



Spillover Effects of Covid-19 Induced Lockdown on Onion Prices in India

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Authors' contributions

This work was carried out in collaboration among all authors. Author SG designed the study, performed the statistical analysis, and wrote the first draft of the manuscript. Author RKP edited the manuscript and author AKP reviewed the manuscript. All authors read and approved the final manuscript.

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ABSTRACT

In a normal situation onion prices vary in a highly unprecedented way in India. So, it is worth noticing the effect of an uncertain situation on onion prices. In this article an efficient Artificial Intelligence (AI) tool, i.e., Support Vector Regression (SVR) has been used to predict the price fluctuation of onion over the lockdown period, unlock condition and the period including the pre-pandemic situation. Results obtained are compared with prediction of traditional Multiple Linear Regression (MLR) model. Several metrics such as R^2 , Root Mean Squared Error (RMSE), Mean Absolute Deviation (MAD), and Relative Mean Absolute Percentage Error (RMAPE) have been used for this purpose. The result of Machine Learning (ML) algorithm indicates that in the nationwide lockdown condition pandemic indicator variables are having more than 70% influence on the onion price variability. The effect is reduced to near about 60% in unlock condition and if considering the whole year data this effect is near about 45%. The results also indicate that ML algorithm is more efficient to capture the variability than the traditional model.

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1. INTRODUCTION

Nationwide lockdown in pan India affected the food chain, distribution and consumption. This affected several agricultural commodities worldwide which therefore created remarkable price changes, social, economic and policy crisis [1,2,3,4,5,6,7,8]. Changes in agricultural prices occur mainly due to several endogenous factors like demand and supply relationship, crude oil price, and monetary policies [9,10,11,12,13,14,15,16,17,18]. External factors related to agricultural price changes are directly connected to natural shocks and climate changes [19,20,21,22,23,24,25,26,27]. Rapid spread of the disease caused sheer decline of global economy [28,29,30]. Cariappa et al. [31] studied impact on prices of agricultural items due to the lockdown. Panic purchase during incarcerated condition caused food wastage and increase in prices caused food losses in supply chain. Hung et al. [32] studied connectedness between crude oil price and agricultural markets during covid-19 outbreak. It has been found by wavelet coherence analysis that the effect is more conspicuous during covid-19 crisis than pre-covid era and there is heterogeneity in the degree of spill-over effect over several markets. In the study of Cariappa et al. [33] it can be found that observed price changes in wheat were due to the coincidence of wheat harvesting period and lockdown due to covid-19 pandemic. It was also found that pandemic induced shock could cause disaster if government had not bolstered by staggered procurement and provided logistic supports. Just and Echaust [34] provided insights on transmission of return spill over among agricultural commodities due to combined effect of covid-19 induced pandemic and Russia-Ukraine war. Sharing views regarding the risks of the disease created unnecessary panic and anxiety among people [35,36,37,38,39]. Liu et al. [40] used text mining tool and time dependent variance autoregressive model to study the negative sentiments of online micro blogs to agricultural commodity prices. They found interesting positive relationships with livestock and vegetable products, negative relationships with fruits, and negative at the early but positive relationships at middle and late stages with aquatic products. Martey et al. [41] studied the effects of covid-19 shock on adoption of sustainable agricultural practices among farmers. Paul et al. [42] pointed out impact of covid-19 shocks on vegetable prices and tried to predict

daily price of brinjal in 17 markets of Odisha, India. Paul and Yeasin [43] also applied Generalized Autoregressive Conditional Heteroscedastic (GARCH) model to investigate the effects of covid-19 pandemic on prices of major pulses in India. Tiwari et al. [44] employed a new technique related to Variance Autoregressive (VAR) model to measure the spillover effect between energy and agricultural commodity prices. Zahraee et al. [45] evaluated the impact of covid-19 induced disruptions on resilience of supply chain of agricultural sector.

Machine learning techniques are proven to be effective in capturing volatility in time series datasets especially, in agricultural price series [46,47]. Support Vector Machine (SVM) has recently been widely in use by researchers in the field of time series modelling. It is an unsupervised learning technique where input variables are provided with very few information about the results. The 'Vapnik ϵ -insensitive Loss Function' was introduced by Vapnik et. al [48] which clarifies the use of SVR technique in the domain of regression and time-series problems. Non-linear dynamics present in the price structure of agricultural products allow SVR to be implemented for prediction. Extreme price fluctuation of onion in one of the major consumer markets i.e. the Delhi market has been observed in 2020, the year of Corona pandemic. Due to lockdown condition rural people could not transport their agricultural products to nearby markets for around 2 months which may be a reason for price change and their deteriorating economic condition [49]. In this situation an efficient AI tool namely support vector regression (SVR) has been applied to model the daily price of onion and investigate the effect of pandemic on onion price in Delhi.

2. MATERIALS AND METHODS

2.1 Data

Daily price of Onion (Y) in Delhi has been collected from the National Horticultural Research and Development Foundation (NHRDF) website for the year of 2020 from 1st of January to 27th of October. Dataset is divided into two parts: data of lockdown period (25th March-31st May) and another is of Unlock period (1st June-27th October). Dataset of Covid-19 infection is also collected for this time period on a daily basis from the website

<https://www.kaggle.com/sudalairajkumar/covid19-in-india>.

