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A Novel Model Selection Framework for Forecasting Agricultural Commodity Prices using Time Series Features and Forecast Horizons

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ABSTRACT

The oscillations of agricultural commodity prices have abundant impact on people's daily lives and also the inputs and outputs of agricultural production. To take proper decisions one should require an accurate forecast of commodity prices. Accuracy of crop price forecasting techniques is important because it enables the supply chain planners and government bodies to take appropriate actions by estimating market factors such as demand and supply. In emerging economies such as India, the crop prices at marketplaces are manually entered every day, which can be prone to human-induced errors like the entry of incorrect data or entry of no data for many days. In addition to such human prone errors, the fluctuations in the prices itself make the creation of stable and robust forecasting solution a challenging task. To forecast prices more adaptively, this study proposes a novel model selection framework which includes time series features and forecast horizons. Twenty-nine features are used to depict agricultural commodity prices and three intelligent models are specified as the candidate forecast models; namely, artificial neural network (ANN), support vector regression (SVR), and extreme learning machine (ELM). Both random forest (RF) and support vector machine (SVM) are applied to learn the underlying relationships between the features and the performances of the candidate models. Additionally, a minimum redundancy and maximum relevance approach (MRMR) is employed to reduce feature redundancy and further improve the forecast accuracy. The trial that's what results exhibit, firstly, the proposed model determination system has a superior figure execution contrasted and the ideal competitor model and basic model normal; besides, highlight decrease is a useful way to deal with further work on the exhibition of the model determination structure; and thirdly, for bean and pig grain items, various disseminations of the time series highlights lead to an alternate determination of the ideal models.

Keywords : Time series analysis data, crop prediction model, agricultural commodity, price forecasting, forecast horizons.

I. INTRODUCTION

India is an agriculture-based country where 54.6% of the total workforce is engaged in agricultural and allied sector activities, accounting for 17.1% of the country's Gross Value Added (GVA). Hence, it becomes important for the government bodies associated with agriculture to estimate market factors and take suitable actions to benefit the farmers. Therefore, having a robust automated solution, especially in developing countries such as India, not only aids the government in taking decisions in a timely manner but also helps in positively affecting the large demographics. The price of crops is one such market factor that requires the attention of the government. Accurate crop price forecasting can be useful for the government to take proactive steps and decide various

policy measures such as adjusting MSP (Minimum Support Price) so that farmers get a decent price for their produce, restricting the export price by imposing an MEP (Minimum Export Price), so that exporters are forced to sell locally, thus bringing down the crop prices. At the same time, it will also be useful for the farmer for making better decisions like when to sell their produce or when to harvest the crop. The crop prices are affected due to several factors such as the area under cultivation for a particular crop, supply projection, government policies, consumer demands, supply chain aspects of producers for agriculture-based products, etc. Additionally, weather conditions also play an important factor since the majority of agricultural production in India is rainfed. Therefore, the study of fluctuations in agricultural crop prices is interesting as well as an important problem to solve from the government's perspective. Apart from the above-stated reasons, agricultural crop price forecasting is quite challenging due to many factors such as data quality issues, unreliability in future weather predictions, high fluctuation present in the historical crop price, crop price variations across neighboring marketplaces, etc. Moreover, the manually recorded data is prone to human-induced errors such as no data or wrong data entered for a certain day. Considering ML/DL based models, with a new price data arrival every day, updating the models might cause stability issues because of quality issues associated with the crop price data. Since the 1990s, feature-based model selection has been applied to time series forecasting. For instance, Prudêncio and Ludermir [8] used decision tree to select between two models to forecast stationary time series.

II. LITERATURE SURVEY

This section presents all the relevant methodologies belonging to three main domains, statistical, machine learning, and deep learning, applied in the prediction of agricultural prices. Dairi et al. (2021) state that in this era, many advances have been seen in artificial intelligence (AI), especially in deep learning (DL), an important part of AI. DL extracts relevant characteristics of the data automatically.

