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Comparative study of neural network variants for potato (*Solanum tuberosum)* price modeling

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ABSTRACT

The intricate nature of agricultural price data possesses a formidable challenge in the modeling process, necessitating the careful selection and fine-tuning of methodologies. Deep learning emerges as a potent tool for enhancing the predictive accuracy and understanding the complexities of agricultural prices. The effectiveness of deep learning methodologies in handling the complex patterns of agricultural price datasets was demonstrated using monthly potato (*Solanum tuberosum* L.) price data collected from the National Horticultural Board across four distinct markets. The study was carried out during 2023 aimed to compare the performance of deep learning models, including Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) with feed forward Artificial Neural Networks (ANN) using the error metrics such as Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE). The GRU model performed best for the Chandigarh (16.26% MAPE) and Delhi (6.09% MAPE) markets where LSTM model showed superior performance in the Dehradun market (17.81% MAPE) and CNN for Shimla market (12.53% MAPE). The error percentage of deep learning models were remarkably low when compared to the machine learning model.

Keywords: Deep learning, Error metrics, Gated recurrent unit, Long short-term memory, Price volatility

Agricultural price data are inherently complex with their dynamic and multifaceted patterns. This complexity poses challenges for traditional modeling methods. The temporal dynamics of these prices are influenced by distinct seasonal patterns and lags (Shankar *et al.* 2023b). Additionally, spatial variability introduces significant disparities across different regions due to its variations in demand-supply dynamics (Garai *et al.* 2023). External influences such as climate conditions, government policies, and supply chain disruptions further contribute to the intricate nature of agricultural prices. Sparsity and noise present in the data make it incomplete and inconsistent, hindering the efficacy of traditional statistical models. Non-linear relationships among variables, coupled with the influence of dynamic economic factors, add layers of complexity to the analysis (Zhao 2021). In the face of these challenges, the application of deep learning techniques becomes imperative. In recent years, the incorporation of deep learning techniques has revolutionized various sectors, particularly in agriculture (Coulibaly *et al.* 2022). The agricultural sector has traditionally relied on statistical models and conventional machine learning techniques for price prediction and analysis (Purohit *et al.* 2021). However, deep learning, a subset of machine learning, has emerged as a dominant force, surpassing its predecessors in handling the intricacies of agricultural price fluctuations. The unparalleled capability of deep learning models to automatically learn and extract intricate patterns from vast datasets makes them particularly suited for the dynamic and complex nature of agricultural markets. The supremacy of deep learning over traditional machine learning techniques in agricultural price analysis lies in its adaptability and ability to handle high-dimensional data. The robustness of deep learning models ensures improved accuracy and reliability, crucial for making informed decisions in the volatile agricultural market (Wazirali *et al.* 2023).

Potato (*Solanum tuberosum* L.), being a staple food in India, experience price volatility influenced by various factors such as climate conditions, demand-supply dynamics, transportation costs, and regional economic variations. The demand for potatoes in India is driven not only by their widespread availability but also by their affordability, making them an integral part of the daily diet for a large segment of the population. The conventional models struggle to capture the shades of these multifaceted price data, especially potato (Badal *et al.* 2022). Many studies

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have reported the application of deep learning models like Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU) in price, especially in agricultural sectors (Cahuantzi *et al.* 2023, Seabe *et al.* 2023, Wu *et al.* 2023, Wang *et al.* 2023). Several authors have highlighted the significance and applications of deep learning models in agriculture (Guo *et al.* 2020, Bal and Kayaalp 2021). These models are also extensively utilized in crop modeling using weather variables (Mohan and Patil 2018). The study was aimed to compare the performance of different deep learning models with base Artificial Neural Networks (ANN) and examining the nature of volatility in potato prices in markets situated in different topographies. The overall findings aimed to enhance the understanding of volatility in the potato price across the markets, providing a valuable insight for farmers and policymakers to facilitate more informed decision-making.