Firstly, Pearson's correlation coefficient (CC) was computed to see if there is significant correlation among the onion prices with number of daily covid-19 infected (CO), number of daily deaths due to covid-19 infection (D) and number of daily cured (CU) individuals after covid-19 infection. Secondly, suitable statistical test was conducted to check for presence of any non-linearity pattern in the datasets. MLR and SVR models have been fitted to these datasets taking onion prices as dependent variable and others as predictors to predict onion price for the whole year, lockdown and unlock condition.

2.2 Traditional MLR Model

A tradition MLR model can be represented as

$$\widehat{y}(t_n) = a_0 + a_1 CU + a_2 D + a_3 CO \quad (1)$$

Where;

$\widehat{y}(t_n)$ is the predicted onion price (equation 1). CU, D, CO are the potential predictors and a_i 's are the regression parameters used in the MLR model. The a_i values are estimated from the data given. In order to prevent overfitting of the data and to find the optimal (final) regression model, a stepwise regression algorithm (Draper and Smith, 1998) is employed to select significant predictors from all the candidate variables in this study. Finally, the predicted prices are computed.

2.3 SVR

SVM got extensive popularity in the field of classification, regression, and dimensionality reduction. It simply utilizes a hyperplane to linearly separate a series into two classes. Optimal hyperplane can be obtained by- a) convex hull, b) maximizing the margin between two parallel boundaries.

In linear case training set $(x_1, y_1), (x_2, y_2), \dots (x_n, y_n)$; $x \in R_n, y \in \{+1, -1\}$ is classified by hyperplane: $(w \cdot x) + b = 0$ such that margin between nearest vectors

$$L = \frac{1}{2} \|w\|^2 + C \left[\sum_{i=1}^N (y_i + \gamma_i^*) \right] - \sum_{i=1}^N \alpha_i (w^T \varphi(x_i) + a - y_i + \varepsilon + \gamma_i^*) - \sum_{i=1}^N \alpha_i^* (y_i - w^T \varphi(x_i) - a + \varepsilon + \gamma_i) - \sum_{i=1}^N (\eta_i \gamma_i + \eta_i^* \gamma_i^*) \quad (8)$$

where;

w, a, γ_i and γ_i^* are primal variables, and $\alpha_i, \alpha_i^*, \eta_i,$ and η_i^* are nonnegative Lagrange multipliers. Karush-Kuhn-Tucker (KKT) condition (Vapnik et al., 1992) is used to solve the problem. Partially differentiating (equation 6) we get:

to this is maximized. $(w \cdot x_i) + b \geq +1$ if $y_i = 1$, or $(w \cdot x_i) + b \leq -1$ if $y_i = -1$, where w and b are weight and bias respectively.

Non-linear datasets are mapped into higher dimensional feature space for linear separation. Nonlinear SVR is represented as (equation 2):

$$f(x) = w^T \varphi(x) + b \quad (2)$$

Where;

$\varphi(\cdot): R^n \rightarrow R^{n_h}$, which is a non-linear mapping function for linear separation. The following function (equation 3) is maximized:

$$R(C) = \frac{1}{2} \|w\|^2 + C \left[\frac{1}{N} \sum_{i=1}^N L_\varepsilon(y_i, f(x_i)) \right] \quad (3)$$

where;

$x_i \in R^n$ and $w \in R^{n_h}$ is the weight vector. Both C and ε are arbitrary hyper-parameters. 'Regularized term', i.e., $\frac{1}{2} \|w\|^2$ measures the flatness of the function in equation 3. 'Empirical error', i.e., $\frac{1}{N} \sum_{i=1}^N L_\varepsilon(y_i, f(x_i))$ is estimated by 'Vapnik ε -insensitive Loss Function' (equation 4), given by:

$$L_\varepsilon(y_i, f(x_i)) = \begin{cases} |y_i - f(x_i)| - \varepsilon & |y_i - f(x_i)| \geq \varepsilon \\ 0 & |y_i - f(x_i)| < \varepsilon \end{cases} \quad (4)$$

where;

y_i denotes actual value and $f(x_i)$ is the estimated value at i^{th} period.

Then the $R(C)$ can be reframed as (equation 5):

$$R(C) = \frac{1}{2} \|w\|^2 + C \left[\frac{1}{N} \sum_{i=1}^N (y_i + \gamma_i^*) \right] \quad (5)$$

Subjected to the constraints:

$$\begin{cases} w^T \varphi(x_i) + a - y_i \leq \varepsilon + \gamma_i^* \\ y_i - w^T \varphi(x_i) - a \leq \varepsilon + \gamma_i \\ \gamma_i, \gamma_i^* \geq 0 \quad i = 1, 2, \dots, N \end{cases}$$

where;

γ_i and γ_i^* are positive slack variables measuring distance from actual values, y_i and corresponding 'boundary values of the ε -tube'. The primal Lagrange function (equation 6) for solving this problem:

$$\frac{\partial L}{\partial b} = \sum_{i=1}^N (\alpha_i^* - \alpha_i) = 0$$

$$\frac{\partial L}{\partial w} = w - \sum_{i=1}^N (\alpha_i^* - \alpha_i) \varphi(x_i) = 0$$

$$\frac{\partial L}{\partial \xi_i^*} = C - \alpha_i^* - \eta_i^*; i = 1, 2, \dots, N$$

