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

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 metrices 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) algorithmindicates 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.

Key words: *AI; Covid-19; Lockdown; Volatility; MLR; SVR.*

1. Introduction

Nationwide lockdown in pan India affected the food chain, distribution and consumption. This affected several agricultural commodities world-wide which therefore created remarkable price changes, social, economic and policy crisis (Chen *et al.*, 2019; Shiferaw, 2019; Su *et al.*, 2019; Vo *et al.*, 2019; Chang *et al.*, 2020; Goodell *et al.*, 2020 and 2021; Sharif *et al.*, 2020). Changes in agricultural prices occur mainly due to several endogenous factors like demand and supply relationship, crude oil price, and monetary policies (Durevall*et al.*, 2013; Paul and Ghosh, 2014; Fowowe, 2016; Mitra et al., 2019; Wei Su *et al.*, 2019; Liu *et al.*, 2020; Yeasin et al., 2020; Li *et al.*, 2020 and 2021). External factors related to agricultural price changes are directly connected to natural shocks and climate changes (Jebabli *et al.*, 2014; Bhardwaj et al., 2015; Priyanka and paul, 2017; Klomp and Hoogezand, 2018; Seok *et al.*, 2018, and Yi *et al.*, 2019; Chatzopoulos *et al.*, 2020; Siddig *et al.*, 2020; Paul et al., 2022).Rapid spread of the disease caused sheer decline of global economy (Verikios, 2020, Wu *et al.*, 2020; Mofijur*et al.*, 2021). Cariappa *et al.* (2021) 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.* (2021) 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.* (2022) 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 (2022) 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 (Loureiro and Allo, 2020; Naseem *et al.*, 2020; Zou *et al.*, 2020; Islam *et al.*, 2020;Nicomedes and Avila, 2020). Liu *et al.* (2022) 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.* (2022) studied the effects of covid-19 shock on adoption of sustainable agricultural practices among farmers. Paul *et al.* (2022) 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 (2022) 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.* (2022) employed a new technique related to Variance Autoregressive (VAR) model to measure the spillover effect between energy and agricultural commodity prices.Zahraee*et al.* (2022) 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 (Das et al., 2020, Garai et al., 2023). 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‘Vapnikε-insensitiveLossFunction’wasintroduced by Vapnik *et.al* (1992) whichclarifiestheuseofSVRtechniqueinthedomainofregressionandtime-seriesproblems.Non-linear dynamics present in the price structure ofagricultural productsallow 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 (Imai*et al.*, 2020). 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 MLRmodel

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 theregression 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 simplyutilizesa 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$(x_1, y_1), (x_2, y_2), \ldots (x_n, y_n)$; $x \in R_n, y \in \{+1, -1\}$is classified by hyperplane:$(w.x) + b = 0$ such that margin between nearest vectors to this is maximized. $(w.xi) + b \geq +1\ if\ yi = 1, or\ (w.xi) + b \leq +1\ if\ yi = -1$, where w and b are weight and bias respectively.

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

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

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

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

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.