MATERIALS AND METHODS

The application of stochastic and machine learning techniques in time series analysis encounters various constraints. One primary constraint for conventional model likely ARIMA models is the assumption of stationarity. Achieving stationarity often demands data transformations, and the presence of trends or seasonality can pose challenges to accurate modeling. Similarly, the linear nature of ARIMA models may limit their ability to capture intricate non-linear relationships within the data. On the other hand, machine learning techniques, while more flexible in handling non-linearity may fails sometimes because of the complex nature of the data. All these models may face difficulties when dealing with time series data that exhibits abrupt changes, non-constant variance, or complex, non-linear patterns (Gowthaman *et al.* 2023). Understanding these constraints is crucial for selecting appropriate models and pre-processing steps, ultimately influencing the reliability of predictions in time series analysis. The study was carried out in 2023 which utilized data obtained from the National Horticultural Board, focusing on the monthly wholesale prices of potatoes (₹/q) across prominent northern Indian markets, including Chandigarh, Delhi, Dehradun, and Shimla. The data set covered the period from January 2008 to December 2022, encompassing 180 observations for each market. To assess forecasting performance, the dataset was splitted into training and testing series at the ratio of 90:10. The analysis employed in the study were achieved using python and R software.

Artificial neural networks (ANN): Neural networks are powerful machine learning technique that is highly known for its efficacy in handling non-linear data. The fundamental structure of an ANN involves the layers of interconnected nodes, with the input layer, hidden layers, and output layer (Paul *et al.* 2022) (Supplementary Fig. 1). The decision on the number of nodes in input and hidden layer involves experimentation and iterative refinement to find the optimal architecture. The hidden layers play a pivotal role in capturing complex relationships through the application of weights and biases to the input data (Garai *et al.* 2023). Although ANN is a foundational model, it has several limitations, including a tendency to overfit, especially when working with small or noisy datasets, which can compromise its ability to generalize effectively to unseen data. Additionally, it struggles with capturing complex temporal dependencies or long-term patterns in sequential data, making it less suitable in some cases. The basic ANN model is given by:

$$y_{t+1} = g[\sum_{i=0}^{q} \pm_i f(\sum_{j=0}^{p} {}^{2}{}_{ij} y_{t-j})] \, y_{t+1}$$

Where y_{t+1} is the observation at time t+1; f and g are the activation functions at hidden and output layer; p is the number of input nodes; q is the number of hidden nodes; β_{ij} is the weight attached to the connection between its input nodes and the i^{th} hidden node; α_i is the weight attached to the connection from an i^{th} hidden node to the output nodes; y_{t+1} is the j^{th} input (lag) of the model.

Convolutional neural networks (CNN): Convolutional Neural Networks are special type of neural networks that are highly used for image classification and pattern recognition (Supplementary Fig. 2). They are also capable for efficiently capturing the temporal dependencies within sequential data (He *et al.* 2023). The essential components of CNN are input layer, convolutional layer, pooling layer, and an output layer. These layers serve a dual purpose i.e. enabling dimensionality reduction and extracting crucial features from the data. In case of time series data, the neurons in the fully connected layers, allow the network to extract high-level temporal features and understand global dependencies across the time steps.

$$O_t = \tanh(x_t \times k_t + b_t)$$

Where O_t, Convolved output value; x_t, Input vector; k_t, Weights of the convolution kernel and b_t, Bias.

Recurrent neural networks (RNN): Recurrent neural networks are specialized class of neural networks that are well-suited for tasks such as natural language processing, speech recognition, and time series analysis i.e. handling the sequential types of data (Gu *et al.* 2022) (Supplementary Fig. 3). The fundamental architecture of an RNN consists of three main layers, an input layer to receive the sequential input; a hidden layer to capture information from previous inputs through a dynamically updated hidden state; and an output layer that produces the final output based on the information in the hidden state (Kumari *et al.* 2023). The recurrent connections within the hidden layer allow the network to retain the memory based on the current input and the previous hidden state which make them unique from ANN. However, traditional RNNs face challenges such as the vanishing gradient problem, which limits their ability to capture long-term dependencies (Gowthaman *et al.* 2023). Let x_t is the input, b_t is the bias, h_t and h_{t-1} are the hidden node of current and previous cell, respectively. W_i, W_p, W_y were the weights of the input, previous hidden layer and current hidden layer, respectively. There the hidden and output state is given by:

$$h_t = \tanh (W_i \times x_t + W_p \times h_{t-1} + b_t)$$

$$O_t = \tanh (W_y \times h_t + b_y)$$

Long short-term memory networks (LSTM): Long short-term memory network is an extension of recurrent neural network that was developed to address the limitations of long-range dependencies and vanishing gradient. LSTMs are known for their sophisticated memory cell structure that allows them to capture and store information (Zaheer *et al.* 2023) (Supplementary Fig. 4). The architecture facilitates the flow of information, allowing LSTMs to selectively remember or forget specific information at each time step. This is achieved through the use of three interacting gates- the forget gate (f_t), input gate (i_t), and output gate (O_t). In the forget gate, the information from the current state (x_t) and the previous hidden state (h_{t-1}) is combined. This combined information with a certain weight passes through the activation function (***σ***) (Ray *et al.* 2023). It results in forget gate, where the unnecessary data is removed.

$$f_t = \sigma\, [W_{f\,*}\, (h_{t-1}\, ,\, x_t) + b_f\,]$$

The cell memory i.e. long-term memory (C_t) in the input gate layer, is updated with the help of the input gate and update value i.e., a new candidate value ($\check{C}_t$). The input gate filters the information updated using the candidate value which is free from unnecessary information and is updated with significant information (Paul *et al.* 2023).

$$i_t = \sigma\, [W_i \times (h_{t-1}\, ,\, x_t) + b_i\,]$$

$$\check{C}_t = \tanh\, [W_c \times (h_{t-1}\, ,\, x_t) + b_c\,]$$

$$C_t = f_t \times C_{t-1} + i_t \times \check{C}_t$$

In the output gate, the short-term memory (h_t) is formed based on the long-term memory and output gate. It provides the input that is filtered from long term memory.

$$O_t = \sigma\, [W_o \times (h_{t-1}\, ,\, x_t) + b_o\,]$$

$$h_t = O_t \times \tanh\, (C_t)$$

Gated recurrent unit (GRU): Gated recurrent unit is a variant of recurrent neural networks that are designed to overcome certain limitations of traditional RNNs, particularly the vanishing gradient problem (Zhang *et al.* 2023) (Supplementary Fig. 5). Input layer, reset gates, update gates, candidate hidden state, and the output layer are the part GRU architecture. The input layer receives sequential data where the reset and update gates control the flow of information in the network. The reset gate (r_t) determines the extent to which the previous hidden state should be forgotten, while the update gate (z_t) determines how much of the new information should be incorporated. The candidate hidden state ($\hat{h}_t$) represents the new information that is added to the hidden state (h_t). These components work together to update the hidden state, which retains memory of previous inputs and captures temporal dependencies. Let x_t be the input; h_t and h_{t-1} are the hidden state of current and previous cell. W_r and W_z are the weights of the reset and update gate.

$$z_t = \sigma\, [W_z \times (h_{t-1}, x_t)]$$

$$r_t = \sigma\, [W_r \times (h_{t-1}, x_t)]$$

$$\hat{h}_t = \tanh\, [W_*\, (r_t \times h_{t-1}, x_t)]$$

$$h_t = (1 - z_t) \times h_{t-1} + z_{t\,*}\, \hat{h}_t$$

Model selection: In the process of choosing the most effective time series model for a given dataset, different error metrics are used which compare the predicted values to the actual values (Shankar *et al.* 2023a). Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE) are used in this study.

$$\text{RMSE} = \left(\sqrt{\sum_{t=1}^{n} \left\{ \frac{Y_t - \widehat{Y}_t}{Y_t} \right\}^2 \Big/ n} \right)$$

$$\text{MAPE} = \left(\sum_{t=1}^{n} \left| \left\{ \frac{Y_t - \widehat{Y}_t}{Y_t} \right\}^2 \right| / n \right)$$

$$\text{MAE} = \frac{1}{n} \sum_{t=1}^{n} | Y_t - \widehat{Y}_t |$$

Let Y_t is the actual values; Y_t is the fitted value and n is the number of observations.