Kernel Functions are used by SVR to transform the input dataset into required form. Mathematically a Kernel function can be represented as (equation 7)

$$K(x, y) = \begin{cases} 1, < f(x), f(y) > \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

where;

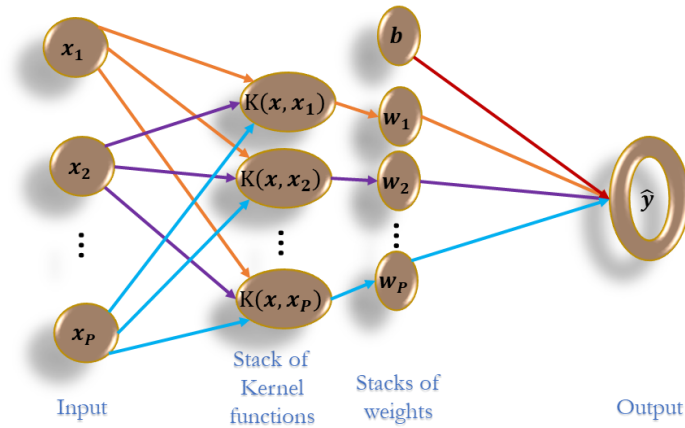
K is the kernel function, x, y are n dimensional inputs. f is a map from n -dimension to m -dimension space. In Fig. 1 (a) schematic diagram of SVR model has been represented and in Fig. (b) ϵ -insensitive Loss Function is introduced.

Some commonly used kernel functions are linear, polynomial, Radial Basis Function (RBF), sigmoid kernel, etc. Introducing the 'Kernel function' ($K(x_i, x_j)$) [i.e., inner product of $\varphi(x_i)$ and $\varphi(x_j)$], the final form of the equation of nonlinear SVR will be (equation 8):

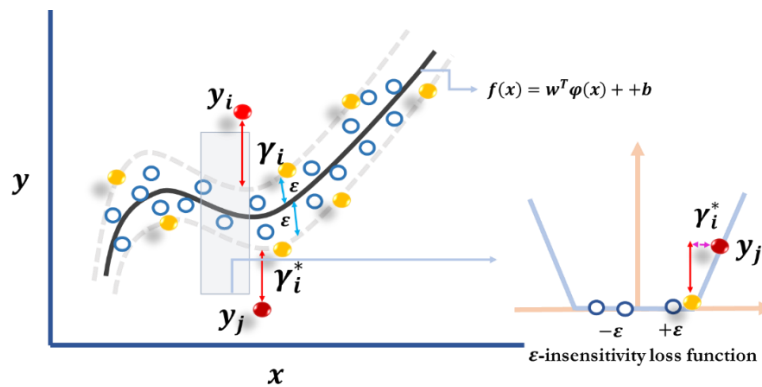
$$f(x) = \sum_{i=1}^N (\alpha_i - \alpha_i^*) K(x_i, x_j) + b \quad (8)$$

However, efficiency of nonlinear SVR models depends on the hyper-parameters. The most efficient technique to optimize them is real valued Genetic Algorithm (GA). Albeit, due to the capacity of escaping local minima Particle Swarm Optimization (PSO) technique is extensively used.

MLR and SVR models have been fitted to the mentioned datasets taking onion prices as dependent variable and others as predictor variables for the whole year, lockdown and unlock conditions.



a. Schematic view of SVR model



b. Data calibration with ϵ -insensitivity loss function in the SVR model

Fig. 1. SVR model

3. RESULTS AND DISCUSSION

3.1 Data Description

Total 301 observations were obtained for each of the 4 datasets mentioned in this study. Minimum onion price in Delhi market was 567 rupees/Quintal (Rs/Q) and maximum price of 4550 Rs/Q was observed during the stipulated time period. Average price during this period was 1650 Rs/Q with a standard deviation (SD) of 964 and Coefficient of Variation (CV) as 58.4%. 1st, 2nd (Median), and 3rd quartile (Q) values of prices were 916, 1310 and 2000 Rs/Q respectively. It can be observed from Table 1 that price dataset was positively skewed and leptokurtic in nature. Maximum number of daily confirmed cases was 4473 with an average case of 1194. Dataset is slightly positively skewed with a platykurtic feature. Maximum number of cured cases in a day was 437. Average number of cured cases was 20 with a SD of 33 and CV of 165%. The dataset is highly positively right tailed and possesses extreme leptokurtic nature.

Maximum number of deaths observed in a day was 7725. Average number of death cases was 1088 with SD and CV values were 1357 and 125%. Dataset related to death cases is positively skewed and leptokurtic in nature.

Time plots of 301 observations covering onion price patterns and covid-19 related figures are represented in Fig. 2. Pearsonian correlation measure is useful for an overall view of the relation of any two datasets. Relation between each of the predictor variables, i.e., CU, D and CO with price dataset has been found by calculating CC values between them and represented in Table 2. For checking the significance of each of the correlation measure t-test was applied and calculated statistics value and corresponding degrees of freedom (df) have been mentioned in Table 2. Correlation measures were calculated for each of the variables on the full data, only lockdown period data and unlock condition data separately and represented in Table 2.

