Proceedings of the Fifth International Conference on Electronics, Communication and Aerospace Technology (ICECA 2021)
IEEE Xplore Part Number: CFP21J88-ART; ISBN: 978-1-6654-3524-6

Meta-Learning Based Adaptive Crop Price Prediction for Agriculture Application

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2021 5th International Conference on Electronics, Communication and Aerospace Technology (ICECA) | 978-1-6654-3524-6/21/$31.00 ©2021 IEEE | DOI: 10.1109/ICECA52323.2021.9675891

***Abstract*—Dealing with unexpected changes in agricultural product prices that affect the farmers and the economic growth of a country is inevitable in the current day context. A unique approach is proposed for time-series prediction, which utilizes the power of crop price prediction and crop yield prediction of select crops to identify the relevant information with respect to the market prices, and crop yields. Many uncertain conditions such as climate changes, fluctuations in market, flooding, etc., cause problems to the agricultural process. In this work, the prices of selected essential crops analyzed for time-series prediction using meta-learning. The Self-Organized Map (SOM), LSTM (Long-Short Term Model), and this proposed Meta-Learning Based Adaptive Crop Price Prediction (MLACPP) was trained using crop price dataset, and crop yield dataset. Meta-learning function used in the approach utilizes the input, optimization-output, and task-related estimators for calculating meta-loss over multiple meta-network. The meta-learning with self-organizing capability learns a meta-network observing additional information from specialized support set. Moreover, this method deals with a task-oriented loss. Interestingly, it compares the current optimal-output of the optimization function g with the target-specific information. Experimental results show significant improvement in terms of prediction accuracy and cross-correlation entropy over the existing crop price prediction approaches. This research work provides the basis for making better decisions for price-fixing and crop yield maximization based on insights obtained from the dataset.**

Keywords—Agriculture, Crop Price Prediction, Crop Yield Prediction, Deep Learning, Time-Series Prediction

I. INTRODUCTION

The agricultural system need to deal with various issues in the process that reduces the operational efficiency and provides ineffective solution due to the optimality constraint. In addition, the quality of extracted knowledge has direct relationships with the set targets. The effective utilization of the past and present data supports the knowledge discovery process to modify the agricultural process. It is important to establish the correspondence between the features derived from plans and the target sequences. From the literature review, it was observed that there is no effective crop price prediction and crop yield prediction model for analyzing possible solutions to the agriculture issues in case of uncertain price increase or uncertain crop yield.

To address various problems, a number of methods developed until now. Most of them apply a planning approach and introduce workflow, but a meta-learner based self-organizing prediction that yields optimal prediction accuracy is of great interest to achieve the best results. The applications of proposed models include crop management, agriculture market price prediction, and harnessing the power of resources for reliable agriculture. The major contributions of this paper are: a) accurate insights b) efficient utilization of resources for better agriculture c) optimal prediction accuracy d) meta-Learning based self-organizing that generates more expressive feature representation.

The goal of this approach is to propose meta-learning based multivariate time-series prediction method, which applies self-organizing mechanism to remove train-test mismatch and learns features from unlabelled data to allow efficient fine-tuning. This work introduces a better approach for utilizing the knowledge with respect to the crop-plan, marketer-plan, and farmers-plan. Other major concerns include the process of enhancing the quality of extracted knowledge, providing user support, and suggesting profitmaximization strategy based on available information, and achieving the best results to solve the agriculture-related issues.

II. LITERATURE SURVEY

Traditional approaches use manual feature extraction. On the other hand, deep learning enables automatic feature extraction. To utilize the predictive capabilities of manual extraction, a classification model that combines both surface features and automatically extracted features presented using word embedding technique and a linear algorithm relied upon machine learning [1]. In order to analyze the agriculture-related data and to predict the target labels of certain patterns and trends, Artificial Neural Network used as a popular technique. Agriculture commodity prices are used for forecasting by using Naïve Bayes Algorithm [2]. Fluctuations on agricultural produce prices cause problems between buyers and sellers. Considering time-series data of onion and potato trading, a price-forecasting model is evaluated using anomaly detection and classification [3].

