Multi-Model Ensemble Depth Adaptive Deep Neural Network for Crop Yield Prediction

M. Saranya, S. Sathappan

Abstract: ***Accurate prediction of crop yield enables critical tasks such as identifying the optimum crop profile for planting, assigning government resources and decision-making on imports and exports in more commercialized systems. In past few years, Machine Learning (ML) techniques have been widely used for crop yield prediction. Deep Neural Network (DNN) was introduced for crop yield. The crop yield prediction accuracy based on DNN was further improved by Multi-Model DNN (MME-DNN). It predicted the crop yield by modeling climatic, weather and soil parameters through statistical model and DNN. The MME-DNN is not scalable when new data appears consecutively in a stream form. In order to solve this problem, an Online Learning (OL) is introduced for crop yield prediction. In OL, DNN is learned in an online setting which optimizes the objective function regarding shallow model. But, a fixed depth of the network is used in ODL and it cannot be changed during the training process. So, Multi-Model Ensemble Depth Adaptive Deep Neural Network (MME-DADNN) is proposed in this paper to adaptively decide the depth of the network for crop yield prediction. A training scheme for OL is designed through a hedge back propagation. It automatically decides the depth of the DNN using Online Gradient Descent (OGD) in an online manner. Also, a smoothing parameter is introduced in OL to set a minimum weight for every depth of DNN and it also contributes a balance between exploitation and exploration. The crop yield is predicted from the soil, weather and climate parameters and their variation over four years by applying the MME-DADNN. Thus, by adaptively changing the depth of the DNN the performance of crop yield prediction is enhanced.***

Keywords **:** ***Crop yield prediction, Depth Adaptive Deep Neural Network, Multi-Model Ensemble, Online Gradient Descent, Online Learning.***

I. INTRODUCTION

Crop yield prediction [1] is a major in a food-security early warning system. It assists farmers in preparing themselves for the next growing season. It also functions as the principal indicator of national income for agriculture contributions to the Gross Domestic Product (GDP). If culinary activities are less complex and individuals depend on a single crop to fulfill the most dietary demands, they get worse than that. Agro-economists need simpler and reliable estimation methods to estimate yields in the agricultural planning process.

Prediction of crop production depends on input characteristics such as area, irrigation methods, temperatures, soil, climate, weather, etc. The detailed development of crops can be accomplished without affecting the nature and processes of agricultural production by getting appropriate inputs and models [2]. Agriculture researchers looked at superior yield prediction according to the agricultural data collection and development of crop yield forecasts to boost statistics for agriculture and rural areas.

Data mining techniques [3] are widely used for crop yield prediction. A Deep Neural Network (DNN) [4] was introduced for crop yield prediction. It has stacked hidden layers that converted raw input data into some specific representation. The stacked hidden layer extracted more informative features which enhance the accuracy of crop yield prediction. The DNN-based crop yield prediction accuracy was further improved by Multi-Model Ensemble Deep Neural Network (MME-DNN) [5]. The MME-DNN predicted accurate crop yield by modeling climatic, weather and soil parameters through statistical model and DNN.

In MME-DNN, DNN was trained by back propagation which includes all training data before the learning task is completed. For many real-world scenarios, this cannot be adaptable, as new data occurs in a stream format. This issue was solved by using Online Learning (OL). However, it faces several issues with convergence. To address these issues, Multi Model Ensemble Depth Adaptive Deep Neural Network (MME-DADNN) is proposed for crop yield prediction. In MME-DADNN, a training scheme for ODL through a Hedging strategy called Hedge Back propagation (HBP) is designed. HBP requires a complete network and decides how and when to change the network's depth.

II. LITERATURE SURVEY

A Support Vector Machine (SVM) [6] was introduced to predict the yield of agriculture. It built a system for decision making on agriculture and explained how numerous features influence yields. SVM separated the set of items based on their class membership using decision plane boundaries. Thus, it enhanced unambiguousness.

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However, it has lack explanation of prediction. It was resolved by extending SVM with efficient techniques to describe regression models through analysis of feature contributions. However, the selection of proper kernel function for SVM is more difficult.

A Bayesian Network [7] was presented for rice yield prediction. Initially, the data were gathered from 27 districts of Maharashtra and the most discriminative features were selected.

The chosen features were processed in BayesNet and NaiveBayes for better yield prediction. However, Bayesian network is computationally infeasible.