RESULTS AND DISCUSSION

The results of summary statistics (Table 1) showed that the average price of potatoes was highest in Shimla market (1162.24 ₹/q) and lowest in Chandigarh market (907.52 ₹/q). An exploration of the statistical characteristics of the data reveals a positive skewness, implying that the distribution of prices is skewed towards higher values. This departure from a symmetrical distribution is further substantiated by the results of the Shapiro-Wilk test, confirming the non-normal distribution of the price data. The Cuddy Dell Valle index which measures the data instability indicate a high level of instability in the price series. Particularly, the price series in Dehradun exhibited pronounced instability when compared to rest of the markets. These results were in par with the results of the coefficient of variation, emphasizing the considerable variability and unpredictability in the pricing trends. Fig. 1 showed the time series plot of the price series of potato at different markets. The price series were found to be non-linear in nature moving in similar patterns across the years. The density plot and strip plot of the price series, as shown in Fig. 2, confirm that the data deviates from normality and contains more outliers. The BDS (Brock-Dechert-Scheinkman) test is used to assess the non-linearity and chaotic behaviour in time-series data. Table 2 presents the BDS test results using embedding dimensions 2 and 3, representing the number of past observations used to reconstruct the state space, across different threshold values (eps[1], eps[2], eps[3], and eps[4]). The results confirm the presence of non-linearity in all price series. Similar kinds of report on potato prices were already reported in prior studies (Kumar *et al.* 2023, Mishra *et al.* 2023a, Mishra

Table 1 Descriptive statistics of potato price across different markets

Statistics	Chandigarh	Delhi	Dehradun	Shimla
Mean (₹/q)	907.52	1113.60	1029.37	1162.24
Median (₹/q)	786.50	970.50	822.00	1133.50
Mode (₹/q)	600.00	646.00	251.00	1407.00
Maximum (₹/q)	3472.00	3040.00	4010.00	3258.00
Minimum (₹/q)	194.00	278.00	231.00	338.00
Standard deviation (₹/q)	491.87	574.55	656.65	496.67
Standard error (₹/q)	36.66	42.82	48.94	37.02
Kurtosis	4.51	0.05	4.16	2.23
Skewness	1.52	0.72	1.71	1.02
Shapiro-Wilk test (*p*-value)	0.90	0.94	0.86	0.94
Coefficient of Variation	54.20	51.59	63.79	42.73
Cuddy Della Valle Index	45.44	46.81	55.50	39.31

Table 2 Results of non-linearity BDS test

Locations	Statistics	Embedding dimension	
		2	3
Chandigarh	eps[1]	50.69	66.26
	eps[2]	31.02	32.99
	eps[3]	18.63	18.34
	eps[4]	15.05	14.22
Dehradun	eps[1]	66.74	93.96
	eps[2]	42.00	45.63
	eps[3]	27.21	26.34
	eps[4]	21.06	19.53
Delhi	eps[1]	33.06	42.29
	eps[2]	23.82	24.95
	eps[3]	17.85	17.36
	eps[4]	14.47	13.70
Shimla	eps[1]	57.52	72.51
	eps[2]	28.94	30.54
	eps[3]	20.77	20.32
	eps[4]	16.73	15.81

*All the above values have p values less than 0.01, confirming the significance of the results. eps, Epsilon.

