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Research Paper

Impact of temporal granularity on machine learning models for time series forecasting

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ABSTRACT

This study examines the impact of timestep variation on the predictive performance of machine learning (ML) forecasting models, emphasizing the importance of optimal timestep selection for improved accuracy. The results show that Support Vector Regression (SVR) performs best with shorter timesteps but struggles with longer sequences. In contrast, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks excel at 26 timesteps, leveraging their ability to capture patterns from extended contexts. RNNs demonstrate consistent performance across various timesteps, with their peak accuracy also observed at 26 timesteps. These findings highlight the need for careful timestep selection to enhance model efficiency and forecast reliability.

Key words: Comparative analysis, machine learning, model performance, temporal dependencies, time series forecasting, timesteps

Time series forecasting has emerged as a pivotal tool for predicting agricultural prices, leveraging historical data patterns to make future predictions (Montgomery *et al.*, 2015; Ayineni *et al.*, 2014; Nayak *et al.*, 2024). In markets where price volatility can significantly impact livelihoods and economic stability, accurate forecasts empower stakeholders to make informed choices about production, storage, marketing, and trade (Lanfranchi *et al.*, 2019; Chavas and Li, 2020; Mustafa *et al.*, 2024). However, a key challenge in this domain is the selection of an appropriate timestep, the number of previous observations used as input to predict future values. Timestep selection has far-reaching implications for forecasting accuracy, computational efficiency, and the interpretability of models (Papacharalampous *et al.*, 2018; Ismail *et al.*, 2020; Leites *et al.*, 2024). An incorrect timestep can result in either oversimplified models that overlook important data patterns or overly complex models that fail to generalize well. For agricultural markets, where long-term trends and sudden shocks coexist, choosing an optimal timestep is even more crucial. Despite its importance, limited research has systematically investigated the role of timesteps, especially in the context of agricultural price forecasting, leaving a critical gap in the literature (Fischer *et al.*, 2020; Petropoulos and Spiliotis, 2021; Suradhaniwar *et al.*, 2021; Wang, 2022). The lack of consensus on the best timestep approach hinders the development of universally applicable forecasting systems, especially in regions with distinct agricultural market dynamics. The primary objective of this paper is to analyze the influence of timesteps on forecasting accuracy and to establish guidelines for selecting optimal timesteps in agricultural markets. In doing so, the aim is to bridge the gap between theoretical research and practical applications, offering stakeholders tools and insights to improve their forecasting strategies. Moreover, this study contributes to the broader field of time series forecasting by highlighting the interplay between model architecture and timestep selection, an area with significant potential for further research (Widodo *et al.*, 2016; Polyzos and Siriopoulos, 2024).

MATERIALS AND METHODS

Data for this study was sourced from the Agmarknet website *(https://agmarknet.gov.in/),* for the Parimpore market in Srinagar, Jammu and Kashmir, to investigate the role of timesteps in enhancing the accuracy of apple price forecasting. The dataset spans a period of nearly 11 years, from 2014 to 2024, ensuring a robust temporal coverage of market dynamics. It includes daily records of minimum, maximum, and modal price for apples traded in the given market. To focus on the most active trading periods, data from September, October, November, December, January and February, were selected.

Modeling approach: This study explores the impact of timestep selection on the performance of ML models viz. SVR, RNN, and LSTM networks. These models were chosen for their proven capabilities in handling non-linear and sequential data structures, making them well-suited for agricultural price forecasting. In time series forecasting, SVR is employed to predict continuous values based on historical data. The objective of SVR in regression is to find a function that best fits the data while minimizing errors and controlling the complexity of the model (Cortes & Vapnik, 1995; Smola & Scholkopf, 2004). The goal of SVR is to find a function $f(x)$ that maps input vectors x_i to output values y_i, such that the error between the predicted values and actual values is minimized within a certain margin. The basic form of the SVR model is represented by the equation $f(x) = wx + b$, where w is the weight vector and b is the bias term. Recurrent Neural Networks (RNNs) are a class of neural networks designed for sequential data, making them ideal for time series forecasting. RNNs process input data sequentially, maintaining a hidden state that captures information from previous time steps (Rumelhart, Hinton, & Williams, 1986; Hochreiter & Schmidhuber, 1997). Mathematically, an RNN is defined by the following recurrence relation (Werbos, 1990):

$$h_t = \sigma(W_{hh}\, h_{t-1} + W_{xh}\, x_t + b_h)$$

$$y_t = W_{hy}\, h_t + b_y$$

where h_t is the hidden state at time step t, x_t is the input at time step t, y_t is the output at time step t, W_{hh}, W_{xh}, and W_{hy} are weight matrices, b_h and b_y are bias terms, and σ is the activation function (typically *tanh* or ReLU).LSTMs are highly effective for sequential data tasks such as time series forecasting because they can capture long-term dependencies by maintaining a memory cell state across time steps Hochreiter & Schmidhuber, 1997; Gers, *et al.*, 2000). An LSTM unit consists of three primary gates: the forget gate, the input gate, and the output gate. The forget gate is mathematically represented as $f_t = \sigma\left(W_f\,[h_{t-1}, x_t] + b_f\right)$ where σ is the sigmoid activation function, W_f is the weight matrix, and b_f is the bias term. The input gate is given by $i_t = \sigma(W_i\,[h_{t-1}, x_t] + b_i)$. The cell state update is defined as $\tilde{C}_t = tanh(W_C\,[h_{t-1}, x_t] + b_C)$, and the memory cell state is updated as $C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$. The output gate is represented by $o_t = \sigma(W_o\,[h_{t-1}, x_t] + b_o)$, and the hidden state at time step t is given by $h_t = o_t * tanh\,(C_t)$. The memory cell state C_t is updated based on the forget gate and input gate. The forget gate controls how much of the previous memory cell should be retained, while the input gate decides how much of the new information should be added. The output gate controls the hidden state, which is used in the next time step and as the final output of the model.

