function, support vector machine (SVM) which was initially proposed for classification problems, has been successfully extended to regression problems by Vapnik *et al.* (1997), and it is called as Support Vector Regression (SVR). Sreelakhmi and Ramakanth Kumar (2008), developed an nonlinear SVR model for predicting short term wind speed using weather parameters. Many findings in literature shows that by employing SVR in hybrid methodology, one can improve the prediction accuracy of univariate models (Kumar and Prajneshu 2015, Alonso *et al.* 2013, Chen and Wang 2007).

With these backgrounds, efforts have been made to develop the hybrid models by combining ARIMA-TDNN and ARIMA-NLSVR for forecasting banana production in Karnataka. The remaining part of the paper is organized as follows. In the next section, the data description and detailed description of the models used are described. The hybrid methodology is explained in section 3. Results and discussion is reported in section 4 and finally the concluding remarks are given in section 5.

2. MATERIAL AND METHODS

Yearly data on production (000' MT) of banana crop from 1954-55 to 2014-15 of Karnataka state were collected from National Horticulture Board (NHB) data base and www.indiastat.com . The data from 1954-55 to 2011-12 were used for model building and 2012-13 to 2014-15 were used to check the forecasting performance of the models.

The statistical softwares viz., SAS and R were used for modeling and forecasting banana production time series of Karnataka. SAS v.9.4 software available at ICAR-Indian Agricultural Statistics Research Institute, New Delhi, were used to build the suitable ARIMA model. R v.3.3 software, package 'f Nonlinear' was used to test the nonlinearity test for residuals obtained from ARIMA models using BDS test. Package 'Forecast' was used for modeling and forecasting using TDNN. Package 'e1071' was used for modeling and forecasting using NLSVR.

2.1 ARIMA Model Building

Generally a ARIMA model (Box and Jenkins 1970), denoted as ARIMA (*p,d,q*), is expressed as follows

$$\phi(B)(1-B)^d y_t = \theta(B)\varepsilon_t \tag{1}$$

where,

$$\phi(B) = 1-\phi_1 B-\phi_2 B^2-\cdots-\phi_p B^p \tag{2}$$

(Autoregressive parameter)

$$\theta(B) = 1-\theta_1 B-\theta_2 B^2-\cdots-\theta_p B^q \tag{3}$$

(Moving average parameter)

ε_t = white noise or error term

d = differencing term

B = Backshift operator i.e. $B^a Y_t = Y_{t-a}$

The ARIMA model building consists of three stages, *viz*. identification, estimation and diagnostic checking. Parameters of this model are experimentally selected at the identification stage. Identification of d is necessary to make a non-stationary time series to stationary. A statistical test can by employed to check the existence of stationarity, known as the test of the unit-root hypothesis. Popularly Augmented Dickey Fuller (ADF) test is utilized to test the stationarity. At the estimation stage, the parameters are estimated by employing iterative least square or maximum likelihood techniques. The efficacy of the selected model is then tested by diagnostic checking stage by employing Ljung-Box test. If the model is found to be insufficient, the three stages are repeated until satisfactory ARIMA model is selected for the time-series under consideration.

2.2 Time Delay Neural Network (TDNN)

Artificial neural networks (ANNs) are nonlinear model that are able to capture various nonlinear structures present in the data set. ANN model specification does not require prior assumption of the data generating process, instead it is largely depend on characteristics of the data. Single hidden layer feed forward network is the most popular for time series modeling and forecasting. A key feature for TDNN is the ability to express the relation between inputs over a period of time. In time series analysis, the determination of number of input nodes which are lagged observations of the same variable is very crucial as it plays important role in modeling autocorrelation structure of the data. Input layer plays a crucial role as it helps in modelling the autocorrelation structure of the data. Determination of output layer is relatively easy as we require one output most of the time and we predict future time series using multistep ahead forecast as followed in Box-Jenkins ARIMA methodology. The general expression for the final output y_t in a multi-layer feed forward time delay neural network is expressed in the following equation.