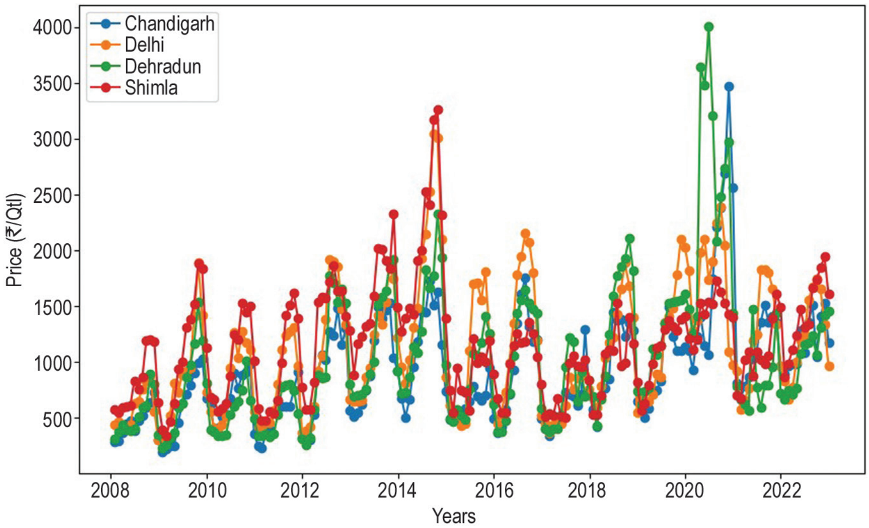

Fig. 1 Time series chart of potato prices.

et al. 2023b, Shankar *et al.* 2023b). These multifaceted data necessitate the application of advanced modeling approaches to address the limitations of traditional models.

Hyperparameter tunning in model fitting: Deep learning techniques are recognized for its efficacy in handling such complex datasets which emerges as a highly recommended solution. Utilizing the default models without fine-tuning of hyperparameters may not lead to an optimal result. Therefore, it is crucial to carefully assess the hyperparameters of the models and fine-tune them for enhanced performance (Bacanin *et al.* 2023). Hyperparameter tuning is an art which often necessitates

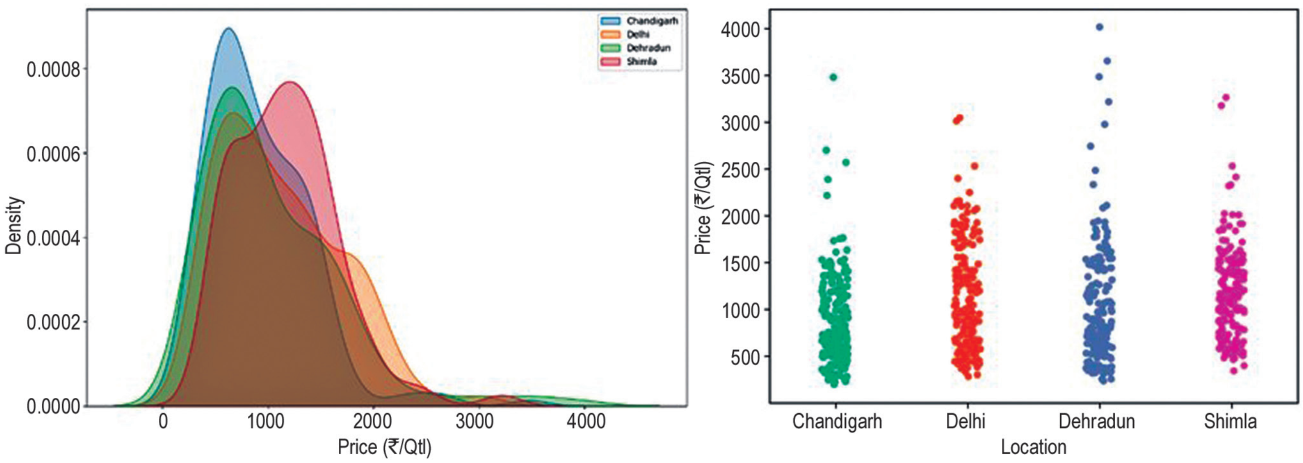

Fig. 2 Descriptive plots on price data.

a trial-and-error approach i.e. systematically applying different values for hyperparameters and evaluating their impact on the model's performance to find the most suitable configuration for the given dataset (Paul *et al.* 2023). The study utilized the different lags in which 12 lags were considered to be best fitting the model as the data were monthly in nature. A Feed Forward Neural Network was applied with the network size varying between 1 to 15 using a sigmoid activation function. This configuration enables the ANN to capture the temporal dependencies within the dataset. The CNN model was implemented with parameters including epochs ranging from 50 to 100, kernel sizes of 3, 5, 7, 9, and 12, filters ranging from 16 to 64, RMSprop (Root Mean Square Propagation) optimizer, and ReLU (Rectified Linear Unit) activation function. RNN, LSTM, and GRU models were also fitted to the data, configured with units ranging from 10 to 50 and batch sizes of 1 to 5. The models were trained for 50 to 100 epochs using the RMSprop optimizer and ReLU activation function (Supplementary Table 1). This comprehensive modeling strategy aims to extract intricate patterns and dependencies, providing a nuanced understanding of the underlying dynamics within the dataset.