Data mining involves decision tree algorithm for predicting prices of agricultural products. Price prediction poses many challenges under uncertain situations such as weather changes, market trend, and soil pH changes, insufficient Nitrogen levels etc. In the literature, a price prediction method developed based on decision tree. This existing approach has used association rules focusing on prices [4]. Another work applied machine-learning techniques such as neural network, XGBoost, and decision tree to work with integrated data for crop price prediction. This work observes dependencies between soybean yields and imports/exports [5].

A work on price prediction system presents [6] the use of k-Nearest Neighbor (kNN) to learn from parameters like crop price, yield, rainfall, minimum_price, and maximum_trade. Nowadays, climate changes predicted by the weather prediction system broadcasted to the peoples, but, in the real-life scenarios, many farmers are unaware of this information in time. A study presented recently [7] focused on price prediction that works based on short-term and long-term time series data.

A deep neural network approach [8] estimated the performance of crop yield prediction with root-mean-square-error and prediction accuracy. In addition, feature selection used to decrease the number of dimensions. Many research works have aimed to develop crop models based on machine learning techniques. One of the works used machine-learning techniques and presented the creation of user-friendly interface for crop price prediction based on the previous trends [9].

In developing countries, many discussions about climate changes are going on regarding how to find insights from climate data. In this perspective, a research paper discussed a method of developing information portals for climate analysis [10]. Given the location, finding profitable crop and finding the price of vegetables discussed in one of the recent works [11]. With respect to the estimation of crop prices, a methodology has adopted feed forward back propagation scheme [12]. This work aimed at increasing the crop prediction accuracy by minimizing the mean-squared-error, which calculated over price forecast values.

One of the multi-class classification used as a supervised approach tried to generate a task distribution using meta-learning. That work has shown that meta-training achieves a better generalization [13]. Although reinforcement learning is capable of solving complex tasks, the solutions generated through the training would be static and it doesn't adapt to new information (N Elias, 2020). This existing work proposed a search method to help self-organization of neural networks, the searching works with Hebbian learning rules. Nitrogen is one of the important factors that affects crop yield. Nitrogen deficiency in crop identified from yellowed leaves and dwarfed seedlings. Nitrogen management studied with a crop-model for decision recommendation (Jin, 2016).

This work has used climate data collected from National Climate Data Center (NCDC) for calibration of the system. It observed that the sidedress recommendation leads to increase in crop yield. Predictive analytics expected to provide a better solution to solve the agricultural problems, which occur due to unstable climate conditions. Arecanuts price prediction used LSTM model [16] and the performance evaluated based on the root-mean-squared-value.

The heavy rainfall region has high probability of affecting crop cultivation and productivity. To predicting suitable crop cultivation, weighted self-organizing map and linear vector quantization are combined to improve the prediction accuracy by minimizing the within cluster errors [17].

One work considered weather forecasting as a complex task for mining large datasets. To deal with this issue, self-organizing map used as a dimension reduction technique [18]. In addition, this work applied deep neural network to find approximate information to forecast season value for crop cultivation.

A recent study discussed a supervised hybrid feature selection, which used Particle Swarm Optimization (PSO) and rough sets to deal with medical diagnosis problems [19]. Another work dealt with a way of adapting fault diagnosis [20]. A study on Extreme Learning Machine discussed using classification method [21]. Another work proposed a self-monitoring mechanism for solar power station. Authors of that work used Internet of Things and data mining [22].

Table 1 Existing models vs. limitations

Existing models	Limitations
Price forecasting using Naïve Bayes method.	Different factors influence changes in the price. Independence assumption violates the property of multivariate analysis.
Anomaly detection and price forecasting using LSTM	Only qualitative analysis, not handled anomalies for low prices. It requires verification service.
Price prediction using Hybrid Association rule based Decision Tree (HADT)	Difficult to handle large dataset. The scalability issue remains to be solved.

Many farmers sow the crops without having sufficient information about market price, and profitable crops. This causes problems when a large number of farmers are bringing the same products to the market. The above existing works relied on the independence assumption and normal distribution.

In contrast, recent works focused on time-series prediction using neural networks. Deep learning adds advantages such as non-parametric, non-bias, self-learning, and noise reduction. The research-questions are: 1) can meta-learning improve crop price prediction? 2) Can self-organization using support set discover useful insights from the dataset? 3) How does the crop yield influence crop price?