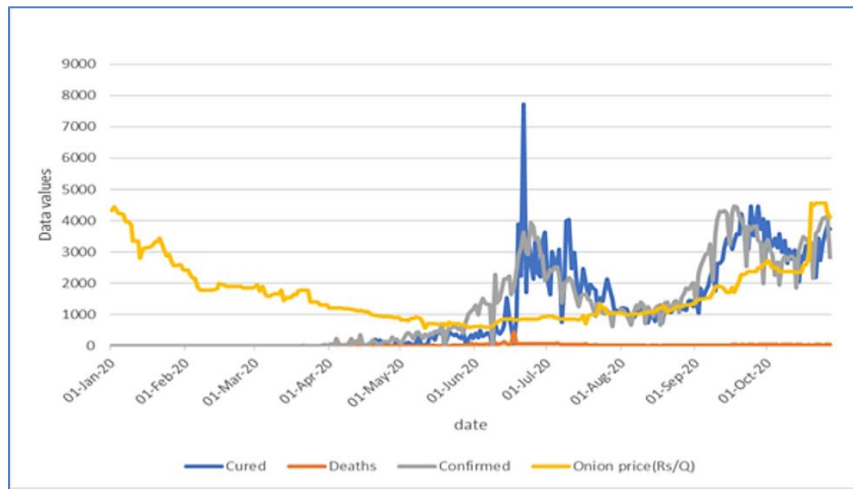


Fig. 2. Line charts describing the pattern of different variables

Table 1. Descriptive statistics of the full data set

	Y	CU	D	CO
N	301	301	301	301
Min	567	0	0	0
1st Q	916	0	0	1
Median	1310	13	375	674
Mean	1650	20	1088	1194
3rd Q	2000	34	1973	2089
Max	4550	437	7725	4473
Range	3983	437	7725	4473
SD	964	33	1357	1334
CV (%)	58.4	165	125	112
Skewness	1.34	6.82	1.18	0.86
Kurtosis	1.29	78.22	0.98	-0.53

Table 2. Correlation coefficient values (CC) of different predictor variables with onion market arrival prices (Rs/Q)

Predictors	CC			t-value and df			p-value		
	Full	Lockdown	Unlock	Full	Lockdown	Unlock	Full	Lockdown	Unlock
CU	0.14	-0.66	0.52	2.41, 299	-7.11, 66	7.35, 147	0.02	<0.0001	<0.0001
D	-0.17	-0.48	-0.13	-2.93, 299	-4.44, 66	-1.56, 147	0.004	<0.0001	0.12
CO	0.11	-0.76	0.57	1.86, 299	-9.50, 66	8.49, 147	0.06	<0.0001	<0.0001

It can be observed that CC values are higher in case of lockdown data. In unlock situation number of deaths due to Corona does not affect much to onion prices but other two predictors are affecting significantly to the onion price data. By observing CC values, it can be concluded that predictors have less influence on price series for the full-length data. Brock-Dechert-Scheinkman (BDS) test [50] had been applied to all the four variables. BDS test is a two-tailed test [51-53]. The null hypothesis (H_0) and

alternative hypothesis (H_1) of the BDS test are as follows:

H_0 = Time series is linear (data series are identically and independently distributed, i.e., i.i.d)

H_1 = Time series is nonlinear (presence of nonlinear dependency)

It is proved from Table 3 that all the variables are having non-linear pattern in the given time period.

Table 3. BDS test results for four variables

Statistics	Embedding dimension								Conclusion (at 1% level)
	2				3				
	Value				Value				
	Y	CU	D	CO	Y	CU	D	CO	
eps [1]	65.54	42.40	46.22	54.81	103.90	64.50	63.28	89.81	Nonlinear with maximum embedding dimension-3
eps [2]	43.54	38.93	26.88	47.79	50.70	47.91	31.36	58.75	
eps [3]	34.37	33.74	21.17	40.06	35.42	37.60	20.97	44.73	
eps [4]	27.81	24.08	7.05	33.74	26.93	26.18	7.01	35.81	