The results of the model performance were given in the Table 3. The model which returns minimum error will be considered as the best fitted model for the data. RMSE,

Table 3 Model performance

Locations	Models	RMSE	MAPE (%)	MAE
Chandigarh	ANN	535.79	38.42	419.73
	CNN	277.96	20.2	246.44
	RNN	258.98	18.72	225.68
	LSTM	250.52	16.32	189.13
	GRU	229.97	16.26	184.76
Dehradun	ANN	332.86	31.96	283.97
	CNN	229.17	19.18	184.74
	RNN	269.64	25.28	230.45
	LSTM	238.47	17.81	158.36
	GRU	249.03	19.12	175.26
Delhi	ANN	540.34	36.51	487.83
	CNN	135.95	9.9	113.92
	RNN	121.35	8.32	101.66
	LSTM	95.62	6.91	81.46
	GRU	87.95	6.09	67.89
Shimla	ANN	306.99	21.52	275.15
	CNN	192.39	12.53	148.71
	RNN	227.61	14.79	198.08
	LSTM	207.62	13.56	160.93
	GRU	208.8	14.04	166.39

MAPE and MAE were the error metric used to select the best performing model. The results showed that the GRU was found as the best fitted model for Chandigarh and Delhi markets with RMSE, MAPE, MAE value of 229.97, 16.26, 184.76 and 8795,6.09, 67.89 respectively. LSTM came out as best fitted model for the Dehradun market with RMSE of 238.47. MAPE of 17.81% and MAE of 158.36. For Shimla market, CNN came out as best fitted model with low error rate, i.e. RMSE of 192.39, MAPE of 12.53% and MAE of 148.71%. Although CNNs are primarily used in image processing, their ability to capture local patterns through convolutional layers makes them effective for time-series data as well. In price forecasting, CNNs can detect short-term dependencies, trends, and volatility. This capability allows them to perform well in applications beyond traditional image tasks. Thus, deep learning models demonstrate their efficiency by handling data more effectively than traditional baseline models. The main key advantages are the ability to automatically extract complex patterns from raw data which eliminate the need for extensive manual feature engineering. Additionally, they can capture both short- and long-term dependencies and handle large, high-dimensional datasets robustly, delivering accurate prediction even in volatile market conditions. These findings are supported by several studies that highlight the significance of deep learning in capturing complex patterns and improving predictive accuracy (Manogna and Mishra 2021). Jaiswal *et al.* (2022) showed the efficiency of deep LSTM in agricultural price forecasting. Nayak *et al.* (2024) also confirmed the superior performance of deep learning models over machine learning models using data from TOP crops. Paul *et al.* (2023) showcased the effectiveness of deep learning models compared to machine learning and conventional models in handling agricultural price datasets. Fig. 3 showed the graph with actual values and fitted values of all the models for price series of all the markets.

The study undertakes a comprehensive exploration into the utilization and effectiveness of various deep learning models for the agricultural datasets, using the price series of potatoes as a primary focus. The preliminary examination through basic statistics and visual plots conclusively establishes that the dataset deviates from normality, exhibits non-linearity, and displays a high degree of instability. In response to these intricate data characteristics, the study employs a diverse set of deep learning models, including ANN, CNN, RNN, LSTM and GRU. These sophisticated models are chosen for their innate ability to capture temporal dependencies and glean insights from historical pricing data, thereby enhancing the precision of predictions related to future price trends. The performance of these models was evaluated using metrics such as RMSE, MAPE and MAE. The GRU model was found superior in fitting for the Chandigarh and Delhi markets with MAPE value of 16.26% and 6.09%, respectively. LSTM model excels in Dehradun market with lowest MAPE value of 17.81%. CNN model, highly known for its efficiency in handling in image data, turns out to be the best fit for Shimla market with