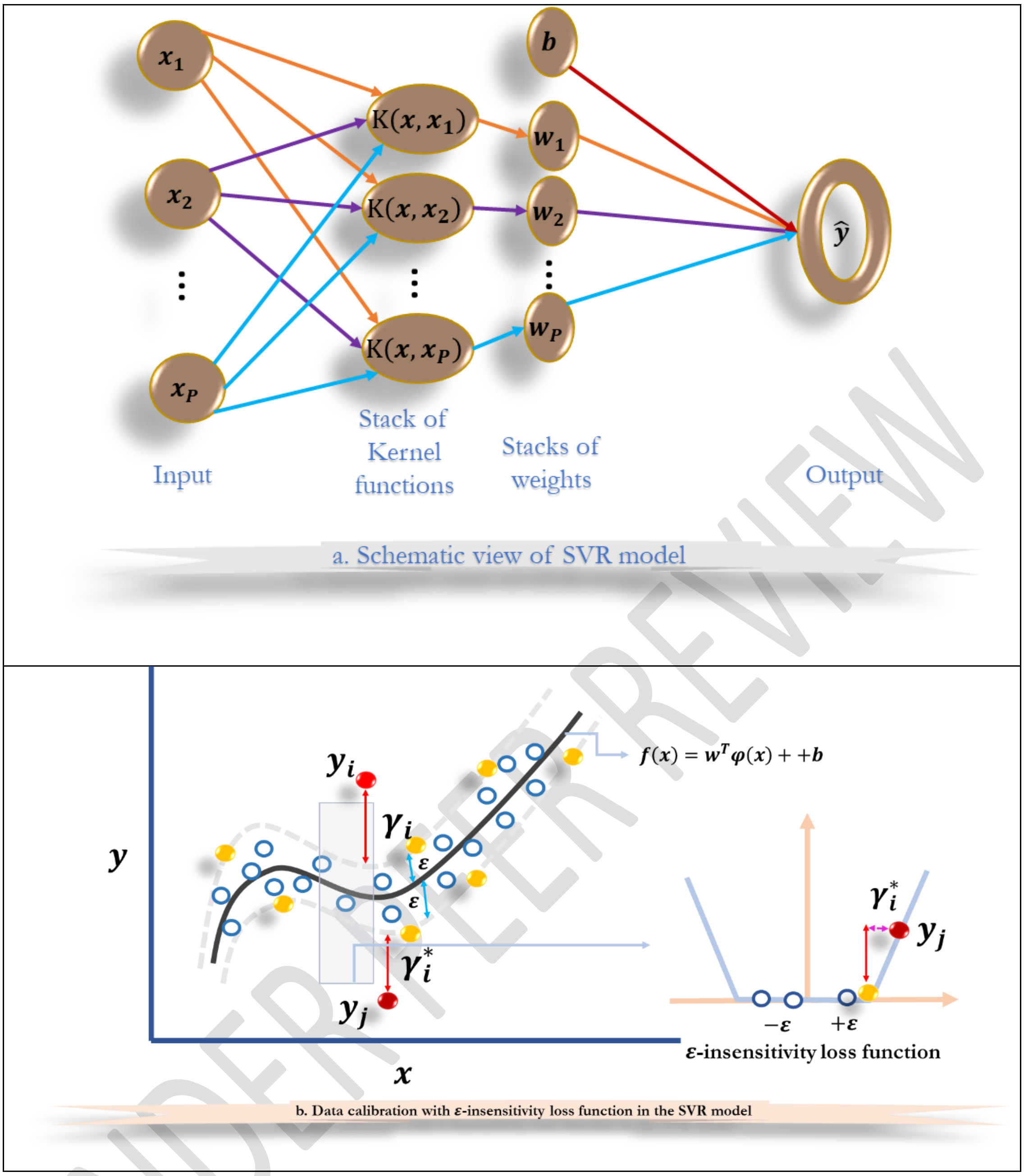

Figure 1: SVR model

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

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

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

where γ_i and $\gamma_i^*$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:

$L = \frac{1}{2}\|w\|^2 + C\left[\sum_{i=1}^{N}(\gamma_i + \gamma_i^*)\right] - \sum_{i=1}^{N}\alpha_i\left(w^T\varphi(x_i) + a - y_i + \varepsilon + \gamma_i^*\right) - \sum_{i=1}^{N}\alpha_i^*\left(y_i - w^T\varphi(x_i) - a + \varepsilon + \gamma_i\right) - \sum_{i=1}^{N}(\eta_i\gamma_i + \eta_i^*\gamma_i^*)$(6)

Where w,a,γ_i and γ_i^* are primal variables, andα_i, α_i^*, η_i,and $\eta_i^*$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:

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

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

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

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

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

were$K$ is the kernel function, x, y are n dimensional inputs. $f$is a map from n-dimension to m-dimension space. In figure 1 (a) schematic diagram of SVR model has been represented and in figure(b) ε-insensitive Loss Function is intpduced. Some commonly used kernel functions are linear, polynomial, Radial Basis Function (RBF), sigmoidkernel, 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):

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

3. Results and Discussions

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.