Table 1. Forecasting agricultural commodity prices using intelligent models

Commodity	Forecast Model	Authors
Xu, et al. [8]	Sugar	BP Neural Network
Jha, et al. [9]	Oilseed	Time delay Neural Network
Zhang, et al. [10]	Tomato	Wavelet Neural

		Network
Xiong, et al. [11]	Cotton, Corn	VECM-MSVR, SSVR
Ayankoya, et al. [12]	Grain commodities	BP Neural Network
Cai, et al [13]	Pork	EMD-SVR
Adya, et al. [6]	Sugar, cotton, corn, soyabean, coffee	MSS-ANN
He, et al. [14]	Soyabean	APSO-SVR
Li, et al. [15]	Potato	Dynamic Chaotic Neural Network
Wang, et al. [16]	Corn	SSA-ELM
Xiong, et al. [5]	Cabbage, pepper, cucumber, green bean and tomato	STL-ELM, TDNN, SVR-ELM

As the deep learning-driven methods do not depend on feature engineering, it benefits other ML methods. Nassar et al. (2020), while comparing the achievement of deep learning price prediction models with eight statistical as well as bench mark machine learning models, on the time series datasets of Vegetables, Fruits and Flowers, demonstrated that deep learning models, LSTM and CNN-LSTM are efficient in precise prediction of Fresh Produce prices for up to three weeks advance. Sabu and Kumar (2020) used time-series and machine learning models for predicting the monthly prices of are cannot in Indian Kerala state and found that LSTM neural network was good. Weng et al. (2019), while finding the suitability of ARIMA and Deep Learning models on different data sets, daily, weekly, and monthly, identified the deep learning method as the standard agricultural goods prices forecast. In the context of development of effective models, authors Ribeiro, M. H. D. M, & dos Santos Coelho (2019) used RF, GBM, and XGB while adopting SVR, MLP and KNN as baseline models and ranked the models as 1. XGB, 2.GBM, 3. RF, 4.MLP, 5. SVR and 6. KNN and finally concluded that that the ensemble approach was found to be doing good in the investigation of price sequences data.

The literature provides a number of methods to forecast the prices of agricultural commodities, including statistical methods and intelligent methods. Statistical methods are the most popular methods for forecasting a time series. For instance, Darekar and Reddy [1] predicted the cotton price of major producing states in India with auto-regressive integrated moving average model (ARIMA). Xu et al. [2] used an exponential smoothing model (ETS) to forecast the carrot price in China. Evans and Nalampang [3] employed a multivariate regression model to forecast the price trend of U.S. avocado. In recent years, as agricultural commodity price series become more volatile, powerful AI models with favorable self-learning capability have emerged to handle with the complex price forecasting task.

III. RELATED WORK

In another study by Chen et al. (2019), the noise of the cabbage data was reduced using Wavelet Analysis (WA). LSTM model then was applied on the fine-tuned normalized data which was found to be producing better results in achieving accuracy. While providing a concise summary of major deep learning techniques, Zhu et al. (2018) showed that DL methods such as CNN, RNN and GAN, are gaining momentum to help researchers in agriculture price forecast. Rasheed et al. (2021) analysed the wheat prices dataset with LSTM technique. Their study presented that LSTM was performing significantly when compared to other conventional machine learning and statistical time series models. The study also stated that deep learning is fairly a new direction in agriculture.

Table 2. Related works

Name of the authors	Name of the commodities	Deep Learning Models used for prediction	Results
R L et al. (2021)	Cottonseed, Castor seed, Rape mustard seed, Guar seed, soybean seed	LSTM Base line models: ARIMA, TDNN	The LSTM model provided a better forecast.
Ouyang et al. (2019)	Cotton, Sugar, bean, bean II, soya bean oil, cardamom, strong Wheat, Corn, Coffee, cocoa, Frozen orange juice	LSTNet Base Line Models: CNN, RNN, ARIMA, VAR	The LSTNet performed better results over the r baseline methods on average.
Kurumatani K. (2020)	Cabbage, Tomato, Lettuce	LSTM (Recurrent neural network)	The LSTM performed the best result.
Jin et al. (2019)	Chinese cabbage, Radishes	LSTM	The optimum performance was obtained by the LSTM.
Prakash & Farzana, (2019)	Tomato	LSTM	The LSTM is one of the most effective models for dealing with nonlinear patterns in prediction.
Chen et al. (2021)	Chicken, Chili, Tomatoes	LSTM Baseline models: ARIMA, SVR,Prophet, XGBoost	Among the five baseline models, the LSTM was forecasted to produce the best results.