The remaining sections of this paper contain the following: Section 3 illustrates meta-learning based self-organizing method for crop price prediction. Section 4 presents experimental results and discussion. Moreover, Section 5 concludes the work.

III. MATERIALS AND METHOD

To utilize the benefits of multivariate time-series data analytics, the study presents an adaptive crop price-forecasting model to predict commodity prices considering a mixture of long term and short-term information based on new concept called meta-learning based self-organization.

In this case, Noisy data implies insufficient information. In order to deal with this issue, cross correlation calculated according to the rules given by the self-organized meta-learner. The proposed method integrated meta-learning and self-organizing capability utilizes the long-term dependence for time-series data analytics.

The feedback control of the proposed network has memory nodes for capturing the correlation from lag values. This model uses sequence values as input for price forecasting. The advantage of this model is that it avoids the vanishing gradient problem of RNN deep learning, which gradually diminishes the gradient values towards zero. This network model uses memory nodes and forgotten nodes for various operations that include read, delete, and update.

The network consists of input layer, hidden layer, and output layer. The information flows from one layer to the subsequent layer. The middle layer is responsible for summation and point wise multiplication.

The values of the softmax function and the cross correlation entropy (CCE) function organized for further navigation. The output values of the output layer determine the new information that will feed into the network. The proposed systemarchitecture is as shown in Figure 1.

The learning mechanism applied over a loss function M uses two loops, namely, inner loop for training the model, and the outer loop for taking care of optimization of meta-loss function through minimization of the regression-task loss. The function g takes a variable x as input and gives y as output. This deep learning function learns a network using α for its parameterization.

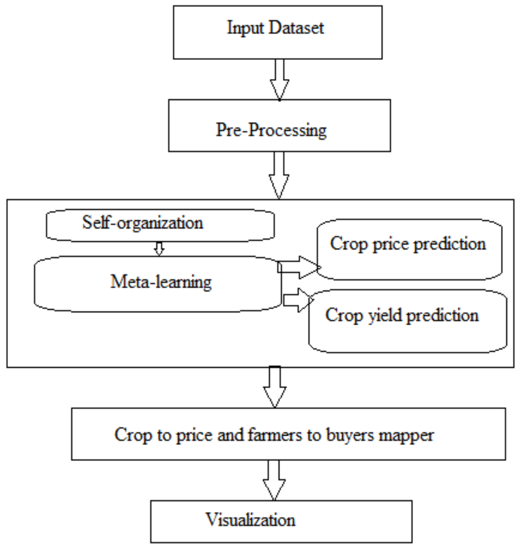

Fig. 1. System Architecture

A. Self-organizing meta-learner for Crop Yield Prediction

Meta-learning based neural network uses 20 hidden layers and 50 neurons in each layer. These dimensions found to be good at maintaining the balance between prediction accuracy and samples overfitting. A batch size of 18 is used. The g_α optimizer implemented in this work used with a learning rate of 0.05%. Latent Dirichlet Allocation (LDA), and Cross correlation were applied before learning takes place in the hidden layer. This technique establishes the relationships between price components, and crop yield components and reduces less significant dimensions for enhancing the performance. The maximum iterations for training are 50 iterations. Cross-Validation (CV) is used to minimize overfitting error. Figure 2 shows the meta-network functioning.

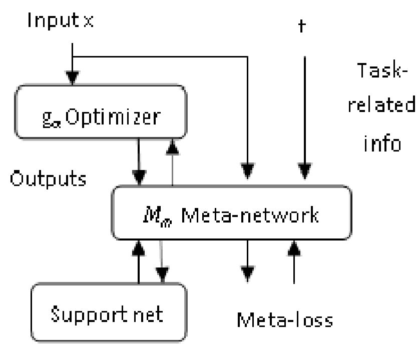

Fig.2. Representation of meta-loss function

RQuefts package helped to perform quantitative evaluation of the soil fertility that impacts crop yield performance. The nutrients supply such as N, P, and K to the soils analyzed by using some soil chemical properties. This quantitative evaluation computes crop yield based on the amount of nutrients supplied, and crop parameters. The amount of nutrients supplied and the computed optimal use of fertilizer for a given products and prices are listed in Table 1.