$$y_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j \, g\left(\beta_{0j} + \sum_{i=1}^{p} \beta_{ij} y_{t-p}\right) + \varepsilon_t \quad (4)$$

where, α_j $(j = 0,1,2,\ldots,q)$ and β_{ij} $(i = 0,1,2,\ldots,p,$ $j = 0,1,2,\ldots,q)$ are the model parameters often called the connection weights, p is the number of input nodes and q is the number of hidden nodes. Activation function defines the relationship between inputs and outputs of a network in terms of degree of the non-linearity. Most commonly used activation function is logistic function which is often used as the hidden layer transfer function, i.e.

$$g(x) = \frac{1}{1+\exp(-y)} \quad (5)$$

Thus TDNN model performs a nonlinear functional mapping between the input and output which characterized by a network of three layers of simple processing units connected by acyclic links

$$y_t = f\left(y_{t-1} + Xy_{t-2}, \ldots, y_{t-p}, w\right) + \varepsilon_t \quad (6)$$

where, w is a vector of all parameters and f *is* a function of network structure and connection weights. Therefore, the time delay neural network resembles a nonlinear autoregressive model. Expression (6) indicates one output node in the output layer which is commonly used as one-step-ahead forecasting in out of sample forecast.

In case of time delay neural network, the network forms larger d-dimensional space as compare to dynamic feed forward artificial neural network because, here we consider many input lags and many nodes in hidden layer also. Therefore, it helps the network to train the input training data set in more optimized manner. Graphically, the TDNN model can be expressed in Fig.1. In this study, we used neural network with one hidden layer as it is capable of producing a better modeling performance (Zhang 2003). Though, there are no established theories available for the selection of p and q, various training algorithms have been used for the determination of the optimal values of p and q.

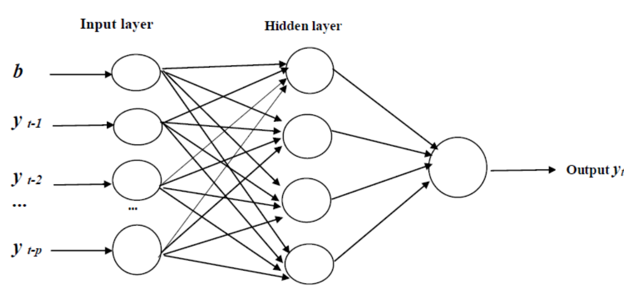

Fig. 1. Time delay neural network

The objective of training is to minimize the error function that measures the misfit between the predicted value and the actual value. The error function which is widely used is mean squared error which can be written as

$$E = \frac{1}{N}\sum_{t=1}^{N}(e_t)^2$$

$$= \frac{1}{N}\sum_{t=1}^{N}\left\{y_t - \left(w_0 + \left(\sum_{j=1}^{Q} w_j \, g\left(w_{oj} + \sum_{i=1}^{p} w_{ij}\, y_{t-i}\right)\right)\right)\right\}^2 \quad (7)$$

where N is the total number of error terms. The parameters of the neural network w_{ij} are changed by an amount of changes in Δw_{ij} as

$$\Delta w_j = -\eta \frac{\partial E}{\partial w_j} + \delta \Delta W_j(t-1) \tag{8}$$

where, η is the learning rate, $\frac{\partial E}{\partial w_{ij}}$ is the partial derivative of function E with respect to weight w_j and δ is the momentum rate. $\frac{\partial E}{\partial w_{ij}}$ can be written as follows

$$\frac{\partial E}{\partial w_j} = e_j(n) * f'(x) * y_j(n) \tag{9}$$

where $e_j(n)$ is the n^{th} iteration residual and $f'(x)$ is derivative of activation function in output layer. In TDNN the activation function in output layer is identity as $f'(x) = 1. y_j(n)$ is desired output. Hence, the connection weights from input nodes to hidden nodes are changed by an amount ΔW_j. Therefore ΔW_{ij} becomes