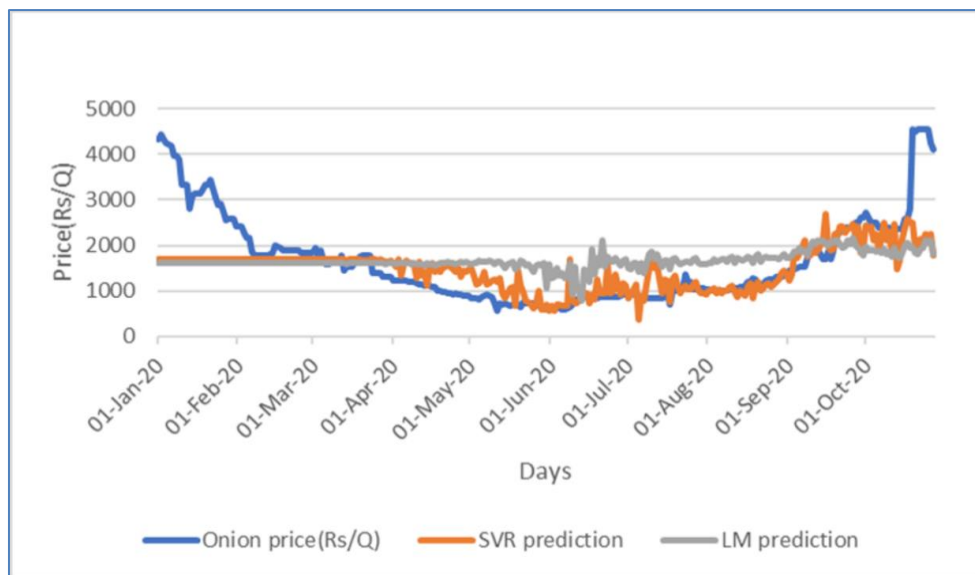


Fig. 3. Line charts comparing SVR and MLR(LM) model prediction on full dataset

3.2 Fitting into MLR and SVR Models

MLR model had been fitted into 3 datasets to predict onion prices on 3 different time frames. A glimpse of impact of covid-19 pandemic on onion prices can be observed by doing so. However, non-linear ML model, i.e., SVR was applied on the series to capture its predictability during 3 different scenarios. Fig. 3 represents line charts of predictions of MLR and SVR models on complete series. How the two models performed during the lockdown period can be observed in Fig. 4. Predictions of these models on onion prices at the unlock situations can be visualized in Fig. 5. It can be seen from Fig. 2 and Fig. 4 that prices of last few days could not be predicted by both of the models. This simply implies that at unlock condition as time passed on dependence of covid-19 related statistics on onion price structure gradually decreased. Hence, there are other influential factors to describe the price pattern.

Comparison statistics are represented for three series on prediction performance of MLR and

SVR models in Table 4. R^2 in a regression model plays very important role which indicates the percentage variability of predictand explained by predictor variables. Error or residuals in prediction is a very important keyword meaning the failure of a model to predict a variable precisely. This is used to produce several metrics of model evaluation. RMSE is the squared root of the average mean squared error. However, MAD is calculated by averaging the absolute error values. Similarly, Relative Absolute Error (RAE) values are calculated for each observation by dividing the absolute error values by actual observation. Thus, RMAPE is obtained by averaging out the RAEs over the whole series followed by multiplication of a cent. In the full data set R^2 values are 8.31 and 45.21 for MLR and SVR models respectively. This means SVR can explain percentage variation in the series more accurately than MLR. Albeit, R^2 value of such a low quantity cannot be considered a good fit for a statistical model, in lockdown condition the predictor variables can explain most of the variability in the onion price series.

Table 4. Comparative performance of prediction models on different datasets

Comparative measures	Full		Lockdown		Unlock	
	MLR	SVR	MLR	SVR	MLR	SVR
R^2 (%)	8.31	45.21	62.78	74.90	38.18	59.94
RMSE	922	756	143.5	118.23	752	643
MAD	707	445	114	84	502	313
RMAPE (%)	52	25	13	9	35	17