Table 2 Fertilizer application with nutrients supplied

Name	N	P	K
Urea (U-46)	46	0.00	0.00
Triple Superphosphat	0	19.18	0.00
Potassium magnesium 0	0	0.00	18.26
Bird guano	11	0.00	1.66

B. Self-organizing meta-learner for Crop Price Prediction

This section presents price prediction related to the crops. The data between the period 2010 to 2020, the LSTM, and meta-learning based crop-price prediction models evaluated using the 65% of the training data and 35% of the testing data, and other combinations of data are considered. The work also considered SOM model as a baseline that uses lag values of the variable and the error terms.

Optimal values obtained through the gα optimization method. Next, considering the data for the year 2020, the data fit in a LSTM model, and the proposed model, price forecasting aimed for the next 10 days. These models take the terms like trend, season, irregularity, and cyclic into account to capture the price variations.

While conducting the experimental study for task learning to support crop-price prediction, a multi-way few-shot task created to form a subset as a support set through sampling of selected classes.

The websites such as FAOSTAT and data.gov.in provides the publicly available dataset for the research purpose. After performing data cleaning, feature vectors formed for both support net and meta-net through LDA and CV respectively. For each of the sampled classes, a random sampling is applied and then labelled in the range {1,…,N}. The 50% of samples of each label considered as the support set and the remaining samples considered as the validation set. Figure 3 shows an example support set. Figure 4 shows price index of various agricultural products.

sentence	class
As per the current market rates, maximum price of Banana is 6400.00 INR/Quintal in Madhavapuram whereas the minimum rate is 850.00 INR/Quintal in Nasik across varieties.	2
The average price is 2818.00 INR/Quintal across varieties	1
The global production of bananas in 2019 was 116.0 million metric ton, and it is projected to register a CAGR of 4.1% during the forecast period of 2021-2026.	2
The global pandemic (COVID-19) has hit this agrosystem hardest	1
Due to lockdown restrictions across the world, there have been shortages of labor and planting materials affecting production	1
The closed markets have resulted in a price crash in few markets, while in others, there was an increase in prices	2

Fig. 3. An example of a support set.

Crop	2004-05	2005-06	2006-07	2007-08	2008-09	2009-10	2010-11	2011-12
Rice	100	101	99	105	112	121	117	110
Wheat	100	101	112	115	117	127	120	108
Coarse Cereals	100	107	110	115	113	123	122	136
Pulses	100	108	134	124	124	146	137	129
Vegetables	100	109	103	118	113	124	128	115
Fruits	100	99	99	98	102	104	114	119
Milk	100	97	98	98	98	112	123	124
Eggs, Fish and Meat	100	102	101	100	99	116	133	137
Oilseeds	100	86	85	97	104	103	99	102
Sugarcane	100	96	91	87	80	81	109	107
Fibers	100	92	91	96	109	107	138	140
All Agriculture	100	99	101	104	106	115	123	122

Fig. 4. An example of agri-price index dataset

In this case, each task has a small number of subset. Since the process of bindings labels to the samples, will sometimes lead to irrelevant training and will lead to poor model generalization to the new tasks, classes containing closest match to the semantically relevant terms used for labelling the tasks.

IV. RESULTS AND DISCUSSION

The experimental setting consists of the following a) an objective function which depends on base-training dataset, base-loss function, and base-model b) training set representing a set of objective functions drawn from a distribution c) test set for a non-overlapping set of objective functions drawn from the same distribution. The main goal is to learn optimization function and it aims at the following aspects: 1) Generalizing to the test set, and 2) Converging quickly.

The meta-loss calculated by the cumulative base-training loss. The line plot shows the mean squared error over the training epochs. The model converges reasonably and quickly. The performance on both the train set and test set remains equivalent. Figure 5 shows the error loss.

Two meta-learning models are trained, one for price prediction and the other for yield prediction. Then the difference of their outputs that gives the prediction for price difference and yield difference to the respective target variable is calculated. Crop yield prediction and price prediction is evaluated using different combination of training data and testing data, the variation on crop indices is illustrated in Figure 6. Figure 7 shows monthly arrivals of Tomato at all India level.