Machine learning and advanced sensing techniques [8] were introduced to predict wheat yield. Supervised Kohonen Networks (SKN), XY-Fusion (XY-F) and Counter-Propagation Artificial Neural Network (CP-ANN) were used for wheat yield prediction. These techniques used supervised learning map crop and soil data with yield productivity. However, it was failure to build on-going production relationships.

A parameter-based customized Artificial Neural Network (ANN) [9] model was proposed for wheat yield prediction. ANN and Multiple Linear Regression (MLR) were used in this model. There are different parameters such as an Extractable Soil Water (ESW), amount of rainfall, soil evaporation, crop biomass, amount of fertilizer applied and soil transpiration were extracted and fed into ANN and MLR for wheat yield prediction. In addition, Default-ANN (D-ANN) and Customized-ANN (C-ANN) was introduced for wheat yield prediction. However, MLR cannot capture the non-linear relationship between the different input parameters.

To measure wheat production and soil organic carbon under a wheat-maize cropping method in northern China, a Decision Support System for Agro Transfer 4.6 (DSSAT) model [10] was implemented. In this model, various factors related to the yield were investigated by using DSSAT-CENTURT soil model. From the analysis, it was known that for N0 treatment the simulated wheat yield. More than cultivar metrics and soil metrics were more sensitive in crop growth. However, this model required more data to analysis the wheat yield.

A fuzzy logic and regression model [11] was introduced for crop yield forecasting. This model centered on the estimation of data values based on a large variety of fuzzy logic equations, relying on relationships between second and third degrees. It was processed on four various types of fuzzy interval based on Fuzzy Logic Relationship (FLR). This model forecasted the production of wheat. However, proper selection of membership function for fuzzy logic and regression model was difficult.

A Convolutional Neural Network (CNN) [12] was introduced for bitter melon yield prediction. Based on definitions of bitter melon leaf, those were categorized as good and bad. CNN had the capability to train huge volume of data. It helped a network to extend its layer which increased learning accuracy and reducing error. The computational process of CNN was described as determining the best set of weights for the neural network. Based on the training data, the leaves were categorized as good and bad and it predicted the yield of bitter melon. However, it requires more number of features to improve prediction accuracy.

III. PROPOSED METHODOLOGY

Here, the MME-DADNN for crop yield prediction is described in detail. The main intention of MME-DADNN is to develop fast convergence of shallow network and the power of deep representation which enhance the crop yield prediction. Initially in MME-DADNN, the agriculture data such as climate weather and soil related data are collected. Then, the data is pre-processed by using multiple imputation techniques. A statistical model is applied on the pre-processed data to know the variation of data from year-to-year and it is used for soil, climate and weather predictions using DADL with hedging strategy. Again, the predicted soil, climate and weather data are processed by DADL with hedging strategy to accurately find the crop yield prediction with faster convergence rate.

A. Online Learning

Consider an online crop yield prediction process without loss of generality. The intention of OL is to learn a function $\mathcal{F}: \mathbb{R}^f \rightarrow \mathbb{R}^C$ based on a sequence of training samples$D = \{(x_1, y_1), \dots (x_T, y_T)\}$, where $x_t \in \mathbb{R}^f$is a d-dimensional instance is denotes the features and y_T is the class label of crop yield prediction. The crop yield prediction is denoted as $\hat{y}_t$ and the prediction performance is evaluated through cross-entropy loss function. In each online implementation, the system shows the ground truth of the class label, when a data x_t is detected and the algorithm forecasts the model and eventually the learner updates the concept with the online gradient descent.

Given an input $x \in \mathbb{R}^f$, the prediction function of MME-DNN with N hidden layers $\left(h^{(1)}, h^{(2)}, \dots h^{(N)}\right)$ is recursively given as follows:

$$\mathcal{F}(x) = softmax\left(W^{(N+1)} h^{(N)}\right) \quad (1)$$

In (1),

$$h^{(n)} = \sigma\left(W^{(n)} h^{(n-1)}\right),\ \forall n = 1,2, \dots N; h^{(0)} = x \quad (2)$$