To the best of our knowledge, forecast models perform differently at each forecast horizon; hence horizon is an important factor in choosing the optimal forecast model. However, this factor is seldom considered in previous studies. Moreover, the datasets used in previous studies were mainly M3, NN3, and NN5, which contain few agricultural time series. Therefore, there is still a research gap in constructing a model selection framework for forecasting agricultural commodity prices.

It can be seen from Table 2 that various kinds of models are widely used for different agricultural

commodity forecasting tasks. According to the `no free lunch' theory [7], there is no single model suitable for all the commodities. When facing a new type of agricultural commodity, it is not easy for people to identify which is the optimal model for this specific forecasting task. Of course, decision makers can compare the performance of several commonly used forecasting techniques
and configure out the most favorable one. However, training various models is a time-consuming process. Obviously, a fast and automatic algorithm is needed to identifying the most suitable forecasting method for agricultural commodities. In the past 30 years, the model selection approach has been used extensively for choosing the optimal model for various types of input data. That is to say, the underlying relationships between the features of the input data and the performance of a candidate algorithm will be discovered by learners through numerous training samples.

IV. PRPOSED WORK

To the best of our knowledge, forecast models perform differently at each forecast horizon; hence horizon is an important factor in choosing the optimal forecast model. However, this factor is seldom considered in previous studies. Moreover, the datasets used in previous studies were mainly M3, NN3, and NN5, which contain few agricultural time series. Therefore, there is still a research gap in constructing a model selection framework for forecasting agricultural commodity prices. In this study, we propose a model selection framework which involves both time series features and forecast horizons for forecasting agricultural commodity prices. Within this framework, twenty-nine features are extracted according to the periodicity, nonlinearity, and complexity of agricultural commodity price time series. Intelligent forecast models (i.e., ANN, SVR, and ELM) are specified as the candidate models. The relationships between these features and the performances of the candidate models are learned by classifiers, which include RF and SVM. Feature reduction (the minimum redundancy and maximum relevance method) is also utilized to reduce feature redundancy and improve the forecast accuracy of the model selection framework. We test the effectiveness of considering the forecast horizon as the input feature and apply the feature reduction strategy to improve the performance of the classifier. Finally, we use principal component analysis to analyze the relationship between different commodities and the corresponding optimal forecast models.

The main contributions of this study are as follows. We propose a model selection framework for forecasting agricultural commodity price time series based on time series features and forecast horizons. We verify that the minimum redundancy and maximum relevance method can effectively reduce the redundancies between the features and is a workable approach to improving the performance of the classifier.

V. MODEL SELECTION

Meta-learning has been employed for algorithm recommendation tasks for some time and, since 2004, it has also been investigated in the area of time series forecasting [8]. In this special case of meta-learning, the aspect of interest is the relationship between data features and algorithm performance [32]; a classier is usually applied to learn that relationship. Three main steps are involved in this research; namely, feature extraction, feature selection, and classification.

In Step 1, twenty-nine time series features are extracted, including complexity features, linearity features, and stationarity features. The optimal forecast model for the time series is specified by comparing the forecast errors of the three candidate models at each horizon. Hence, both horizon information (horizon features) and the optimal model for the corresponding horizon will be recorded in the classification sample.

In Step 2, feature reduction is performed using an MRMR approach, with the aim of reducing feature redundancy and improving the generalization capability of the classier. The ranking of the Mutual Information (MI) values of all the features will be obtained by the MRMR algorithm, and the ultimate features selected will be generated by the backward search method.