Model evaluation: By systematically varying timesteps and evaluating model performance across metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean

Square Error (RMSE), the aim is to uncover optimal timestep ranges and provide actionable insights for both researchers and practitioners. The mathematical formulations for these metrics are:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_i - \hat{Y}_i| \qquad RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \qquad MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

where n is the number of data points, y_i is the actual value and $\hat{y}_i$ is the predicted value. All three metrics were calculated on the test set after model training to evaluate the performance of the forecasting models.

RESULTS AND DISCUSSION

The descriptive statistics for the minimum, maximum, and modal apple prices are presented in Table 1. The minimum price ranged from 1200 to 7500 Rs/quintal, with a mean of 3024.28 Rs/quintal, while the maximum price ranged from 1500 to 8122.5 Rs/quintal, averaging 3557.65 Rs/Quintal. The modal price showed similar variability, with a mean of 3262.36 Rs/quintal and a range of 1350 to 7806.67 Rs/quintal.

Table 1: Descriptive statistics for minimum, maximum, and modal prices (Rs/quintal)

Statistic	Min. Price	Max. Price	Modal Price
Mean	3024.28	3557.65	3262.36
Std.	1212.11	1446.56	1286.88
Min.	1200.00	1500.00	1350.00
Q_1	2075.00	2444.00	2267.00
Q_2	2798.00	3213.00	2993.00

The 30-day rolling mean trends for minimum, maximum, and modal apple prices (Fig. 1) highlights significant price variability over time. Sharp price surges occurred during 2016–2017, 2021–2022, and 2023–2024, with maximum prices peaking above 6000 Rs/quintal. The widening gap between maximum, modal, and minimum prices during these periods indicates increased market disparity.

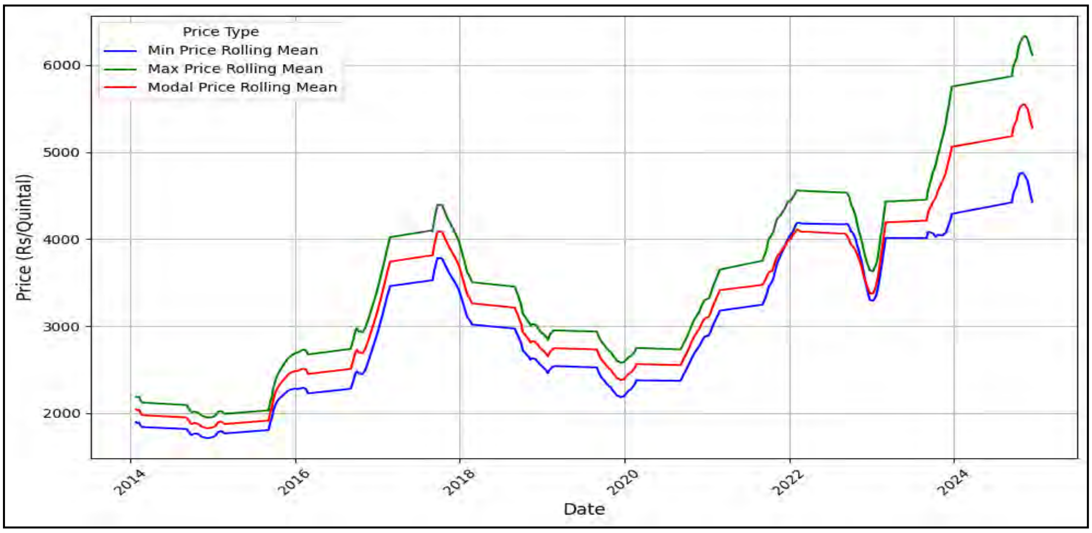


Fig. 1: 30-day rolling mean of minimum, maximum, and modal prices

The seasonal decomposition of scaled modal prices (Fig. 2) highlights the underlying trend, seasonal fluctuations, and residual variations. The trend shows a steady rise, particularly from the year 2021 to 2023, reflecting market dynamics such as increasing demand or supply constraints. These findings align with studies that emphasize the influence of seasonality, demand-supply balance, and external shocks on agricultural commodity prices (Arroyo, 2019; Bodhanwala *et al.*, 2020; Bondarenko, 2023), reinforcing the importance of seasonal analysis in price forecasting and market strategy development.