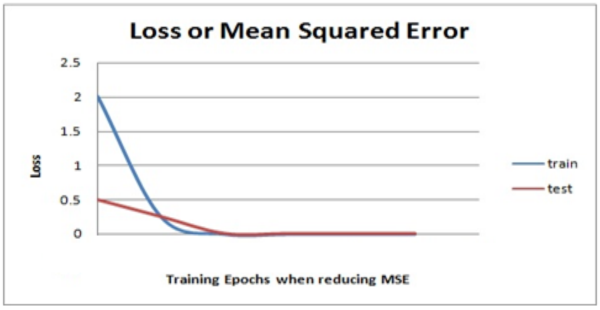

Fig. 5. Mean Squared Error Loss

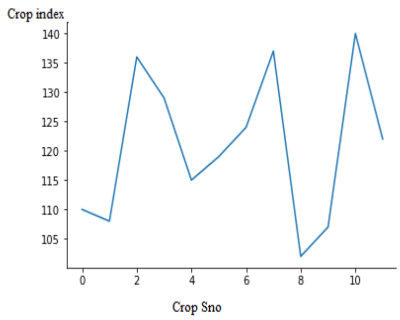

Fig. 6. Crop S. No. Vs. Crop Index

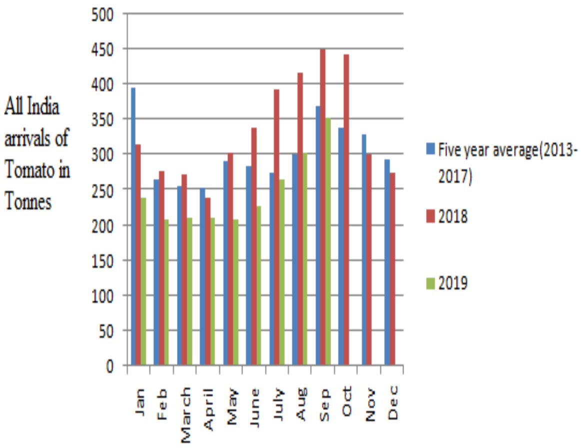

Fig. 7. All India Monthly Arrivals for Tomato

Data for 8 different attributes are acquired according to the type of data which includes the past 7 to 10 year's data. Under various scenarios and conditions, yield prediction and price forecasting is performed which will deal with the agricultural risks.

With the knowledge of best practices, farmers can apply the right strategy that influences the yield and prices of select crops. Farmers can see the impact of changes on yields under different weather conditions. They can understand the impact of yields and market fluctuations on the product prices.

The crop model and crop price model are calibrated by applying data assimilation. Insights about consumer prices, producer prices, and Production-value, and Prediction performance are as shown in Figure 8, Figure 9, Figure 10, and Table 1.

The subsets of features used for evaluating the performance of the feature selection model. All the features sorted based on the values of variables influencing the crop yield, market variables, and selected seven most important yield components and four most important price components. To utilize the highly correlated price values within the self-organized region, meta-learning based predictive analytics makes use of the dependencies between variables including data points of a small dataset.