$$\Delta W_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} + \delta \Delta W_j(t-1) \tag{10}$$

where

$$\frac{\partial E}{\partial w_{ij}} = g'(x) * e_j(n) * w_j(n) \tag{11}$$

where

$g'(x)$ is first derivative of activation function in hidden layer

$$g'(x) = \frac{\exp(-x)}{(1-\exp(-x))^2} \tag{12}$$

Finally, the learning rate and momentum term are user defined parameters known as tuning parameters of network. The learning rate is set to be smaller amount to avoid divergence. Though, there are no set rules for constant learning rates and momentum term, typically which are lies between 0 and 1. Generally learning rate and momentum terms are defined in such a way that the error of the network is very low. After generation of final weights by above discussed procedure the final output is obtained by equation 4.

2.3 Nonlinear Support Vector Regression (NLSVR) Model

Support vector machine (SVM) was originally developed for classification problems. With the introduction of Vapnik's ε-insensitive loss function, it has been extended to the domain of nonlinear regression estimation problems, and is called as Nonlinear Support Vector Regression (NLSVR). The basic idea of NLSVR is to transform the original input space into a high dimensional feature space and then construct linear regression in the new feature space, which corresponds to nonlinear regression in the original dimensional input space. Consider a vector of data set $Z = \{x_i\, y_i\}_{i=1}^{N}$ where $x_i \in R^n$ which contains both is the vector of input and $x_i \in R$ is the scalar output and N is the size of data set. The general expression of NLSVR estimation function is expressed as follows

$$f(x) = W^T \phi(x) + b \tag{13}$$

where $\phi(.)$: $Rn \rightarrow R^{nh}$ is a nonlinear mapping function from original input space into a higher dimensional feature space, which can be infinite dimensional, $w \in R^{nh}$ is weight vector, b is bias term and superscript T denotes the transpose. The coefficients W and b are estimated from data by minimizing the following regularized risk function:

$$R(\theta) = \frac{1}{2}\|w\|^2 + C\left[\frac{1}{N}\sum_{i=1}^{N} L_\varepsilon\big(y_i, f(x_i)\big)\right] \tag{14}$$

The equation (14) contains two components, one is regularized term i.e. $\frac{1}{2}\|w\|^2$ and another term is $\frac{1}{N}\sum_{i=1}^{N} L_\varepsilon\big(y_i, f(x_i)\big)$ called as empirical error term, which is estimated by using Vapnikε-insensitive loss function which is function given by

$$L_\varepsilon(y_i, f(x_i)) = f(x) = \begin{cases} |y_i, f(x_i) - \varepsilon|; & |y_i - f(x_i)| \geq \varepsilon, \\ 0 & |y_i - f(x_i)| < \varepsilon, \end{cases} \tag{15}$$

where y_i is actual value and $f(x_i)$ is estimated value. In Equation (14), C is denoted as regularized constant which determines the trade-off between empirical error and regularized parameter. Both C and ε are user-determined hyper-parameters. The final form of Nonlinear SVR function is:

$$f(x) = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*)K(x_i, x_j) + b, i = 1,2,\ldots,N \tag{16}$$

where α_i and α_i^* are called Lagrange multipliers. Selection of optimal hyper-parameters is a key step in NLSVR modelling. The performance of NLSVR model is strongly depends on the kernel function and set of hyper-parameters. The most commonly used kernel function is radial basis function (RBF) which is given as follows.

$$k(x_i, x_j) = exp\{-\gamma\|x - x_i\|^2) \tag{17}$$

The RBF kernel function in NLSVR requires optimization of two hyper-parameters, i.e. the regularization parameter C, which balances the complexity and approximation accuracy of the model and the kernel bandwidth parameter γ, which defines the variance of RBF kernel function (Vapnik 2000).