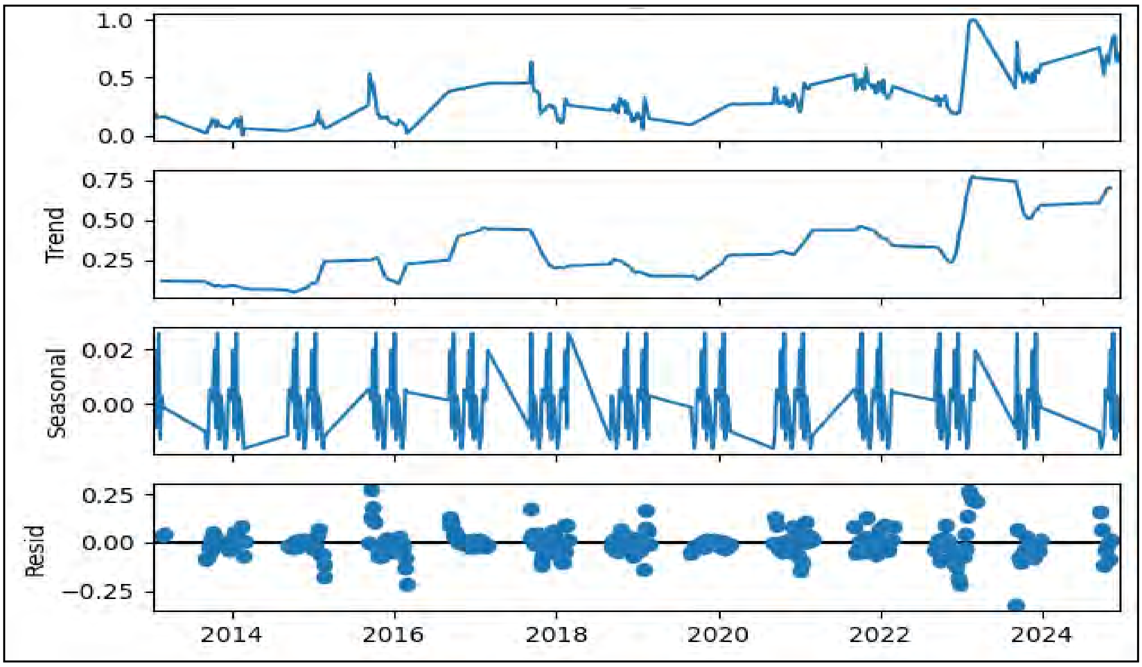


Fig. 2: Seasonal decomposition of scaled modal prices

Data preparation for model training: The dataset was cleaned and scaled using z-score normalization to ensure all features fell within a uniform range, as described in prior research. Temporal data was structured into sequences, with timesteps varying from 1 to 50 in increments of 5, depending on model requirements, aligning with approaches used in time series forecasting (Chang *et al.*, 2012; Zhao *et al.*, 2017; Wang *et al.*, 2022). This range captures both immediate and longer-term dependencies, while the chosen increment balances granularity with computational efficiency. The training and test sets were split using an 80:20 ratio, maintaining the temporal order to prevent data leakage, a critical practice emphasized in time series analysis literature.

Model configuration and performance: For the SVR model as shown in Table 2, the radial basis function (rbf) kernel is used, which is effective in handling non-linear relationships within the data. The regularization parameter C is set to 1.0, balancing the model's ability to fit the data without overfitting, while the epsilon value is set to 0.1, defining the margin of tolerance within which no penalty is applied for errors. The gamma parameter is set to 'scale,' helping the model capture complex patterns based on the number of features. These configurations align with best practices in agricultural price forecasting (Zhao *et al.*, 2024; Candelieri *et al.*, 2019). When evaluating the performance across timesteps, the SVR model exhibited consistently high RMSE values across all timesteps, peaking at 1,580.46 for 46 timesteps and achieving its lowest error of 917.91 at 6 timesteps (Table 3). These results support the findings of Maldonado *et al.* (2010), Wang *et al.* (2013) and Yang *et al.* (2019), who demonstrated that SVR models tend to perform better with shorter timesteps in forecasting tasks.

Table 2: Model hyper parameters and configuration for SVR, LSTM, and RNN model

Model and Hyperparameter	Setting value
SVR	
• Kernel	rbf
• C	Default (1.0)
• Epsilon	Default (0.1)
• Gamma	Default (scale)
LSTM	
• Units	50
• Activation	ReLU
• Input Shape	(timesteps, 1)
• Optimizer	Adam
• Loss Function	MSE
• Epochs	50
RNN	
• Units	50
• Activation	ReLU
• Input Shape	(timesteps, 1)
• Optimizer	Adam
• Loss Function	MSE
• Epochs	50

The LSTM and RNN model are configured with 50 units in the LSTM layer and trained for 50 epochs, utilizing ReLU as the activation function to address the vanishing gradient problem commonly encountered in deep networks. The input shape is defined as (timesteps, 1) with optimizer used is Adaptive Moment Estimation (Adam) and MSE as the loss function (Table 2). Regarding performance across timesteps, the LSTM model showed adaptability to longer temporal sequences (Table 3, Fig. 5). The lowest RMSE of 665.71 and MAE of 527.76 were observed at 26 timesteps, with the performance deteriorating significantly at 1 timestep (RMSE of 1,082.84). This suggests that LSTM models are more effective when provided with sufficient temporal context, aligning with studies by Sangiorgio and Dercole (2018), Kim *et al.* (2019), Saini *et al.* (2020) and Goyal *et al.* (2018), who highlighted the advantage of longer timesteps in time series forecasting, especially for agricultural and demand forecasting tasks. Similarly, RNN model demonstrated consistent improvement as the number of timesteps increased. As shown in Table 3, its best MSE of 3,37,956.20, RMSE of 581.34 and MAE of 444.64 were observed at 26 timesteps (Fig 3).

Table 3: Model performance measures across different timesteps

Time steps	SVM			LSTM			RNN		
	MSE	RMSE	MAE	MSE	RMSE	MAE	MSE	RMSE	MAE
1	10,46,365.33	1,022.92	692.75	11,72,542.47	1,082.84	856.27	9,32,248.18	965.53	643.55
6	8,42,558.77	917.91	698.36	9,70,796.38	985.29	664.00	8,42,540.41	917.90	591.41
11	16,33,258.44	1,277.99	1,032.21	5,11,182.10	714.97	598.79	4,31,530.75	656.91	513.66
16	24,03,926.21	1,550.46	1,369.99	6,17,670.25	785.92	679.38	6,62,742.53	814.09	631.44
21	22,91,166.60	1,513.66	1,350.90	8,13,026.82	901.68	803.08	3,73,675.46	611.29	480.85
26	27,92,541.79	1,671.09	1,496.76	4,43,169.80	665.71	527.76	3,37,956.20	581.34	444.64
31	21,77,454.38	1,475.62	1,251.50	9,44,531.30	971.87	823.97	4,16,786.45	645.59	518.6
36	22,31,737.21	1,493.90	1,268.10	22,12,715.75	1,487.52	1,106.78	4,06,508.26	637.58	533.12
41	24,07,679.79	1,551.67	1,330.98	10,39,441.42	1,019.53	923.10	4,66,011.02	682.65	573.03
46	24,97,853.81	1,580.46	1,362.70	6,04,366.31	777.41	652.25	3,70,686.15	608.84	481.80