In Step 3, the classifiers proposed in the study are constructed by two popular machine learning approaches; i.e., SVM and RF. Additionally, there are different schemes or developing the model selection framework, which involve a naïve classifier (abbreviated as MSN), a classifier with forecast horizon features (abbreviated as MSH), and a classifier with the reduced features (abbreviated as MSH-FR). Therefore, we have a total of five competing classifiers in this study; i.e., MSN-SVM, MSN-RF, MSH-SVM, MSH-RF, and MSH-FR-RF. Details of these classifiers (including the reason for excluding MSH-FR-SVM) are provided. The forecast performance of the model selection framework is subsequently evaluated by two criteria; i.e., the mean absolute percent error (MAPE) and the improvement ratio (IR). The classification performance is estimated by classification accuracy (ACC). Finally, principal component analysis is applied to analyze the relationship between commodities and the optimal forecast model.

The implications of the selected features are shown as follows.

1) Complexity features quantify chaos and measure the long-range dependence in a time series.
2) Linearity features are important to determine the selection of models.
3) Stationarity features measure the stationarity of a time series.
4) Periodicity features provide indications on periodicity and seasonality of time series.
5) Model-based features, which characterize a time series by cutting a forecast model, are the parameters in the exponential smoothing model.
6) In other features, peak and trough capture oscillating behavior of time series. Spikiness captures the oscillating behavior of the residue of a time series by STL. Trend features characterize a time series by its degree of trend.
7) Horizon features are four binary numbers related to forecast horizons. They are marks for the corresponding optimal models at four forecast horizons.

VI. FORECAST MODEL

Due to the complexity and nonlinearity features of an agricultural commodity price time series, three workable and widely used AI models in agricultural commodity price forecasting are considered as the forecast models in this paper: artificial neural network (ANN); support vector regression (SVR); and extreme learning machine (ELM). The details are as follows.

Table 3. Statistical description of features of time series

Feature	Mean	Standard deviation	Minimum	Maximum
entropy	0.5166	0.0957	0.4119	0.9278
trend	0.9541	0.0671	0.4798	0.9996
spike	<0.0001	<0.0001	<0.0001	0.0006
linearity	11.9004	3.3175	-5.5354	14.5444
curvature	-1.2945	2.5414	-7.3815	9.9994
e_acf1	0.5132	0.2032	-0.1416	0.8261
e_acf10	0.4758	0.3017	0.0097	1.1692
seasonality	0.2865	0.1564	0.0651	0.7934
peak	6.2414	3.5058	1.0000	12.0000
trough	5.4502	2.9288	1.0000	12.0000
lumpiness	0.0465	0.3184	<0.0001	6.2433
stability	0.9519	0.1177	0.3253	1.0567
hurst	0.9978	0.0130	0.7774	1.0000
unitroot_kpss	3.4473	1.0446	0.1328	4.4699
unitroot_pp	-7.1267	11.7038	-150.8649	0.9937
nonlinearity	0.5168	0.8131	0.0006	6.0814
x_acf1	0.9607	0.0598	0.3962	0.9940
x_acf5	4.1279	0.7502	0.6259	4.7992
diff1_acf1	0.0687	0.2885	-0.5432	0.6454
diff1_acf5	0.1384	0.1258	0.0018	0.9829
diff2_acf1	-0.4133	0.1779	-0.7716	0.0658
diff2_acf5	0.2601	0.1400	0.0593	0.9266
seas_acf1	0.7122	0.2070	-0.2120	0.9091
x_pacf5	0.9940	0.1088	0.2805	1.2651
diff1x_pacf5	0.1386	0.1128	0.0018	0.5100

ANNs are data-driven flexible models which are capable of approximating a large class of nonlinear problems. One of the classic neural networks is the back-propagation neural network (BPNN), which includes feedforward and backpropagation. It is well known for its error learning algorithm in adjusting weights and bias. In general, a BPNN with a single hidden layer can generate the desired accuracy for a time series forecasting application [4]. SVR is originally proposed by Vapnik and based on the structured risk minimization principle. It performs nonlinear mappings through the application of kernels, which include nonlinear and linear kernels. It has been applied to forecast complex time series in industry, agriculture and aviation. ELM is a single hidden layer feedforward neural networks proposed by. Unlike traditional learning algorithms in feedforward neural network, where parameters are tuned iteratively, the Moore-Penrose generalized inverse is applied to determine the output weights in ELM [6], thus requiring little time for training. This advantage has been applied to classification tasks and regression tasks in numerous studies.