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

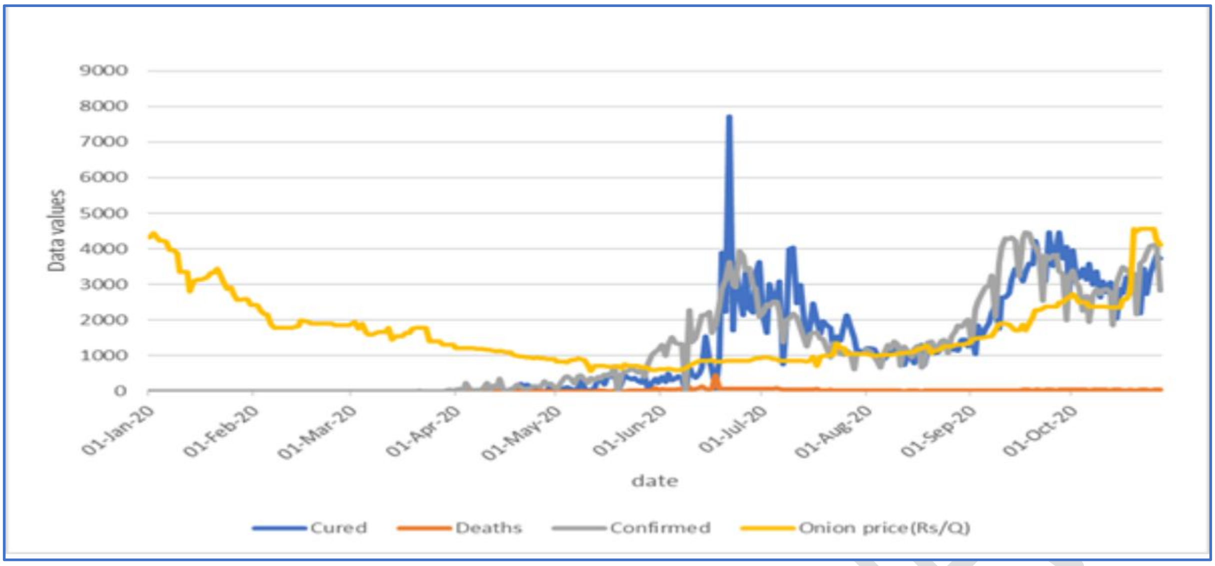

Figure 2: Line charts describing the pattern of different variables

Time plots of 301 observations covering onion price patterns and covid-19 related figures are represented in figure 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.

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 (Brock *et al.*, 1996) had been applied to all the four variables. BDS test is a two-tailed test.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	

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. Figure 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 figure 4. Predictions of these models on onion prices at the unlock situations can be visualized in figure 5. It can be seen from figure 2 and figure 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.