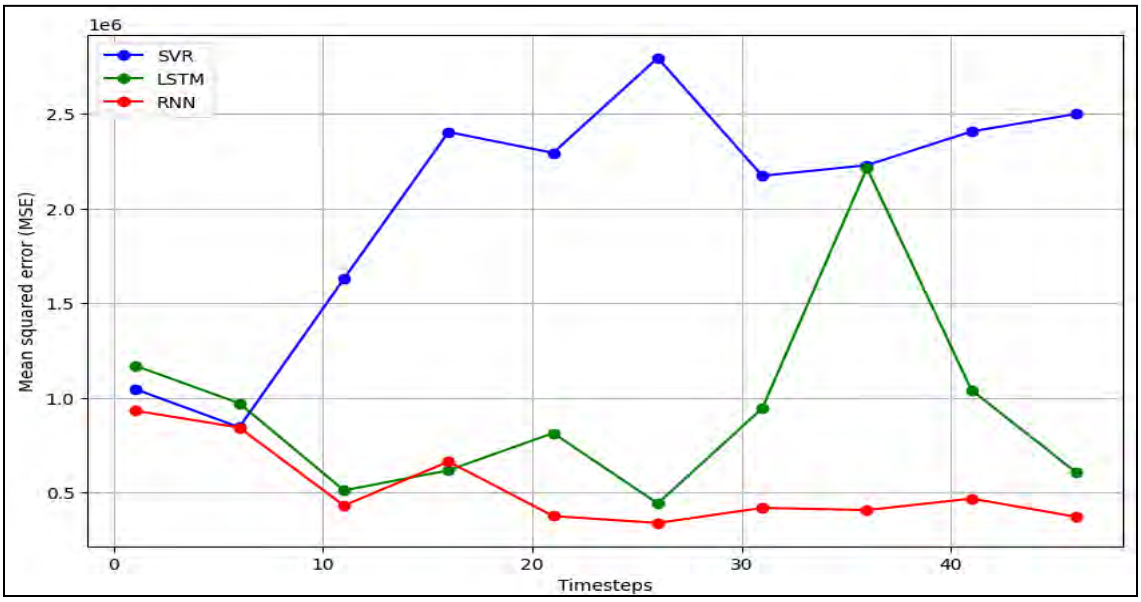


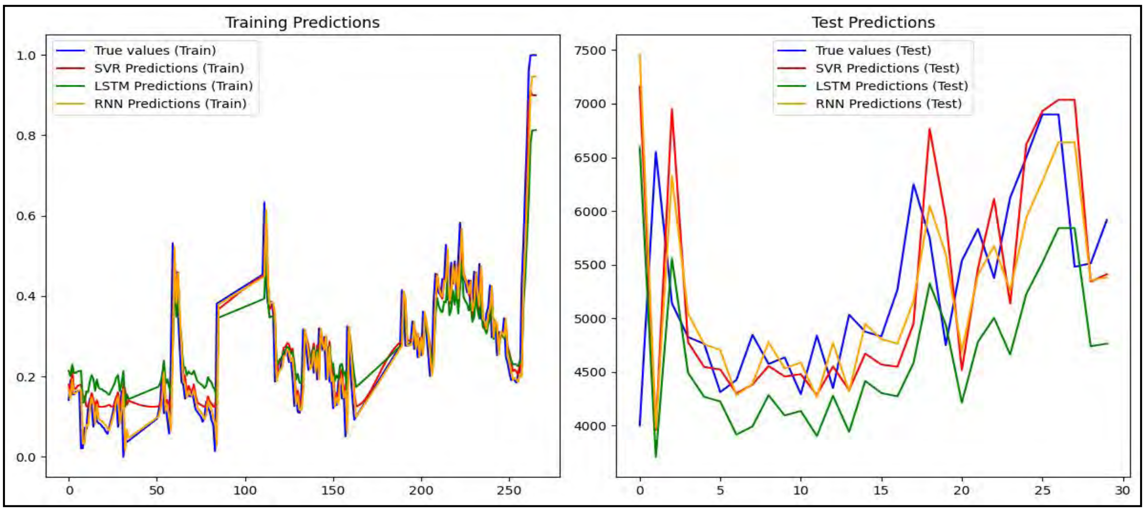
Fig. 3: MSE for fitted models across different timesteps