Table 4. The reserved features after feature reduction

Category	Features
Periodicity features	x_acf5, seas_pacf, x_acf1, diff1x_pacf5, x_pacf5, seas_pacf, seasonality, diff2_acf5
Stability features	unitroot_pp, stability, unitroot_kpss, lumpiness
Linearity features	linearity, curvature, nonlinearity
Complexity features	hurst
Model-based features	alpha, beta
Horizon features	h1, h3, h6, h12
Other features	trend, peak, trough

Table 5. Forecast performance of the MSN in terms of MAPE.

	h=1	h=3	h=6	h=12	average
ANN	3.4988	7.7901	10.5496	12.8591	8.6744
SVR	4.1948	10.0278	12.9542	14.6353	10.4530
ELM	4.2058	8.1399	10.6749	14.6674	9.4220
SMA	3.6617	8.0175	10.4539	12.6093	8.6856
MSN-RF	3.7114	7.8813	10.3578	12.7189	**8.6673**
MSN-SVM	3.7969	7.8901	10.3106	13.0068	8.7511

Table 6. Forecast performance of the MSH and MSH-FR in terms of MAPE.

	h=1	h=3	h=6	h=12	average
ANN	3.4985	7.7772	10.5583	12.8583	8.6731
SVR	4.1918	10.0144	12.9646	14.6332	10.451
ELM	4.2061	8.1293	10.6854	14.6664	9.4218
SMA	3.6610	8.0038	10.4634	12.6104	8.6847
MSH- RF	3.4901	7.4729	9.8113	12.6254	8.3499
MSH- SVM	3.5738	7.7456	10.1239	12.5543	8.4994
MSH-FR-RF	3.4877	7.4733	9.8148	12.5562	**8.3330**

Statistical descriptions of all the features are listed in Table 4. These statistical values indicate that the features have different magnitudes; thus, normalization should be employed before classification. The correlation diagram based on mutual information (MI) is shown in Figure 4. The dark point at the top right-hand corner represents the maximum MI value of all the twenty-nine features. After feature reduction, twenty-five features including twenty-one time series features and four horizon features remained. In general, the average MI of each pair of two features has been reduced by 7.45%. The details of the selected features are listed in Table 5. Four horizon features have been retained, which demonstrates that the forecast horizon features are important for the performance of the classifier.

The model selection experiments for forecasting agricultural commodity prices were conducted using the research design described above. Accordingly, the forecast performances of all the candidate models and the model selection frameworks were evaluated using the two accuracy measures MAPE and IR, and the classification performance was estimated using ACC. Table 6 and Table 7 show the forecast performances in terms of MAPE. The last column labeled ``average'' shows the average performances of the models across all four forecast horizons. In order to illustrate intuitively the advantage of the model selection framework, we compare the performance of each selection framework to the optimal single model ANN. The results are shown in Table 8. Table 9 shows the classification performances of the three model selection frameworks in terms of ACC.

Table 7. Forecast performance of MSN, MSH and MSH-FR in terms of IR.

		h=1	h=3	h=6	h=12	average
MSN	**RF**	-6.0749	-1.1702	1.8187	1.0905	0.0818
	SVM	-8.5193	-1.2833	2.2655	-1.1482	-1.1482
MSH	**RF**	0.2423	3.9126	7.0746	1.8111	3.7259
	SVM	-2.1518	0.4066	4.1141	2.3644	2.0026
MSH-FR	**RF**	0.3089	3.9078	7.0417	2.3499	**3.9212**

Table 8. Classification performance of the MSN, MSH and MSH-FR in terms of ACC.

	RF	**SVM**
MSN	55.78%	53.90%
MSH	61.39%	56.49%
MSH-FR	61.85%	——

Focusing on the model selection framework, Table 6 shows that the average forecast error of MSN-RF is 8.6673 compared to 8.6744 for ANN. This result demonstrates the superiority of the model selection framework, which can reduce effectively the risk in model selection, thus yielding a smaller forecast error. Regarding the two strategies used for improving the performance of MSN, Table 7 shows the performance of MSH and MSH-FR. Both MSH-RF and MSHSVM perform well across four forecast horizons compared to ANN. This may indicate that the performance of MSH is better than that of MSN. As for MSH-RF, the average forecast error is 8.3499, yielding a smaller forecast error compared with MSH-SVM. It can be seen from Table 8 that the average IR of MSH-RF is 3.7259, which is greater than that of MSN. Moreover, it can also be seen from Table 8 that the classification accuracy of MSH-RF is higher than that of MSN. These results verify the superiority of using different forecast horizons as the input features of the classifier. This method can not only improve the forecast accuracy of model selection by using the data on forecast model performance at different forecast horizons, but can also improve the classification performance of the model selection.