3. HYBRID METHODOLOGY

The hybrid method considers the time series y_t as a combination of both linear and non-linear components. This approach follows the Zhang's (2003) hybrid approach, accordingly the relationship between linear and nonlinear components can be expressed as follows

$$y_t = L_t + N_t \tag{18}$$

where L_t and N_t represents the linear and nonlinear component respectively. In this work the linear part is modeled using ARIMA model and non-linear part by TDNN and NLSVR. The methodology consists of three steps. Firstly, an ARIMA model is employed to fit the linear component. Let the prediction series provided by ARIMA model denoted as $\hat{L}_t$. In the second step, the residuals ($e_t = y_t - \hat{L}_t$) obtained from ARIMA model are tested for non-linearity by using BDS test (Brock 1996), once the residuals confirm the non-linearity, then they are modelled and predicted using TDNN and NLSVR. Finally, the forecasted linear and nonlinear components are combined to generate aggregate forecast.

$$\hat{y}_t = \hat{L}_t + \hat{N}_t \tag{19}$$

where, $\hat{L}$ and $\hat{N}$ represents the predicted linear and nonlinear component respectively. The graphical representation of hybrid methodology is expressed in the figure (Fig. 2 & 3).

4. RESULT AND DISCUSSION

The summary statistics of banana production time series presented in Table 1 explains that the series is highly heterogeneous as CV is very high. The time series plots of same is exhibited in Fig. 4. Results of Augmented Dickey-Fuller unit root test is given in Table 2, which indicates the series is stationary at second difference. The unit root test of first difference series is not carried out because the series at first difference are not auto correlated as probability of chi-square is 0.619. Finally, ARIMA (3, 2, 0) was found adequate for considered time series and parameter estimates of the same are given in Table 3. Auto correlation check for residuals obtained from ARIMA model of Banana Production time series indicates the residuals found to be non-auto correlated as probability of chi-square is 0.2321. Further, the model performance in training set and testing data set is given in Table 8 and 9.

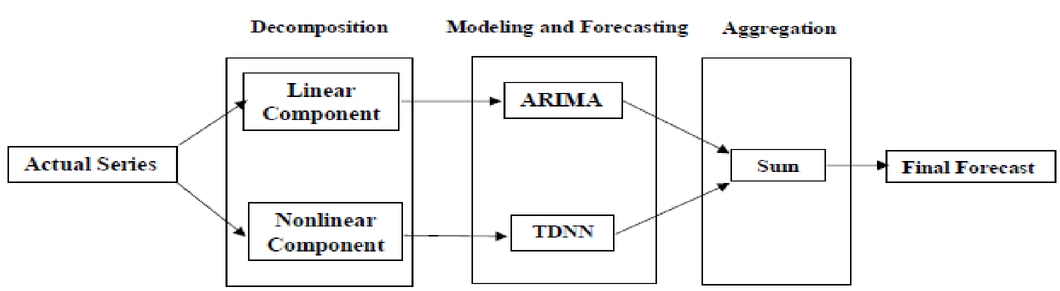

Fig. 2. Schematic representation of ARIMA-TDNN hybrid methodology

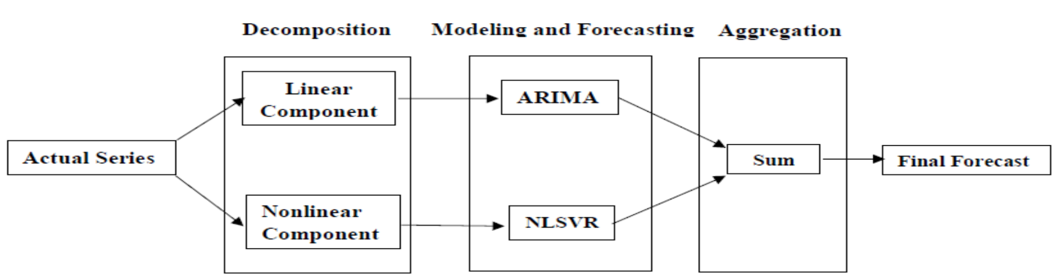

Fig. 3. Schematic representation of ARIMA-NLSVR hybrid methodology

Table 1. Summary statistics of Banana Production time series

Statistic	Banana Production	Statistic	Banana Production
Observation	61	Maximum	2711
Mean	763.44	Standard Deviation	498.97
Median	143	Skewness	0.85
Mode	122	Kurtosis	-0.83
Minimum	58	Coefficient of Variation (%)	65.35