Unlike the LSTM, the RNN showed less variability in performance across different timesteps, reflecting its robustness even with shorter sequences. This aligns with findings by Surakhi and Zaidan (2020) and Sagheer and Kotb (2020), who showed that RNNs tend to maintain stable performance across different timestep lengths in time series forecasting tasks. Notably, the identification of 26 timesteps as optimal for LSTM and RNN models aligns with the seasonal nature of apple sales data of Parimpore market, which spans approximately six months or 26 weeks. These findings support the role of seasonality in determining timestep length, as highlighted by studies on seasonal time series forecasting (Brandt and Bessler, 1983; Holt, 2004; Cheng *et al.*, 2015 Shekhar and Williams, 2007; Sadaei *et al.*, 2017; Wang *et al.*, 2020; Sabu and Kumar, 2020). Table 4: Wilcoxon Signed-Rank Test Results for Model Performance Comparison. To further validate the observed differences in model performance across timesteps, a Wilcoxon signed-rank test was conducted on RMSE values (Table 4). The test revealed statistically significant differences between SVM and LSTM (p=0.0195), SVM and RNN (p=0.00195), and LSTM and RNN (p=0.0039), confirming that the choice of model significantly influences performance outcomes in time series forecasting. This comparative analysis, supported by statistical testing (Table 4), demonstrated that RNN consistently outperformed both LSTM and SVM, establishing it as the most effective model for forecasting apple price patterns in this study. Fig. 4 displays the actual vs predicted prices for the training and test datasets across different models and timesteps. From these figures, it could be seen that SVR performs best at shorter timesteps (1 and 6), fitting both training and test data well, but its performance declines significantly at higher timesteps.

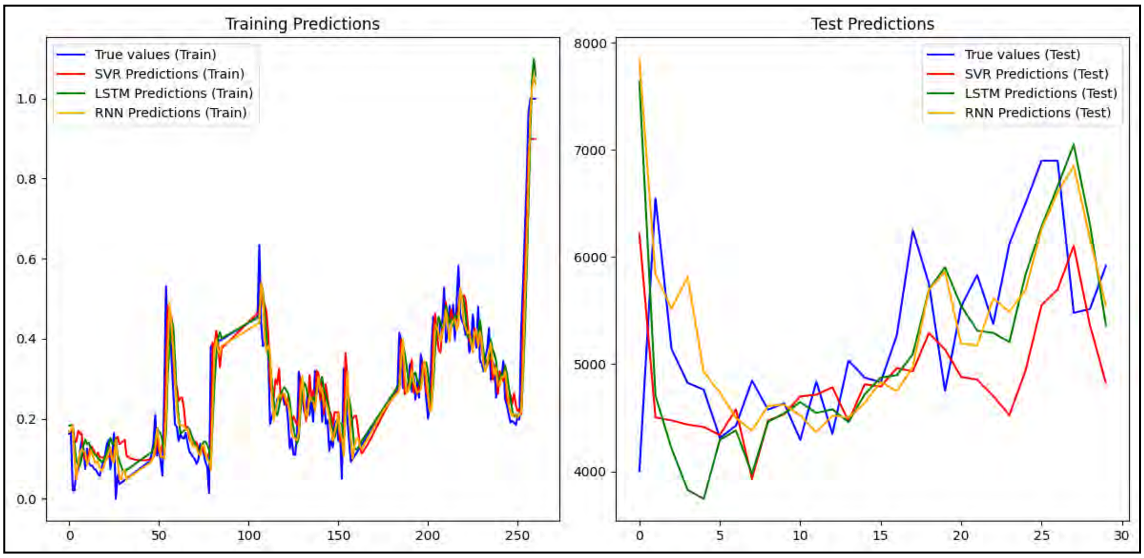
Table 4: Wilcoxon signed-rank test results for model performance comparison

Model Comparison	Test Statistic	p-value
SVM vs. LSTM	5.0	0.0195
SVM vs. RNN	0.0	0.0019
LSTM vs. RNN	1.0	0.0039

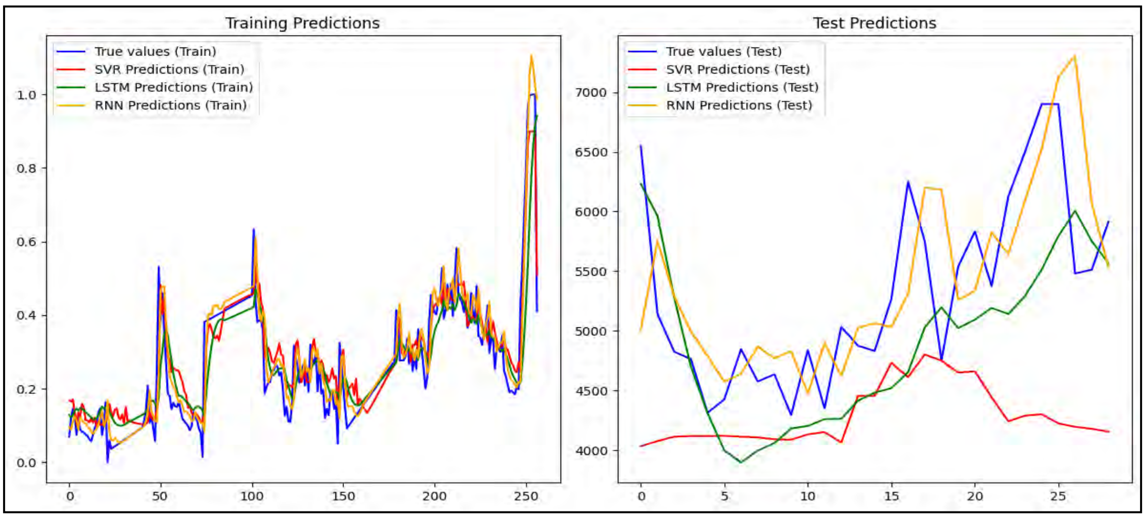
RNN consistently outperforms other models across all timesteps 1 to 46 following the test data closely with the lowest error metrics. It achieves optimal performance at timestep 26, where LSTM also performed well. LSTM, the second-best model, shows stable performance but struggles at high-volatility regions and exhibits a sudden decline at timestep 36, with the highest discrepancy between test predictions and actual values, particularly toward the end of the test set.