In (2), σ is the activation function (Maxout). Equation (2) represents a feed forward step of a neural network. While the training process, the hidden layers $h^{(n)}$ are learnt. The cross entropy loss function $\mathcal{L}(\mathcal{F}(x), y)$is used to train the MME for crop yield prediction. By applying Online Gradient Descent (OGD), the optimal model parameters W_i for $i = 1,2, \dots N + 1$. Equation (3) is the online learning setting where the update of the MME for crop yield prediction in each iteration by OGD is given as follows:

$$W_{t+1}^{(n)} \leftarrow W_t^{(n)} - \eta \nabla_{W_t^{(n)}} \mathcal{L}(\mathcal{F}(x_t), y_t), \forall n = 1,2, \dots N + 1 \quad (3)$$

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In (3), η is the learning rate. In order to calculate the gradient of the loss in relation to $W^{(n)}$ for $n \leq N$, the chain rule of differentiation is used with a back propagation.

B. Problems involved in Online Learning

The conventional online deep learning has several problems with convergence. In particular, a prior decision must be made in OL regarding a specified depth of the neural network. This cannot be modified while training procedure.

It is troublesome because it is difficult to determine the depth. Furthermore, various depths in the OL can help to process various instances in a small number of instances and wider networks in a large number of instances. In OL, vanishing gradient is more challenging problem that slows down learning since OL wants to make predictions and learn concurrently. Moreover, reducing feature reuse leads to losing many the most important features in the feed-forward stage of the prediction. It is very critical for OL.

C. Multi-Model Ensemble-Depth Adaptive Deep Neural Network

In order to avoid the problems in OL, a training procedure for OL is changed by using a hedging strategy called Hedge Backpropagation (HBP) for crop yield prediction. The HBP used an over-complete network and it automatically makes a decision like when and how to change the network's depth in an online manner. Consider MME-DADNN with N hidden layers, the crop yield prediction function is given as follows:

$$\mathcal{F}(x) = \sum_{n=0}^{N} \alpha^{(n)} f^{(n)} \quad (4)$$

In (4),

$$f^{(n)} = softmax\left(h^{(n)}\Theta^{(n)}\right), \forall n = 1,2, \dots N+1 \quad (5)$$

$$h^{(n)} = \sigma\left(W^{(n)}h^{(n-1)}\right), \forall n = 1,2, \dots N \quad (6)$$

$$h^{(0)} = x \quad (7)$$

MME-DADNN introduced two sets of new parameters $\Theta^{(n)}$ and α. In MME-DADNN, the prediction is weighted combination of classifiers learnt utilizing feature representations from $h^{(0)}, h^{(1)}, \dots h^{(n)}$. The weight of each classifier is represented as $\alpha^{(n)}$ and the loss endured by the model is $\mathcal{L}(\mathcal{F}(x), y) = \sum_{n=0}^{N} \mathcal{L}\left(f^{(n)}(x), y\right)$. During the online learning process, the parameters such as $\Theta^{(n)}, \alpha^{(n)}$ and $W^{(n)}$ are need to learn for crop yield prediction. The $\Theta^{(n)}$ is leaned through a online gradient descent in which the input to the n^{th} classifier is $h^{(n)}$. This is equivalent to the update of output layer's weight in the original feed-forward networks.

This is same as the update of the weights of the output layer in the original feed-forward networks. This update is given as follows:

$$\Theta_{t+1}^{(n)} \leftarrow \Theta_t^{(n)} - \eta \nabla_{\Theta_t^{(n)}} \mathcal{L}(\mathcal{F}(x_t), y_t) = \Theta_t^{(n)} - \eta \nabla_{\Theta_t^{(n)}} \mathcal{L}\left(f^{(n)}, y_t\right) \quad (8)$$

The parameter $\alpha^{(n)}$ learns using Hedge algorithm. All weights α are uniformly distributed in the first iteration as $\alpha^{(n)} = \frac{1}{N+1}, n = 0,1, \dots N$. The classifier $f^{(n)}$ makes a prediction $\hat{y}_t^{(n)}$ at each iteration. The classifier's weight is updated according to the loss suffered by the classifier. It is done when the ground truth is revealed. The weight updation is given as follows,

$$\alpha_{t+1}^{(n)} = \alpha_t^{(n)} \delta^{\mathcal{L}(f^{(n)}(x), y)} \quad (9)$$

In (9), the discount rate parameter is represented as δ which is ranges from 0 to 1. Hence, a classifier's weight is cut-rated by a factor of $\delta^{\mathcal{L}(f^{(n)}(x), y)}$ in every iteration. Finally, the weights α are normalized such that $\sum_n \alpha_t^{(n)} = 1$.