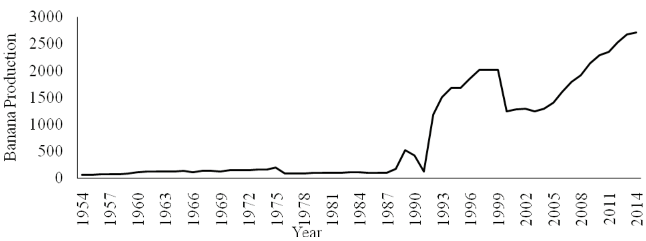

Fig. 4. Time series plot of Banana Production of Karnataka

Table 2. Stationary test of Banana Production time series

Series	Single mean		With trend	
	ADF Statistics	Probability	ADF Statistics	Probability
Actual Series	-0.166	0.8744	-26.23	0.556
Second difference	149.09	0.0010	148.93	0.0009

Table 3. Parameter estimation of ARIMA (3, 2, 0) by Maximum Likelihood Estimation method for Banana production time series

Parameter	Estimate	Standard Error	t Value	Approx. Pr > |t|	Lag
AR1,1	-0.74297	0.12881	-5.77	<.0001	1
AR1,2	-0.58054	0.14298	-4.06	<.0001	2
AR1,3	-0.26638	0.12899	-2.07	0.0389	3

Based on the lowest training RMSE (Table 5) the five TDNN models *viz.* 2:8s:1l, **2:10s:1l,** 3:10S:1l, 4:8s:1l and 4:10s:1l, are selected. These five models were further assessed based on their hold out sampling (testing set) forecasting performance. Out of total 29 neural network structures, a TDNN model with two tapped delay and ten hidden nodes (**2:10s:1l**), was selected for forecasting banana Production of Karnataka. Based on repetitive experimentation, the learning rate and momentum term for all TDNN model (Table 5) is set as 0.03 and 0.01 respectively. The forecasting performance of TDNN model in training and testing data set is given in Table 8 and 9.

Table 5. Forecasting performance of TDNN model for Banana Production time series

Model	Parameters	RMSE	
		Training	Testing
2:2S:1L	9	138.77	70.28
2:4s:1l	17	154.93	67.88
2:6s:1l	25	150.31	67.66
2:8s:1l	33	134.43	57.02
2:10S:1l	**41**	**130.17**	**55.31**
3:2s:1l	11	162.97	78.06
3:4s:1l	21	169.39	80.78
3:6s:1l	31	171.58	81.09
3:8s:1l	41	174.54	89.90
3:10S:1l	51	136.88	61.24
4:2s:1l	13	183.23	97.19
4:4s:1l	25	188.36	81.11
4:6s:1l	37	197.98	79.77
4:8s:1l	49	141.14	61.42
4:10S:1l	61	145.90	64.25
5:2s:1l	15	157.26	91.17
5:4s:1l	29	159.59	83.82
5:6s:1l	43	161.74	59.19
5:8s:1l	57	162.74	61.25
5:10S:1l	71	154.62	73.16
5:12s:1l	85	173.14	83.93
5:14S:1l	99	178.73	98.48
6:2s:1l	17	176.25	68.33
6:4s:1l	33	170.71	65.17
6:6s:1l	49	198.57	66.08
6:8s:1l	65	198.86	72.42
6:10S:1l	81	206.74	97.05
6:12s:1l	97	210.72	98.52
6:14S:1l	113	226.67	92.84

The support vector regression model for banana production time series was built with following parameter specifications (Table 6). Cross validation was carried out for the considered time series and the lowest cross validation error obtained was 0.031. Further the forecasting performance of NLSVR model in training and testing data set are given in Table 8 and 9.