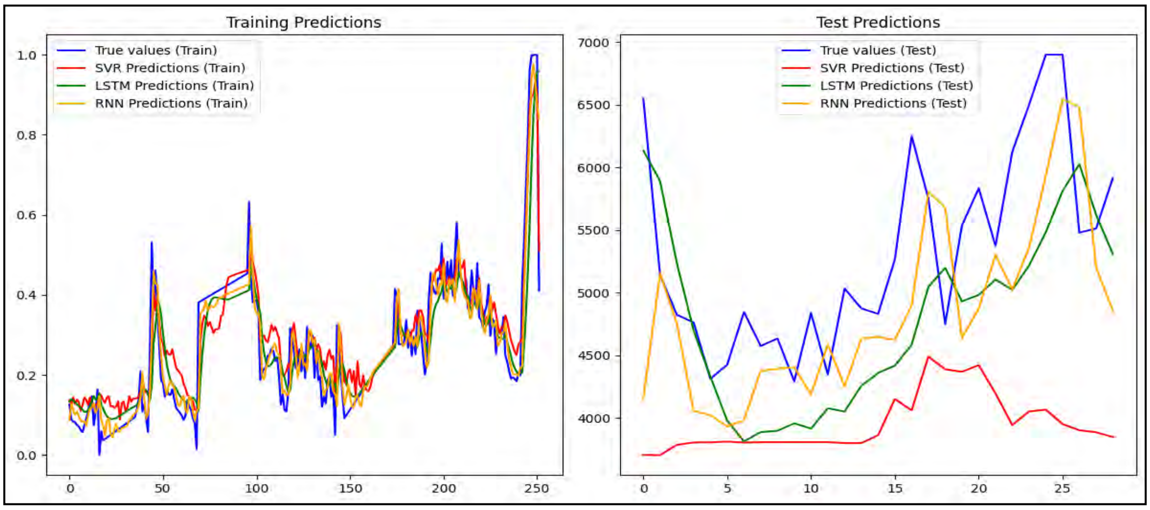
(a) Timestep = 1



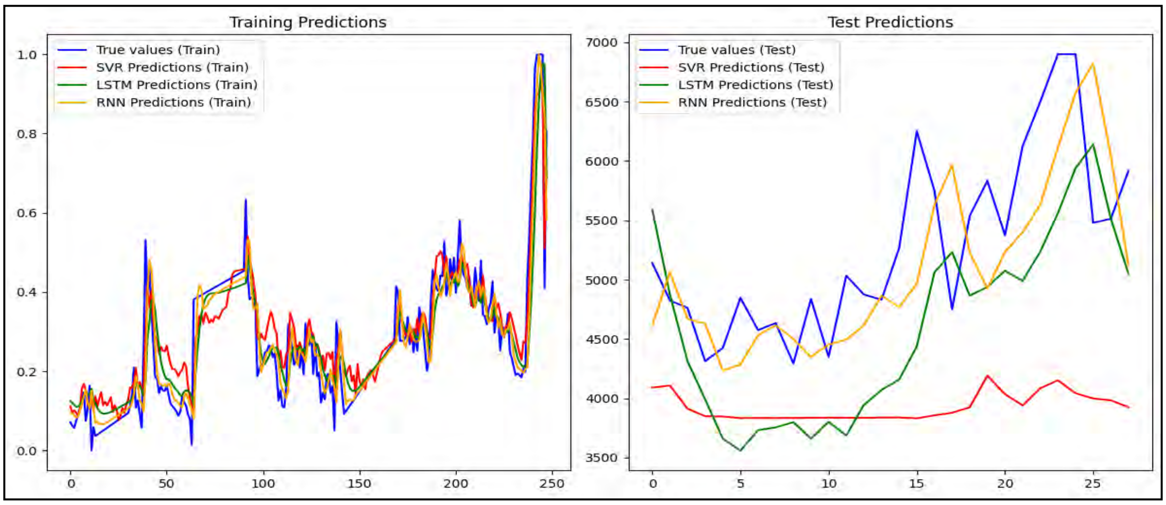
(b) Timestep = 6



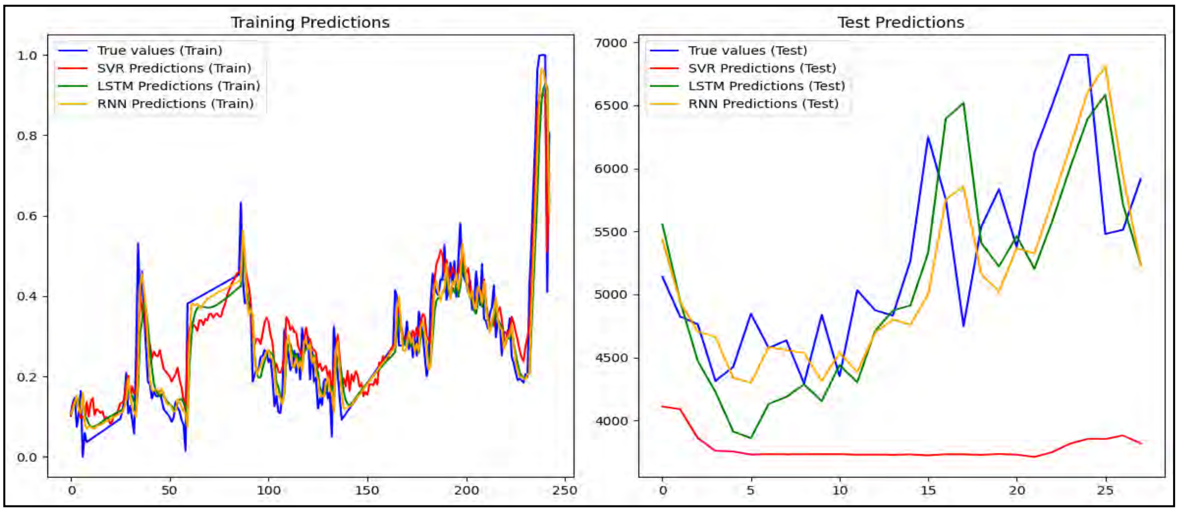
(c) Timestep = 11



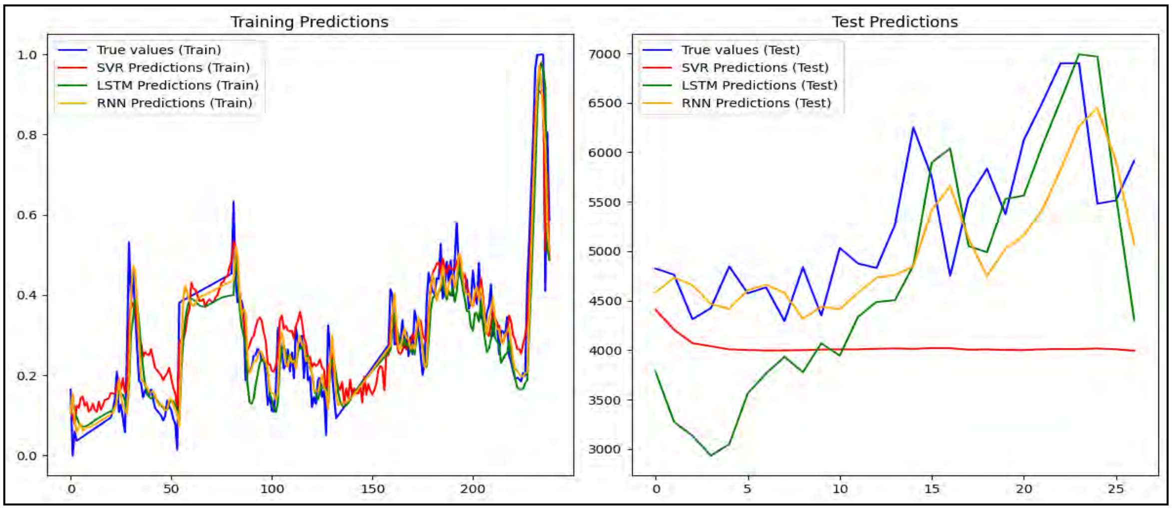
(d) Timestep = 16



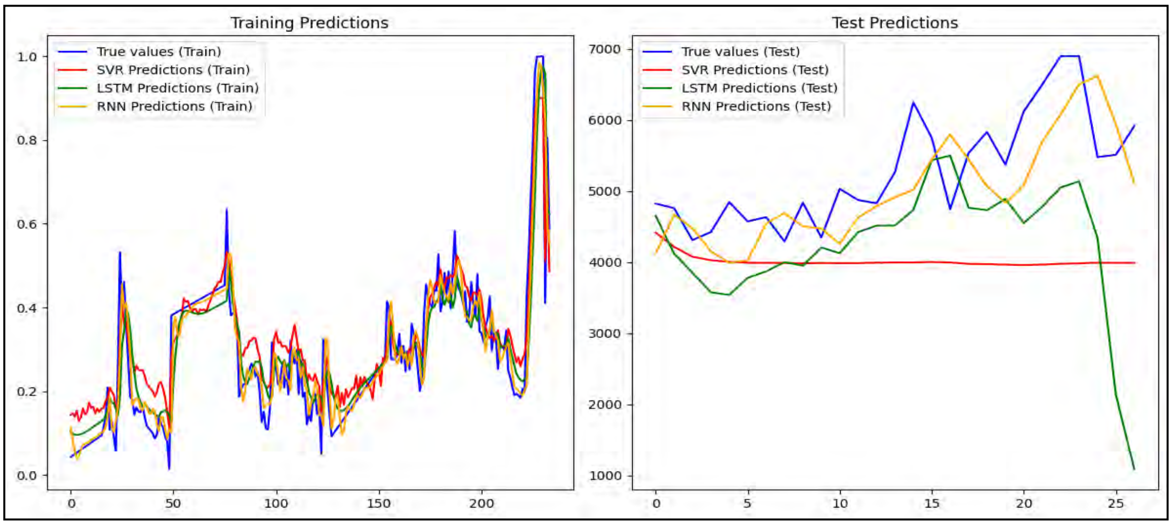
(e) Timestep = 21



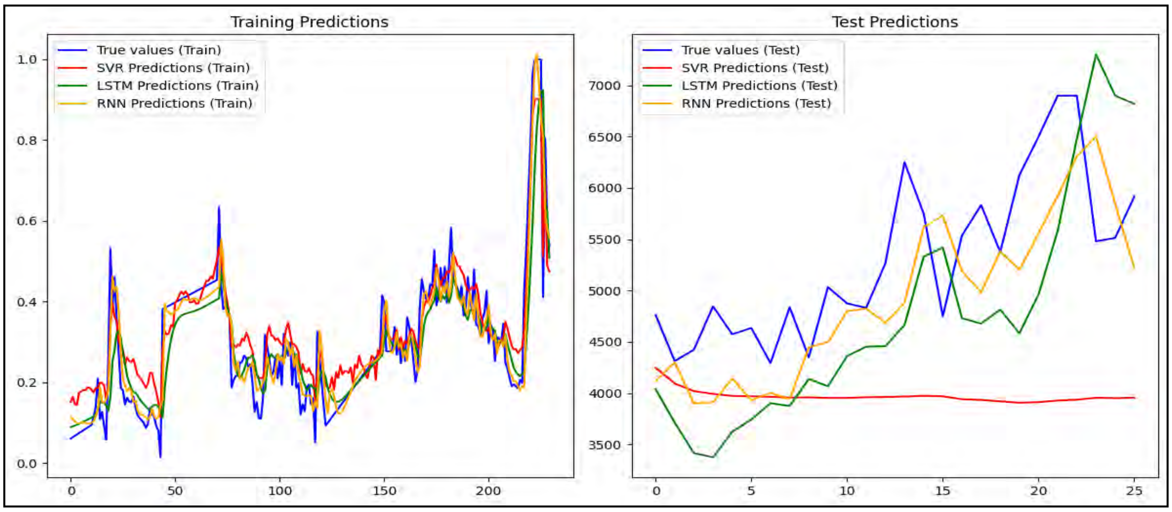
(f) Timestep = 26



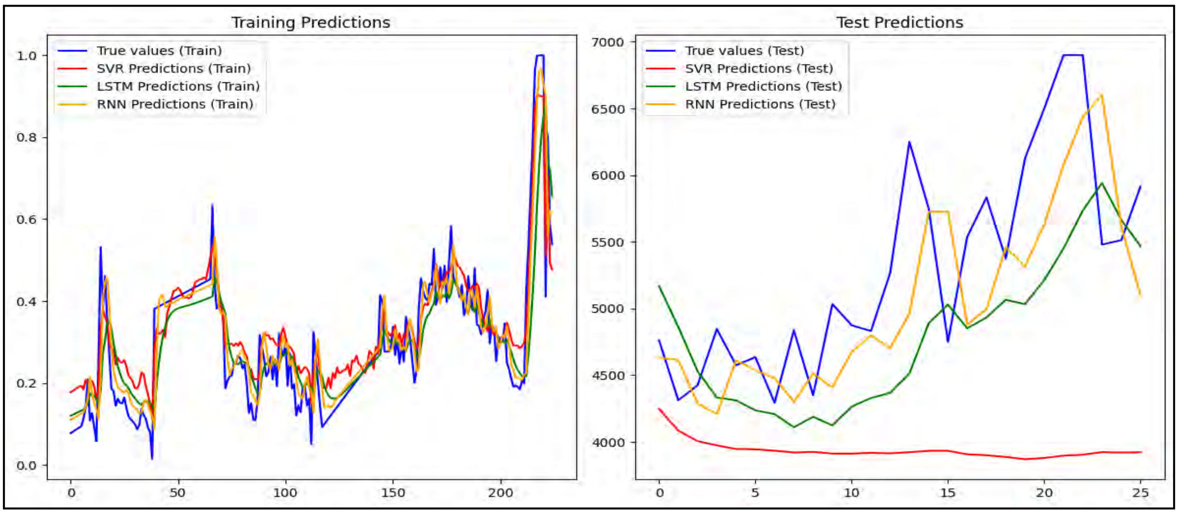
(g) Timestep = 31



(h) Timestep = 36



(i) Timestep = 41



(j) Timestep = 46

Fig 4: Actual vs predicted plots across timesteps with increment of 5

This study examined the effect of varying timesteps on the performance of SVR, LSTM, and RNN models for time series forecasting, using metrics like MSE, RMSE, and MAE across timesteps ranging from 1 to 50, with intervals of 5. The findings reveal key strengths and limitations of each model with respect to the timesteps used. SVR performed well with short-term dependencies or timesteps viz., 1 and 6 and started deteriorating afterwards. Both RNN and LSTM adapted well to longer timesteps and achieving optimal results at 26 timesteps. However, RNN demonstrated more consistent performance across the range of timesteps. This study has several limitations that should be considered when interpreting the results. First, the