It is more difficult to update the feature representation parameters$W^{(n)}$. In MME-DADNN the error derivatives are backpropagated from every classifier$f^{(n)}$. The update rule is given by using adaptive loss function $\mathcal{L}(\mathcal{F}(x), y) = \sum_{n=0}^{N} \mathcal{L}\alpha^{(n)}\left(f^{(n)}(x), y\right)$ and applying OGD. It is given as follows:

$$W_{t+1}^{(n)} \leftarrow W_t^{(n)} - \eta \sum_{j=n}^{N} \alpha^{(j)} \nabla_{W^{(n)}} \mathcal{L}\left(f^{(j)}, y_t\right) \quad (10)$$

In (10), $\nabla_{W^{(n)}} \mathcal{L}\left(f^{(j)}, y_t\right)$ is calculated through backpropagation from error derivatives of $f^{(j)}$. It is noted that the summation starts at $j = n$ since the shallower classifiers do not depend on $W^{(n)}$ for making crop yield prediction. In addition, the gradient of the final prediction is computed with respect to the backpropagated derivatives of a predicator at every depth weighted by $\alpha^{(l)}$. The depth of the network is decided based on the following (11).

$$\mathcal{L}_T \leq \sqrt{T ln\, D} \quad (11)$$

In (11), $\mathcal{L}_T$ is the expected loss of the network at time T and D is the network depth. It adaptively selects the optimal network depth automatically online. It is a shallower model which tends to converge faster than deeper model utilizing a hedging strategy would inferior α weights of deeper classifiers to a very small value, which would affect the update in (10). It results in deep classifiers having slow learning. A smoothing parameter $p \in (0,1)$ is introduced to alleviate the slow learning. For each classifier, the smoothing parameter is used for setting a minimum weight. Once the weights of the classifier is updated, the weights are calculated as shown,

$$\alpha^{(n)} \leftarrow \max\left(\alpha^{(n)}, \frac{p}{N}\right) \quad (12)$$

Equation (12) used to maintain a minimum weight for a classifier for every depth and it also used to achieve a tradeoff between exploitation and exploration. Initially, the OL with hedging strategy is applied for soil, climate and weather prediction. Based on the predicted soil, climate and weather, the yield of the crop is predicted by OL with hedging strategy which is called as MME-DADNN.

MME-DADNN Algorithm

Input: $\delta \in (0,1), \eta, \quad p,$ Training data $T = ((x_1, y_1), \dots (x_t, y_t))$

Output: DADNN decision function for x

1. Initialize $\mathcal{F}(x)$ =DNN with N hidden layers and $N+1$ classifiers $f^{(n)}, \forall n = 0,1, \dots N, \quad \alpha^{(n)} = \frac{1}{N+1}, \forall n = 0,1, \dots N$
2. For $t = 1,2, \dots T$ do
3. Get x_t
4. Predict $\hat{y}_t^{(n)} = \mathcal{F}_t(x_t) = \sum_{n=0}^{N} \alpha_t^{(n)} f_t^{(n)}$using Eq. (4)
5. Decide the depth of the network using (11).
6. Initialize $\mathcal{L}_t^{(n)} = \mathcal{L}(f_t^{(n)}(x_t), y_t), \forall n = 0,1, \dots N$
7. Update $\Theta_{t+1}^{(n)}$ using (8)
8. Update $W_{t+1}^{(n)}$ using (10)
9. Update $\alpha_{t+1}^{(n)} = \alpha_t^{(n)} \delta^{\mathcal{L}_t^{(n)}}, \forall n = 0,1, \dots N$ using Eq. (9)
10. Smoothing $\alpha_{t+1}^{(n)} = max\left(\alpha_{t+1}^{(n)}, \frac{p}{N}\right)$ using (12)
11. Normalize $\alpha_{t+1}^{(n)} = \frac{\alpha_{t+1}^{(n)}}{Z_t}$, where $Z_t = \sum_{n=0}^{N} \alpha_{t+1}^{(n)}$
12. end for

IV. RESULT AND DISCUSSION

The efficiency of MME-DADNN is compared with MME-DL and MME-DNN in terms of accuracy, precision, recall and F-measure. For the experimental use, the climate data are collected from http://www.ccafs-climate.org/climatewizard/, crop data are collected from https://data.world/thatzprem/agriculture-india and soil data are collected from https://data.gov.in/search/site?query=soil. From the collected data, 7000 data are used for training and 30,000 data are used for testing.