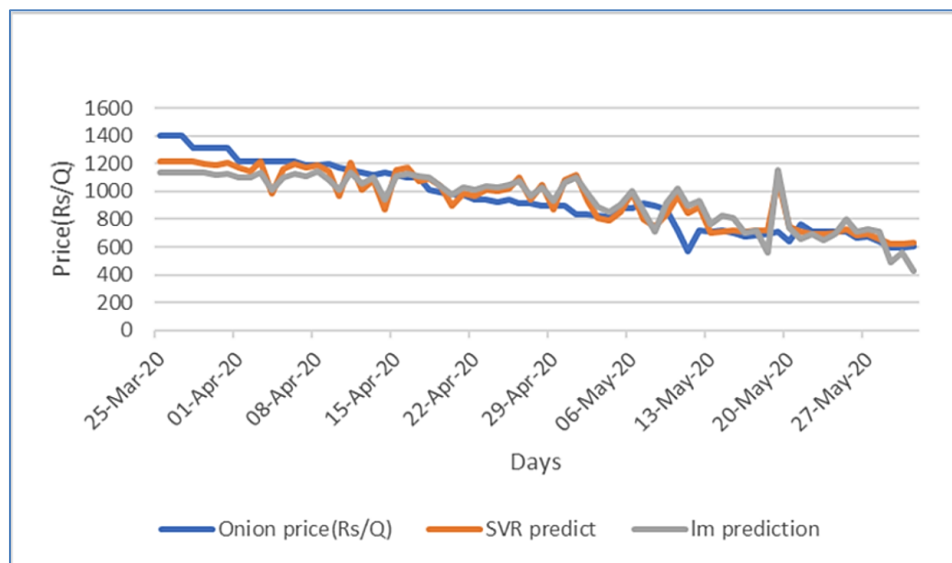


Fig. 4. Line charts comparing SVR and MLR(LM) model prediction in lockdown

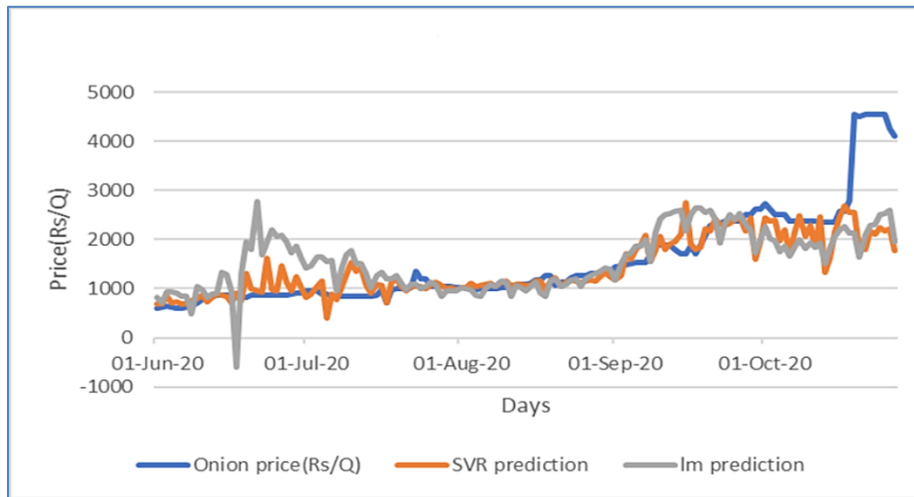


Fig. 5. Line charts comparing SVR and MLR(LM) model prediction in unlock

A significant improvement in prediction has been achieved by utilizing ML algorithm. A steep increase of 19.31% in R^2 value is achieved by fitting the series into SVR model in lockdown condition. Although, number of observations was less in case of lockdown, 74.90% R^2 value has been acquired by fitting the data into SVR model. The spillover effect of covid-19 lockdown was sustained in unlock situation as the statistics related to the disease are capable of explaining the price variability of onion at that time period also. It is obvious that there are many factors which are causing onion price volatility. The previous statement is true because onion price variability could not be explained by using only covid-19 statistics. That's why the R^2 , RMSE, MAD and RMAPE values were quite unsatisfactory when the MLR and SVR models were used to fit price series on whole series. Nevertheless, these metrics prove that SVR performs better than MLR. The statistical metrics used in this study confirms that SVR model is better in capturing the price volatility of onion for the lockdown condition than MLR model. Similar comment can be passed on for unlock condition. These statements are indicating that the specified ML algorithm used in the study, i.e., SVR out performs in all aspects to capture price volatility of onion price either in a normal or crisis situation. RMAPE value less than 10% is considered an outstanding fit for a model. This was achieved by SVR model in lockdown condition. MLR was also capable to predict the series during the period. It is quite interesting to note that at last few days of unlock condition both MLR and SVR were incapable of predicting the price series using the chosen predictor variables. This indicates that effect of covid-19 pandemic

on onion prices was decreasing and other related price factors were reasons for the price volatility.

4. CONCLUSION

Price of perishable agricultural food products is fully dependent on every day transport and supply chain. In the lockdown condition rural people could not be able to market their agricultural products to nearby markets properly due to unavailability of proper transportation facility. Due to less supply, price of food products might have increased in a normal condition but effect of corona virus (covid-19) was so severe that a reverse price scenario had been observed due to less demand during the lockdown condition. In this study the effect of covid-19 was studied on onion prices. MLR and SVR models were applied to fit confirmed, cured and death cases due to covid-19 and onion prices data series during pre-pandemic, nationwide lockdown and unlock condition in India. Price trend of onion series had effectively been captured by the SVR and outperformance of this AI tool was noticed over the traditional MLR tool. It is clear from Table 4 considering the result of ML algorithm that in the nationwide lockdown condition pandemic indicator variables were having more than 70% influence on the onion price variability. The effect was reduced to near about 60% in unlock condition and if considering the whole year data, this effect was near about 45%. The results also indicate that ML algorithm was more efficient to capture the variability than the traditional model. During covid-19 pandemic, panic buying situation was observed among people. They stored essential commodities before the lockdown and for this reason price

hike might be noticed. On the other hand, rural farmers had to go for distress sell also. This trend might be observed on other daily food essentials like potato, egg etc. which were marketed by rural people on a daily basis but hampered due to the pandemic and they had suffered for this. Therefore, it is worth analysing the impact of covid-19 on other food items using several other AI tools.