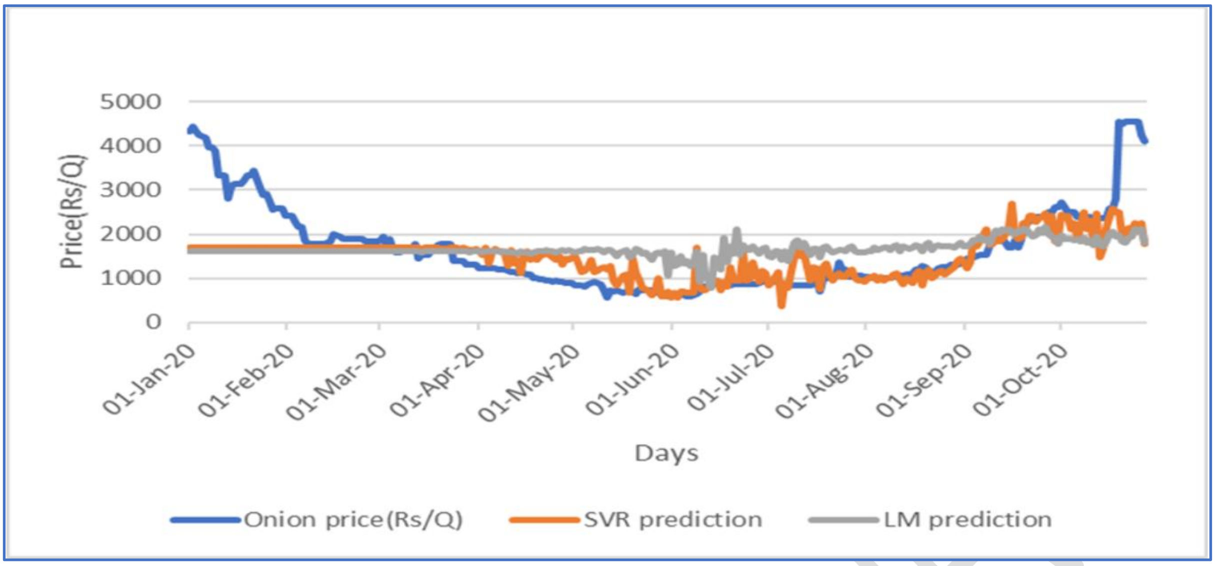

Figure 3: Line charts comparing SVR and MLR(LM) model prediction on full dataset

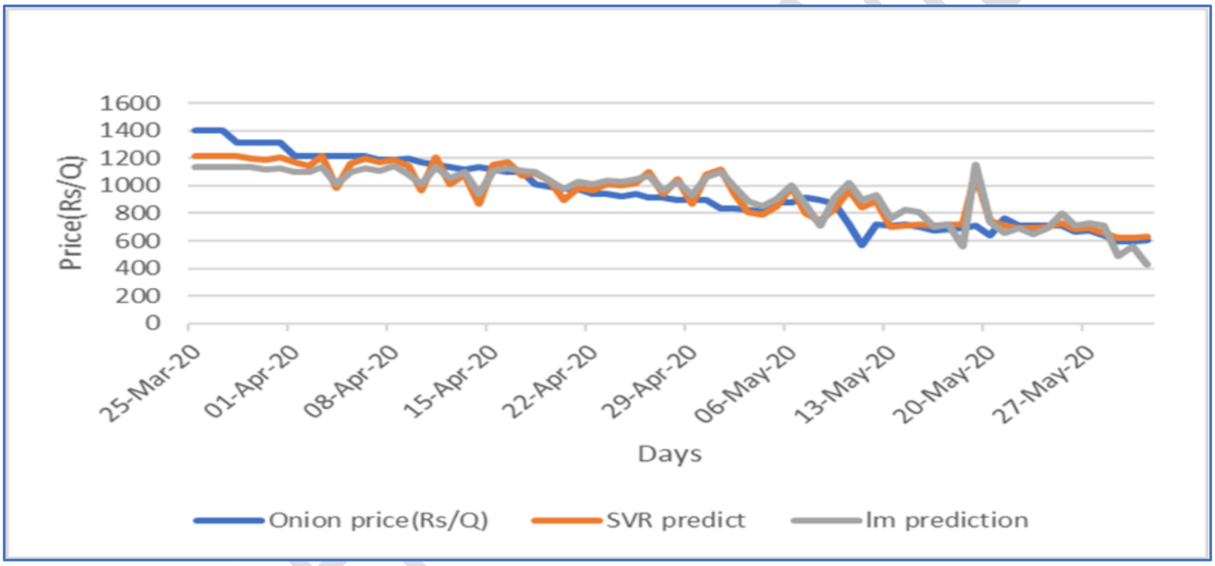

Figure 4: Line charts comparing SVR and MLR(LM) model prediction in lockdown

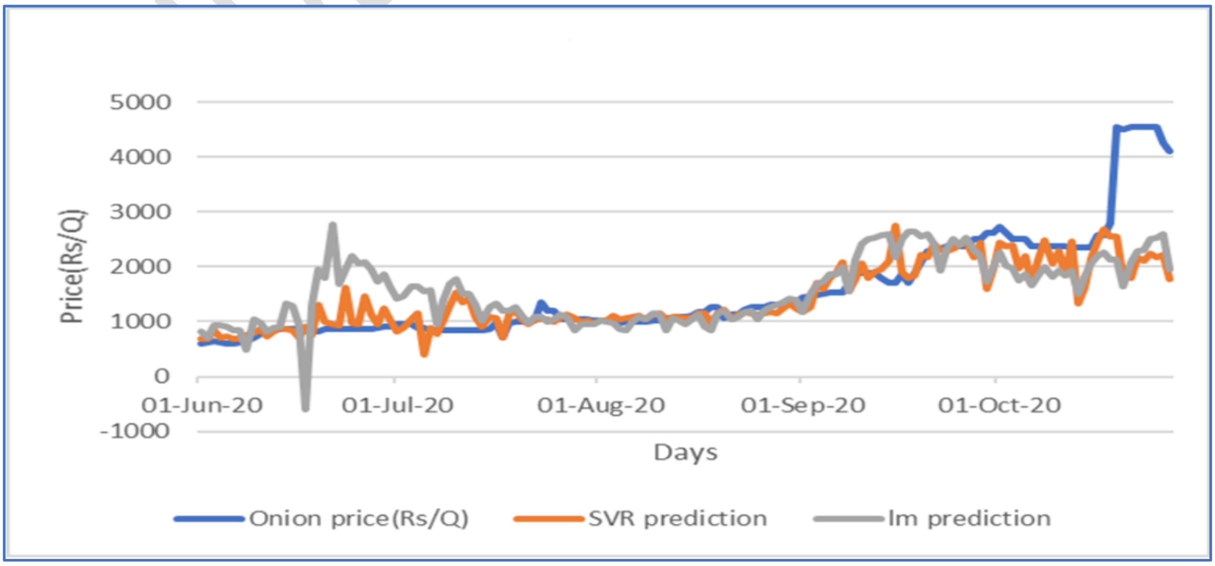

Figure 5: Line charts comparing SVR and MLR(LM) model prediction in unlock

Comparison statistics are represented for three series on prediction performance of MLR and SVR models in table 4. R^2in 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 metrices 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 setR^2values 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

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 metrices 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 outperforms 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. Conclusions

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 wasobserved 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 theyhad suffered for this. Therefore, it is worth analysing the impact of covid-19 on other food items using several other AI tools.

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