Table 6. Model specification of SVR for Banana Production time series

Kernel function	No. of SVs	C	γ	ε	K fold cross validation (K)	Cross Validation Error
RBF	4	10.12	1.90	0.50	10	0.031

As discussed in hybrid methodology section, firstly the BDS test (Table 7) was carried out for residulas obatined from ARIMA (3,2,0) of banana production time series, which shows that residulas of ARIMA models are non-linear. Once the residual series is found to be non-linear then, which can modelled and predicted using non-linear models. The non-linear models namely TDNN and NLSVR are used for modeling and forecasting of ARIMA residuals in this study. The residuals predicted from TDNN and NLSVR are combined with forecast obtained from ARIMA model. Finally, the forecasting performance of hybrid model with ARIMA, TDNN amd NLSVR are compared using mean squared error (MSE), root mean square error (RMSE) and mean absolute percentage error (MAPE).

Table 7. Non linearity testing for ARIMA residuals of Banana Production time series

Parameter	Dimension (m=2)		Dimension (m=3)	
	statistic	probability	statistic	probability
105.66	4.58	<0.0001	5.81	<0.0001
211.33	2.61	0.0090	2.67	0.0073
317.00	2.40	0.0056	2.64	0.0041
422.67	1.89	0.0591	2.01	0.0048

Table 8. Model performance of Banana Production time series for training data set

Criteria	ARIMA	TDNN	NLSVR	ARIMA-TDNN	ARIMA-NLSVR
MSE	45914.67	16946.7	7588.14	2671.28	**663.84**
RMSE	214.28	130.17	87.11	51.68	**25.77**
MAPE	21.61	20.56	14.47	12.49	**6.78**

Table 9. Model performance of Banana Production time series for testing data set

Year	Actual	Forecast				
		ARIMA	TDNN	NLSVR	ARIMA -TDNN	ARIMA -NLSVR
2012	2530.00	2822.82	2507.76	2521.76	2507.55	**2525.56**
2013	2676.00	2955.08	2614.44	2610.44	2666.89	**2668.40**
2014	2711.00	3061.67	2780.95	2780.95	2802.70	**2790.70**
Criteria	MSE	95532.88	3059.18	3086.34	2998.49	**2143.19**
	RMSE	309.08	55.31	55.55	54.76	**46.29**
	MAPE	11.65	1.92	1.79	1.54	**1.13**

Based on the lowest MSE, RMSE and MAPE values of all models obtained for both training (Table 8) and testing data set (Table 9) considered, one can infer that hybrid model consist of ARIMA and NLSVR i.e. ARIMA-NLSVR model out performed over all remaining models. Further the results indicates that among single model NLSVR model performing better as compare to ARIMA and TDNN model. Both hybrid models *viz.,* ARIMA-TDNN and ARIMA-NLSVR outperformed the single model *viz.,* ARIMA, TDNN and NLSVR. And finally among all models studied ARIMA-NLSVR models performance was superior in forecasting banana production of Karnataka. Even though, the coefficient of variation in banana production time series is very high, then also the TDNN, NLSVR and hybrid models were performed better. The reason could be the nonlinear machine learning techniques can capture the heterogeneous trend in the data set and performed well as compare to ARIMA model.

5. CONCLUSION

Based on the results obtained in this work one can conclude that machine intelligence techniques like time delay neural network and nonlinear support vector regression performs better as compare to classical time series models under heteroscedastic and noisy time series data. The main finding of this study is the performance of hybrid time series model are better as compare to single models. If the data set consists, the pattern of both linearity and nonlinearity, the hybrid model performs better as compare to any single time series or machine learning techniques. Among the hybrid models, the ARIMA with Nonlinear Support Vector Regression i.e. ARIMA-NLSVR model performed superior as compare to all other models under both training and testing data set for modeling and forecasting banana production of Karnataka. This approach can be further extended by using some other machine learning techniques for varying autoregressive and moving average orders.

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