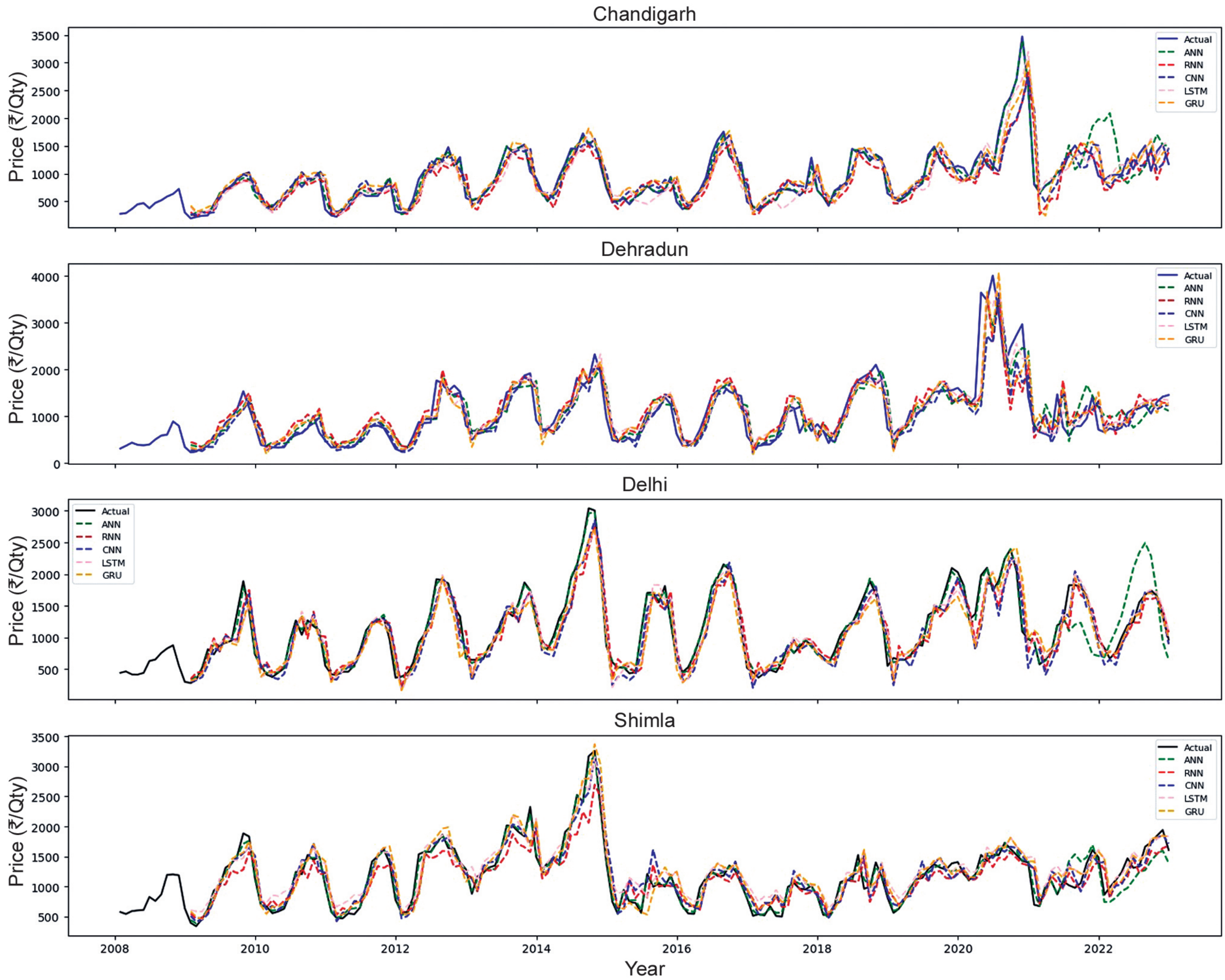

Fig. 3 Actual values vs fitted values.

MAPE value of 12.53%. The study underscores the overall superiority of deep learning techniques over traditional machine learning methods (ANN) in handling agricultural datasets. However, the choice of the most suitable model is contingent upon the unique characteristics of the dataset under consideration. The study can be further extended by exploring advanced deep learning and hybrid deep learning models to enhance the accuracy of the predictions.

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