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Crop Yield Predication using the Deep learning technique

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Abstract:

Agricultural farming is one of the most important and required actions that must be carried out in order to provide food and other nourishment to the rising population. Several agrarian nations rely largely on crop production to ensure their subsistence and promote commerce. The dependence on agriculture has been important for a nation's development and advancement, since a well-fed and healthier population has a far higher life expectancy and profitability than a country with subpar production and nutrition supply. India is primarily an agricultural country, with agriculture accounting for a substantial portion of its trade. The agricultural process is a complicated activity that does not permit for exact prediction of crop production. Without proper production projections, the farmer cannot plan efficiently, which might result in unanticipated losses. As a result, there is a requirement for an effective technique for predicting agricultural yields using machine learning methodologies. To forecast agricultural yield, the suggested method employs Linear Regression, Deep Belief Network, and Fuzzy Classification. The given approach has been thoroughly investigated and found to significantly increase crop production prediction engine performance over previous methodologies.

Keywords— *Crop yield Prediction, Linear Regression, Deep Belief Neural network, Fuzzy classification.*

I INTRODUCTION

Crop cultivation is a large-scale sector that employs a big amount of participants on the Indian subcontinent. A wide range of jobs rely on agricultural production in certain manner for their planning and implementation. Crops grown all over the world are highly dependent on a variety of conditions and traits. Increased agricultural production and an adequate result are essential to provide maximum financial prosperity. It is crucial for the survival of the predominantly agricultural civilization since missed yields lead to the loss of money. As a result, water scarcity might be disastrous for an economy that is entirely reliant on agricultural produce and agricultural activities.

As a consequence, an appropriate measure for predicting crop yield is essential in order to prepare for the oncoming arrival of drought or advantageous conditions [1]. India is an agricultural country. An agrarian country is one that relies heavily on crop farming and other agricultural goods. Nourishing a nation is a tremendous task that can only be accomplished via gardening. India has the most arable land available for farming. Because the country is an agricultural one, agriculture provides a living for the vast majority of its citizens.

Crop cultivation is a significant industry on the Indian subcontinent, employing a massive amount of people. A wide range of occupations rely on crop cultivation in some way for their proper formulation and execution. Crops cultivated throughout the globe are heavily reliant on a range of qualities and factors. To obtain optimum financial prosperity, crop production must be profitable and yield an effective outcome. Failed harvests result in a loss of economics, which can be critical for the sustainability of the predominantly agricultural economy.

As a result, severe drought might be fatal to a country that is fully dependent on agricultural production and agrarian operations. As a result, there is a requirement for an appropriate approach to predict crop output in advance in order to prepare for the impending advent of drought or favorable circumstances. To make any form of prediction, the myriad characteristics that control crop output are exceedingly complicated and need a thorough grasp of the agricultural paradigm [2]. The weather changes throughout time, including the proper use of existing data, can contain the key to a comprehensive and successful forecast system.

Predictions may be quite valuable in anticipating occurrences that could have been disastrous for farmers in a vast agrarian economy. Several studies have been conducted with the goal of making accurate forecasts on agricultural output for a specific time frame in the long term. These studies have been thoroughly examined in order to comprehend the various methodologies used by the researchers to accomplish yield forecasting. These studies have proven beneficial in obtaining an accurate prediction that may be used to provide vital insight into crop yield prediction.

The next session of this research paper is dedicated to the survey of the past work. In section 3 the proposed model is elaborated in detail and then the obtained output results are evaluated in section 4. In section 5 this research paper is concluded with some flash light on future scope.

II LITERATURE SURVEY

Sonal Agarwal [3] suggested a Machine learning strategy to help farmers prevent yield losses owing to a lack of understanding about how to grow in different soil and weather situations. Machine learning (SVM) and deep learning (LSTM, RNN) approaches are used to construct the model. During an evaluation of the forecast characteristics, the model predicts which harvests should indeed be produced on the least expensive acreage between a choices of crops accessible. There aren’t any other research that employs the similar approach for crop yield prediction. As a result, when contrasted to previous crop forecast research that employed diverse methodologies, it is fair to infer that the results of the investigation are more reliable.

S. P. Raja [4] projected plant cultivation yield size utilizing a variety of extracting the features and categorization techniques. The Random Over-Sampling Examples (ROSE), Synthetic Minority Over-sampling Technique (SMOTE), and Majority Weighted Minority Over-sampling Technique (MWMOTE) are being used to supplement the given dataset. Selection of features is an approach for selecting key properties from a dataset, which results in enhanced performances and categorization techniques that help in class recognition. The Boruta, Modified Recursive Feature Elimination (MRFE), and Recursive Feature Elimination (RFE) approaches are used in this study to uncover the dataset's main characteristics. Numerous supervised classification techniques are developed utilizing specified attributes to anticipate an appropriate conclusion from the dataset, including Naive Bayes (NB), Decision Tree (DT), k Nearest Neighbor (kNN), Support Vector Machine (SVM), Bagging, and Random Forest (RF).