It can be seen from Table 6 that the average MAPE of SMA is 8.6856, which is only on average larger than the optimal candidate model (ANN,8.6744). That is to say, SMA can avoid performing the worst result of forecasting and reduce the risk of model selection. Compared to SMA, MAPEs of MSN-RF and MSN-SVM are lower at h=3 and h=6, which indicates that the model selection framework is competitive for SMA. It can also be seen from Table 7 that the average MPAE of SMA is 8.6847 which is only larger than ANN. The MAPEs of MSH-RF and MSH-SVM are almost lower than SMA at each forecast step. It demonstrates the superiority of the model selection framework, which is more effective than SMA in reducing the risk of model selection.

Table 1. A summary of the forecast results for several benchmark forecasting methodologies

Models	Forecast Horizon	RMSE*	MAPE (%)
Proposed Method	Yearly	14.37	4.12
ARIMA	Yearly	60.25	33.45
EMD-ARIMA	Yearly	35.23	25.12
ANFIS	Yearly	24.09	16.35
Persistence	Yearly	68.23	51.15
Proposed Method	Monthly	08.03	3.12
ARIMA	Monthly	45.35	12.19
EMD-ARIMA	Monthly	22.23	8.59
ANFIS	Monthly	14.17	8.51
Persistence	Monthly	55.34	18.24

In order to verify this assumption, we perform a principal component analysis (PCA), following the method proposed by Kang [56]. The first two principal components of the bean and pig grain price time series are plotted into a feature space as shown in Figure 6. The x-axis refers to the first principal component and the y-axis refers to the second principal component. The red points represent the bean price time series which take ELM as the optimal model across all the forecast horizons. The blue points represent the pig grain price time series which identifies SVR as the optimal model across all the forecast horizons. It can be seen that the zone of red points is separated from the zoo of blue points. This phenomenon indicates that the features of those two categories are quite different from each other. Therefore, different distributions of the time series features can be regarded as the main reason for the different model selection results.

VII. CONCLUSION

In this paper, we proposed a model selection framework for forecasting agricultural commodity prices using both time series features and forecast horizons. Generally, three main steps were involved in the proposed model selection framework, i.e., feature extraction, feature reduction and classification. By and large, three primary advances were engaged with the proposed model selection framework, i.e., include extraction, highlight decrease and arrangement. First and foremost, we separated 29 time series highlights of agrarian product costs. Besides, we utilized the base overt repetitiveness and greatest importance technique to decrease highlight overt repetitiveness and work on the presentation of the model determination structure. At long last, five classifiers were built to confirm the exhibitions of various model choice systems. Also, the connection between various products and the ideal model was assessed by head part investigation. Comparative with existing examinations, this study shifts the adequacy of the model determination system in picking the most reasonable gauging models. With rural ware cost series as exploration tests, a few intriguing ends can be made in view of the exact outcomes. First and foremost, taking into account the figure skyline as one of the elements can work on the presentation of both grouping and conjecture, which exhibits the gauge skyline ought to be considered as a significant calculate model determination task. Besides, MRMR can additionally work on the exhibition of the model choice system, which shows a useful element decrease technique ought to be taken advantage of in model determination for expanding the speculation capacity of classifiers.

The proposed model selection framework could be improved according to the accompanying viewpoints. In the first place, the proposed strategy could be utilized as a compelling model determination apparatus for other figure objects. Second, a few strong classifiers, for example, AdaBoost and Bayesian organizations could be used to additionally further develop the grouping capacity. Third, this concentrate just considers three well known estimate models in the space of gauging rural product costs; notwithstanding, different strategies could likewise be acquainted with make the structure more functional.

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