CONFERENCE DISCLAIMER

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Chen ZM, Wang L, Zhang XB, Zheng X. The co-movement and asymmetry between energy and grain prices: evidence from the crude oil and corn markets. *Energies*. 2019;12(7):1373.
2. Shiferaw YA. Time-varying correlation between agricultural commodity and energy price dynamics with Bayesian multivariate DCC-GARCH models. *Phys. Stat. Mech. Appl.* 2019;526:120807.
3. Su CW, Wang XQ, Tao R, Oana-Ramona L. Do oil prices drive agricultural commodity prices? Further evidence in a global bio-energy context. *Energy*. 2019; 172:691–701.
4. Vo DH, Vu TN, McAleer M. Modeling the relationship between crude oil and agricultural commodity prices. *Energies*. 2019;12(7):1344.
5. Chang CL, McAleer M, Wong WK. Risk and financial management of COVID- 19 in business, economics and finance. *J. Risk Financ. Manag.* 2020;13:102.
6. Goodell JW. COVID-19 and finance: agendas for future research. *Finance Res. Lett.* 2020;101512.
7. Goodell JW, Goutte S. Co-movement of COVID-19 and Bitcoin: evidence from wavelet coherence analysis. *Finance Res. Lett.* 2021;38:101625.
8. Sharif A, Aloui C, Yarovaya L. COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: fresh evidence from the wavelet-based approach. *Int. Rev. Financ. Anal.* 2020;101496.
9. Durevall D, Loening JL, Ayalew Birru Y. Inflation dynamics and food prices in Ethiopia. *J. Dev. Econ.* 2013;104:89–106.
10. Paul RK, Himadri G. Development of out-of-sample forecasts formulae for ARIMAX-GARCH model and their application. *Jour. Ind. Soc. Ag. Statistics.* 2014;68(1);85-92.
11. Fowowe B. Do oil prices drive agricultural commodity prices? Evidence from South Africa. *Energy*. 2016;104:149–157.
12. Mitra D, Paul RK, Udgata AR, Paul AK, Bhar LM. Spatio-temporal models for forecasting of rice and wheat yields in India. *Jour. Ind. Soc. Ag. Statistics.* 2019;73(3):181-188
13. Wei Su C, Wang X-Q, Tao R, Oana-Ramona L. Do oil prices drive agricultural commodity prices? Further evidence in a global bio-energy context. *Energy*. 2019; 172:691–701.
14. Abedi A, Zaionchik L. The fundamentals of financial forecasting condition of oil production enterprise. ICEMT, Atlantis Press. 2020;87-90.
15. Liu L, Tan S, Wang Y. Can commodity prices forecast exchange rates? *Energy Econ.* 2020;87:104719.
16. Yeasin M, Singh KN, Lama A, Paul RK. Modelling Volatility Influenced by Exogenous Factors Using an Improved GARCH-X Model. *Jour. Ind. Soc. Ag. Statistics.* 2020;74:209-216.
17. Li X, Wu P, Wang W. Incorporating stock prices and news sentiments for stock market prediction: a case of Hong Kong. *Inf. Process. Manag.* 2020;57:102212.
18. Li T, Rong L, Zhang A. Assessing regional risk of COVID-19 infection from Wuhan via high-speed rail. *Transport Pol.* 2021;106: 226–238
19. Jebabli I, Arouri M, Teulon F. On the effects of world stock market and oil price shocks on food prices: an empirical investigation based on TVP-VAR models

- with stochastic volatility. *Energy Econ.* 2014;45:66–98.
20. Bhardwaj SP, Paul RK, Singh KN. Price forecast an instrument for improvement in agricultural production and marketing in Rajasthan-A case study of rape & mustard seeds. *Jour. Ind. Soc. Ag. Statistics.* 2015; 29(2):155-163.
 21. Priyanka A, Paul RK. Wavelet based hybrid approach for forecasting volatile potato price. *Jour. Ind. Soc. Ag. Statistics.* 2017;71(1):7-14.
 22. Klomp J, Hoogezand B. Natural disasters and agricultural protection: a panel data analysis. *World Dev.* 2018;104:404–417.
 23. Seok JH, Kim G, Reed MR, Kim S-E. The impact of avian influenza on the Korean egg market: Who benefited? *J. Pol. Model.* 2018;40:151–165.
 24. Yi L, Tao J, Tan C, Zhu Z. Avian influenza, public opinion, and risk spillover: measurement, theory, and evidence from China's broiler market. *Sustainability.* 2019;11:1–44.
 25. Chatzopoulos T, P´erez Dom´ınguez I, Zampieri M, Toreti A. Climate extremes and agricultural commodity markets: A global economic analysis of regionally simulated events. *Weather. Clim. Extremes.* 2020;27:100193
 26. Siddig K, Stepanyan D, Wiebelt M, Grethe H, Zhu T. Climate change and agriculture in the Sudan: impact pathways beyond changes in mean rainfall and temperature. *Ecol. Econ.* 2020;169:106566.
 27. Paul RK, Yeasin M, Paul A. The volatility spillover of potato prices in different markets of India. *Curr. Sci.* 2022;123(10): 482-487
 28. Verikios G. The dynamic effects of infectious disease outbreaks: the case of pandemic influenza and human coronavirus. *Soc. Econ. Plann. Sci.* 2020; 71:100898.
 29. Wu Y, Kwakkenbos L, Henry RS, Tao L, Harb S, Bourgeault A, Carrier M-E, Levis B, Sun Y, Bhandari PM, Carboni-Jim´enez A, Gagarine M, He C, Krishnan A, Negeri ZF, Neupane D, Mouthon L, Bartlett SJ, Benedetti A, Thombs BD, Culos-Reed N, El-Baalbaki G, Hebblethwaite S, Patten S, Varga J, Bustamante L, Duchek D, Ellis K, Rice D, Dyas L, Fortun´e C, Gietzen A, Guillot G, Lewis N, Nielsen K, Richard M, Sauv´e M, Welling J. Validation of the COVID-19 fears questionnaires for chronic medical conditions: A scleroderma patient-centered intervention network COVID-19 cohort study. *J. Psychosom. Res.* 2020; 139:110271.
 30. Mofijur M, Fattah IMR, Alam MA, Islam ABMS, Ong HC, Rahman SMA, Najafi G, Ahmed SF, Uddin MA, Mahlia TMI. Impact of COVID-19 on the social, economic, environmental and energy domains: lessons learnt from a global pandemic. *Sustain. Prod. Consum.* 2021;26:343–359.
 31. Cariappa AA, Acharya KK, Adhav CA, Sendhil R, Ramasundaram P. COVID-19 induced lockdown effects on agricultural commodity prices and consumer behaviour in India–Implications for food loss and waste management. *Socio-Econ. Plan. Sci.* 2022;82:101160.
 32. Hung NT. Oil prices and agricultural commodity markets: Evidence from pre and during COVID-19 outbreak. *Res. Policy.* 2021;73:102236.
 33. Cariappa AA, Acharya KK, Adhav CA, Sendhil R, Ramasundaram P, Kumar A, Singh S, Singh GP. COVID-19 induced lockdown effect on wheat supply chain and prices in India–Insights from state interventions led resilience. *Socio-Econ. Plan. Sci.* 2022;101366.
 34. Just M, Echaust K. Dynamic spillover transmission in agricultural commodity markets: What has changed after the COVID-19 threat? *Econ. Lett.* 2022;217: 110671.
 35. Loureiro ML, Allo´ M. Sensing climate change and energy issues: sentiment and emotion analysis with social media in the U.K. and Spain. *Energy Pol.* 2020;143: 111490
 36. Naseem U, Razzak I, Musial K, Imran M. Transformer based deep intelligent contextual embedding for twitter sentiment analysis %. *J. Future Gener. Comput. Syst.* 2020;113.
 37. Zou X, Yang J, Zhang W, Han H. Collaborative community-specific microblog sentiment analysis via multi-task learning. *Expert Syst. Appl.* 2020;114322.
 38. Islam MS, Ferdous MZ, Potenza MN. Panic and generalized anxiety during the COVID-19 pandemic among Bangladeshi people: An online pilot survey early in the outbreak. *J. Affect. Disord.* 2020;276:30–37.
 39. Nicomedes CJC, Avila RMA. An analysis on the panic during COVID-19 pandemic through an online form. *J. Affect. Disord.* 2020;276:14–22.