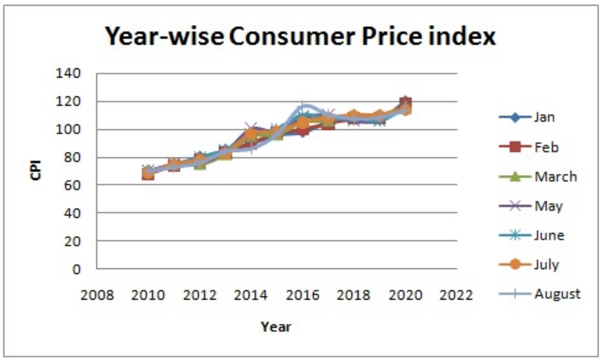

Fig. 8. Consumer price-values

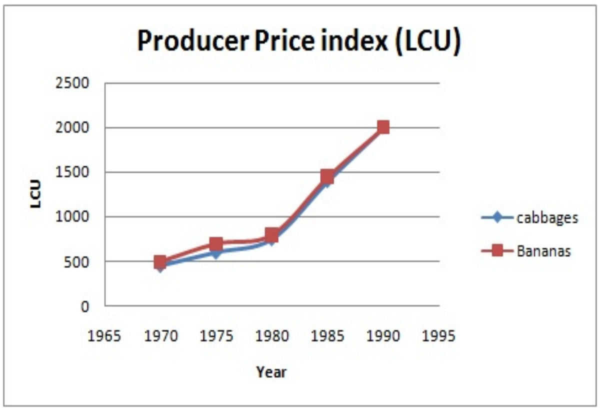

Fig. 9. Producer Price-values

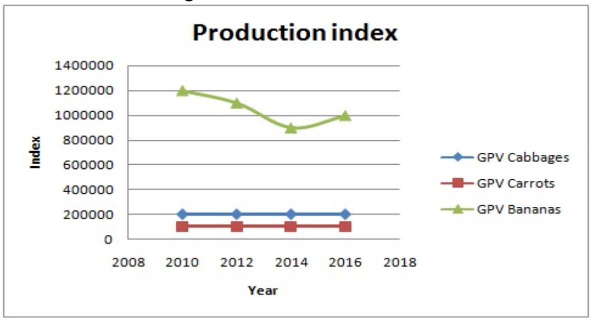

Fig. 10. Production values

In this case, the optimization function g_α as a mapping function finds the optimal value α. M denotes the loss function and t used to denote gradient transformation. The function g designed to update the parameter as it helps to add additional information when meta-learning happens. Here, α^u is for the updation of model parameters. The deep learning function performed using function g. The key idea is that the model has to generalize well on the unseen data for the next tasks. This proposed model efficiently generalizes with the loss function and efficiently optimizes the model for new tasks (Eq.1).

$$\alpha_{new} = t_\omega(\alpha^u, \nabla_\alpha M_\varphi(f, g_\alpha(x))) \qquad (1)$$

The method proposed in this paper can store extra information during meta-training and hence this method provides generalization through regression. The function g learns a meta-loss network M. The network takes the input and optimization-output of function g in addition with additional task-related information. The extra information may include reward for the selection of the best task, ground truth label for regression, or the last point in meta-learning. The output was meta-loss that tuned by φ and θ.

The gradient of Meta Loss computed for updating the function g and then gradient updated using the loss function that learnt as given below (Eq.2).

$$\alpha_{new}=\alpha-\lambda\nabla_{\alpha} M_{\emptyset}(y, g_{\alpha}(x)) \qquad (2)$$

For updating the meta-loss network, the method utilizes a task-oriented loss. Here, it compares the current optimal-output of the function g with the target-specific information. Since the optimization function updated with current loss, the task learning performs updating of gradient to optimize the meta-loss network.

TABLE 1 PREDICTION ACCURACY

Algorithm	**FS**	**LDA (small)**	**LDA (big)**	**CV**
SOM		70.23	62.13	93.20
LSTM		68.57	65.42	95.62
MLRCPP		57.93	84.41	98.64

Here, this approach chose a retail center price that is having a high cross correlation with the target. Further improvement to the performance of the model observed through fine-tuning the models first by using time series actual price values, and then by incorporating the consumer price indices. The improvement gives information about the market trends that influences the prices of agricultural items. Further extension would be possible by tuning the hyper-parameters, and adding more hidden layers. A 10-day price-forecasting model that can provide information for deciding whether to postpone harvesting or hold on selling for a few days or to go ahead with the current prices .

V. CONCLUSION

In this paper, a new meta-learning based self-organizing method is presented that uses multiple data, which extracts insights on the crop yield and crop prices to give useful information to the farmers. The meta-learning based model extracts finest level details to deal with various issues like price variation and uncertain yields in the agricultural system. The proposed method shows better performance over existing models such as SOM, and LSTM which used for the comparison. In future, the proposed method may add more application-specific components that cover a wide range of crop-related and price-related aspects.

ACKNOWLEDGMENT

Author would like to thank SRMIST Management, Chairperson, and HoD of School of Computing, and Head of the Department for their consistent support and encouragement.

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