A. Accuracy

Accuracy is the proportion of true positive and true negative among the total number of cases examined. It is computed as follows:

$$Accuracy = \frac{True\ Positive\ (TP) + True\ Negative\ (TN)}{TP + TN + False\ Positive\ (FP) + False\ Negative\ (FN)}$$

Table I shows the accuracy of MME-DNN, MME-OL and MME-DADNN based crop yield prediction method for banana, groundnut, wheat, sugarcane and maize.

Table- I: Evaluation of Accuracy

Crop yield prediction method	Banana	Groundnut	Wheat	Sugarcane	Maize
MME-DNN	0.90	0.92	0.90	0.91	0.90
MME-OL	0.92	0.932	0.92	0.93	0.92
MME-DADNN	0.94	0.95	0.94	0.95	0.94

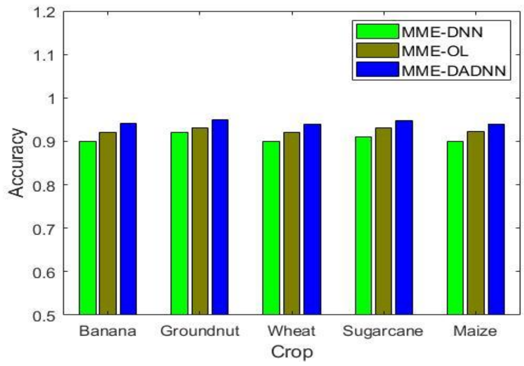

Fig. 1.Evaluation of Accuracy

Fig. 1 shows the accuracy of MME-DNN, MME-OL and MME-DADNN for five different crops are banana, groundnut, wheat, sugarcane and maize. The accuracy of MME-DADNN is 4.44% greater than MME-DNN and 2.17% greater than MME-OL method for banana crop. From Fig. 1 and Table II, it is proved that the proposed MME-DADNN has high accuracy for five crops than MME-DNN and MME-DL based crop yield prediction method.

B. Precision

Precision is calculated based on crop yield prediction at true positive and false positive values. It is given as follows:

$$Precision = \frac{TP}{TP + FP}$$

Table II shows the precision of MME-DNN, MME-OL and MME-DADNN based crop yield prediction method for banana, groundnut, wheat, sugarcane and maize.

Table- II: Evaluation of Precision

Crop yield prediction method	Banana	Groundnut	Wheat	Sugarcane	Maize
MME-DNN	0.56	0.92	0.86	0.86	0.60
MME-OL	0.59	0.925	0.87	0.88	0.63
MME-DADNN	0.62	0.934	0.89	0.9	0.65

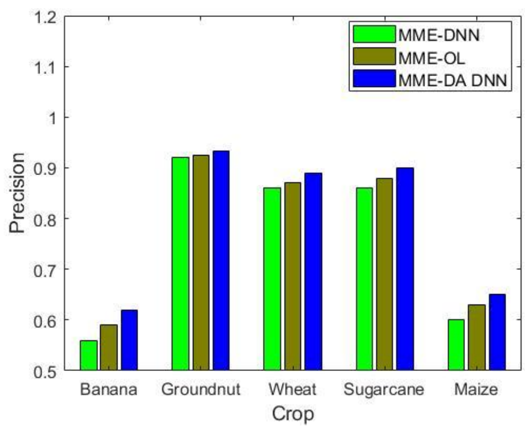

Fig. 2.Evaluation of Precision

Fig. 2 the shows performance comparison of the proposed and existing crop yield methods in terms of precision rate. The performance is evaluated using banana, groundnut, wheat, sugarcane and Maize crops which are represented in t he x-axis whereas precision rate is represented in the y-axis. The precision of MME-DADNN is 10.71% greater than MME-DNN and 5.08% greater than MME-OL for banana crop. From this analysis, it is proved that the proposed MME-DADNN has high precision than the MME-DNN and MME-OL based crop yield prediction method.

C. Recall

Recall is used to measure the fraction of positive patterns that are correctly classified. It is given as follows:

$$Recall = \frac{TP}{TP + TN}$$

Table III shows the recall of MME-DNN, MME-OL and MME-DADNN based crop yield prediction method for banana, groundnut, wheat, sugarcane and maize.