analysis focused solely on the Parimpore market in Srinagar, which may introduce bias and limit the generalizability of the findings to other geographic markets or commodities. Second, while the models demonstrated consistent performance within the selected market and commodity (apple prices), they may not necessarily perform similarly when applied to different commodities with distinct market dynamics or seasonality patterns. Third, the use of aggregated data (daily prices across multiple months) may reduce the models' capacity to capture fine-grained temporal fluctuations or sudden market shocks. Despite these limitations, the primary focus of this paper was to investigate the effect of temporal granularity (timestep selection) on model performance in time series forecasting. The analysis revealed that the optimal timestep for forecasting apple prices was around 26, aligning closely with the apple sales season in the market, which spans approximately 26 weeks or six months. This finding emphasizes the importance of aligning timestep selection with the underlying seasonality of the commodity, demonstrating that model performance is not solely determined by architecture but also by thoughtful design choices in temporal structuring.

CONCLUSION

It was found that while LSTM, which is theoretically designed to handle longer-term dependencies better than RNNs, the later consistently outperformed LSTM across both shorter and longer timesteps in the context of this dataset. This consistent superiority may stem from the specific characteristics of the data, including reduced noise and volatility due to preprocessing and aggregation, which potentially mitigated the need for LSTM's advanced memory mechanisms. The results highlight the importance of selecting an optimal timestep length, as both longer and shorter timesteps lead to suboptimal predictions. SVR is better suited for tasks involving short-term patterns, while RNN and LSTM excel in capturing longer temporal dependencies. This study provides valuable insights for optimizing time series forecasting models and contributes to the literature on timestep selection. Future research could explore hybrid models and domain-specific adaptations to further enhance forecasting accuracy.

CONFLIT OF INTEREST

All the authors affirm that there is no conflict of interest among them. All research activities comply with relevant legal, institutional and ethical standards.

AUTHOR CONTRIBUTION

All the authors contributed equally in the present study.

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