40. Liu Y, Liu S, Ye D, Tang H, Wang F. Dynamic impact of negative public sentiment on agricultural product prices during COVID-19. *J. Retail. Consum. Serv.* 2022;64:102790.
41. Martey E, Etwire PM, Adzawla W, Atakora W, Bindraban PS. Perceptions of COVID-19 shocks and adoption of sustainable agricultural practices in Ghana. *J. Environ. Manage.* 2022;320:115810.
42. Paul RK, Yeasin M, Kumar P, Kumar P, Balasubramanian M, Roy HS, Paul AK, Gupta A. Machine learning techniques for forecasting agricultural prices: A case of brinjal in Odisha, India. *Plos one.* 2022; 17(7):e0270553.
43. Paul RK, Yeasin M. COVID-19 and prices of pulses in Major markets of India: Impact of nationwide lockdown. *Plos one.* 2022; 17(8):e0272999.
44. Tiwari AK, Abakah EJA, Adewuyi AO, Lee CC. Quantile risk spillovers between energy and agricultural commodity markets: Evidence from pre and during COVID-19 outbreak. *Energy Econ.* 2022; 113:106235.
45. Zahraee SM, Shiwakoti N, Stasinopoulos P. Agricultural biomass supply chain resilience: COVID-19 outbreak vs. sustainability compliance, technological change, uncertainties, and policies. *Cleaner Logistics and Supply Chain.* 2022; 4:100049.
46. Das T, Paul RK, Bhar LM, Paul AK. Application of Machine Learning Techniques with GARCH Model for Forecasting Volatility in Agricultural Commodity Prices. *Jour. Ind. Soc. Ag. Statistics.* 2020;74(3):187-194.
47. Garai S, Paul RK, Rakshit D, Yeasin M, Emam W, Tashkandy Y, Chesneau C. Wavelets in combination with stochastic and machine learning models to predict agricultural prices. *Mathematics.* 2023; 11(13):2896.
48. Vapnik V, Bottou L. *Local Learning Algorithms.* AT&T Bell Laboratories, Holmdel, NJ 07733 USA; 1992.
49. Imai KS, Kaicker N, Gaiha R. The Covid-19 impact on agricultural prices in India. Discussion Paper Series DP2020-25, Research Institute for Economics & Business Administration, Kobe University; Oct 2020.
50. Brock WA, Scheinkman JA, Dechert WD, Le B. A test for independence based on the correlation dimension. *Econom. Rev.* 1996;15:197-235.
51. Draper, Norman R, Smith H. [Wiley Series in Probability and Statistics] *Applied Regression Analysis*; 1998. DOI:10.1002/9781118625590.
52. Gurung B, Paul RK, Ghosh H. Fitting exponential smooth transition autoregressive nonlinear time-series model using particle swarm optimization technique. *Jour. Ind. Soc. Ag. Statistics.* 2014;68(3):327-332.
53. Panwar S, Kumar A, Sarkar SK, Paul RK, Gurung B, Rathore A. Forecasting of common carp fish production from ponds using nonlinear growth models-a modelling approach. *Jour. Ind. Soc. Ag. Statistics.* 2016;70(2):139-144.

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