Table- III: Evaluation of Recall

Crop yield prediction method	Banana	Groundnut	Wheat	Sugarcane	Maize
MME-DNN	0.93	0.92	0.92	0.93	0.92
MME-OL	0.94	0.93	0.93	0.94	0.93
MME-DADNN	0.95	0.94	0.945	0.95	0.942

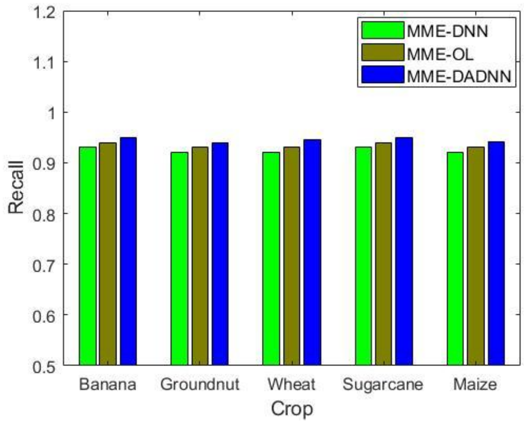

Fig. 3.Evaluation of Recall

Fig. 3 shows the recall of MME-DADNN, MME-OL and MME-DNN for five different crops. Banana, groundnut, wheat, sugarcane and maize crops are taken in x-axis and the recall is taken in y-axis. The recall of MME-DADNN is 2.15% greater than MME-DNN and 1.06% greater than MME-OL for banana crop. From this analysis, it is proved that the proposed MME-DADNN has high recall than the MME-DNN and MME-OL based crop yield prediction method

D. F-measure

It is the mean value of precision and recall. It is given as follows:

$$F - measure = 2 \times \left(\frac{Precision \times Recall}{Precision + Recall}\right)$$

Table IV shows the F-measure of MME-DNN, MME-OL and MME-DADNN based crop yield prediction method for banana, groundnut, wheat, sugarcane and maize.

Table- IV: Evaluation of F-measure

Crop yield prediction method	Banana	Groundnut	Wheat	Sugarcane	Maize
MME-DNN	0.81	0.92	0.90	0.90	0.82
MME-OL	0.83	0.93	0.91	0.91	0.94
MME-DADNN	0.85	0.94	0.92	0.93	0.86

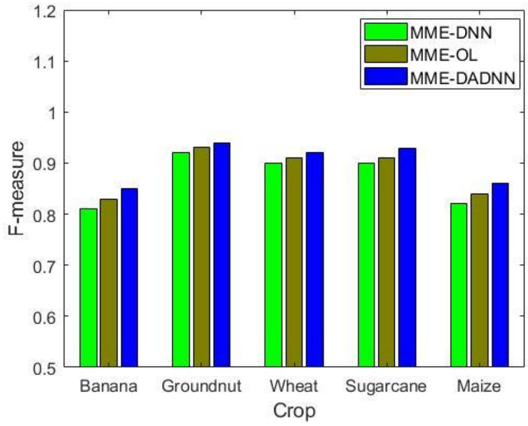

Fig. 4.Evaluation of F-measure

The comparison of MME-DADNN, MME-OL and MME-DNN in terms of F-measure value is shown in Fig. 4. The performance comparison of proposed and existing crop yield prediction method is evaluated using five different crops. The F-measure of MME-DADNN is 4.94% greater than MME-DNN and 2.41% greater than MME-OL for banana crop. From this analysis, it is proved that the proposed MME-DADNN has high F-measure than the MME-DNN and MME-OL based crop yield prediction methods.

V. CONCLUSION

In this paper, MME-DADNN is proposed for efficient crop yield prediction based on online learning. It has created an OL capable of starting with a shallow, fast-convergent network and then moving automatically towards a deeper model when more data is received to learn more complex information. It efficiently enhances online predictive performance by adaptively changing the depth of the network. In MME-DADNN, every hidden layer represents an output classifier and a hedge back propagation is used to evaluate the online efficiency of every result classifier at every online round and broadens the back propagation to train the DNN online by exploiting the classifiers of various depths with the hedge back propagation. Hence it allowed training DNN with adaptive capacity which enhances the crop yield prediction. The experimental results show that the proposed MME-DADNN has better accuracy, precision, recall and F-measure than MME-DNN and MME-OL for crop yield prediction.

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