N. Efremova [5] presents the CycleGAN technique for measuring any physiological parameters utilizing S1 and S2 information. The restrictions and possibilities of SMC prediction using S1 and S2 information with the GAN-based framework are examined for the very first period. The use of autoencoders and CycleGANs to retrieve data using Sentinel-1 and Sentinel-2 photos is the very first occasion. The feasibility of the proposed approach was demonstrated in this study, allowing the authors to integrate two independent pieces of knowledge for accurate SMC forecasting. Because grapevine are among the most extensively consumed horticulture crops on the globe, it was decided to investigate SMC computations in agriculture from space. In situ measurements are performed in conjunction with satellite acquisitions to determine if Sentinel-1/-2 data can also be used to gather soil properties. The dataset experiments demonstrate that the proposed technique is beneficial in regression-based physicochemical component assessment in agricultural research, in which the capacity to capture sonar and optic images at the same time is critical due to their complimentary knowledge.

J. Jiang [6] described HISTIF, a unique spatiotemporal fusion approach that combines spatially sparse high-resolution pictures with recurring medium-resolution imagery. HISTIF addresses the two severe issues of spatial scale mismatch as well as within volatility in only two steps. It was presented in three cutting-edge spatiotemporal fusion algorithms, STARFM, FSDAF, and Fit-FC, using both simulated and real-world GFLandsat as well as GFSentinel datasets. HISTIF's spatial scale mismatch correction culminated in considerable improvements in PSF measurement and geo-registration problems, which influence all pixel-based fusion techniques. As per the visual observation, STARFM rated the poorest in regards of eliminating blocky artifacts and improving spatial characteristics within fields, particularly for real statistics.

Y. Alebele [7] presented two Gaussian-based regression algorithms: Gaussian kernel regression that employs kernel parameters as weighting variables, and PGPR, that employs MCMC sampling. The two Gaussian-based approaches were contrasted with equivalent linear extension, Bayesian linear inference regression, to correlate SAR and optical produced metrics with field-measured crop production. The suggested scheme investigates whether the combined effect of interferometric coherence and optical indices improves crop yield assessment utilizing selected prediction model, validates the predictive accuracy of Gaussian kernel regression models to restricted ground truth specimens, and compares it to other Bayesian regression methods.

N. Rasheed [8] provides a novel paradigm for agricultural production in a limited region based on Spatio-temporal data. The framework addresses policy constraints and the management consequences of the crop assignment problem, and it employs historical information out of each field for the previous seasons, as well as the national necessity and international desire for each commodity, along with all crop output restrictions. This study aims to propose a resolution for countries that suffer to maintain equilibrium between food production and consumption since crops are often farmed only for the advantage of the farmer. The model was developed to confront the problem of agricultural production at the nationally, with the goal of maximizing profits while minimizing expenditures.

M. Qiao [9] presents an excellent model with hierarchical properties for agricultural yield prediction. The authors begin by taking advantage of the 3-D CNN's superiority in extracting spatial-spectral features from raw RSIs. To account for factors other than the RSIs, they use an MKL framework that blends fundamental deep attributes with spatial consistency characteristics amongst pieces of data. Additionally, the prediction method is implemented using the kernel-based GP approach. This study anticipates winter wheat in China at the provincial level. Extensive experimental results demonstrate that not only does the proposed framework beat existing conventional and deep learning approaches, and that also generates stronger discriminative feature descriptions, hinting that it might be used to handle a range of prediction and classification.

Z. Cai [10] created a rotating phenotypic imaging device that uses a single camera and a line laser to acquire point cloud data from the exterior of a potato. The authors repaired the point cloud between the point of intersection and the initial assertion virtualization by looking for the position nearest to the Z-axis as well as the junction with the Z-axis in the input image at the inclination of the closest point. After that, the potatoes were sliced all along Z-axis, with both the coordinates in each section fitting to B-spline curves. Using the whole point cloud, the volumetric and composition of a validated potato were computed. The average volume and density of a calibrated potato were painstakingly determined. The density of the potato was assessed by actually determining the mass and proportion of potatoes in a customized subgroup including using linear regression to develop a linear connection between both the observed and standardized volume. The regression model of volume was used for potato validation, and the size and weight of the potato produced from the input image were contrasted to those determined experimentally.

D. Elavarasan [11] proposes a supervised smart agriculture system based on the deep learning approach. A deep Q-Learning dependent DRL algorithm is used with the greatest rewarding iterations to increase agricultural production forecasting efficiency. By building a yield prediction environment, the proposed approach allows the agent to identify and understand crop yield predictions via self-exploration and knowledge replay. The various prediction agent appeared to manage the process based on the dataset prediction results, suggesting that the proposed approach can accurately characterize crop yield characteristics. The overall objective is to get favorable results by integrating RNN-based information computation with DQN-based self-experimental evaluation. In contrast to supervised learning-based agricultural yield forecasting, the DRQN-based technique provides a comprehensive approach that exploits the non-linear mapping among crop production and environmental, earth, and hydrological parameters separately.

M. Meroni [12] investigated the effects of using PV NDVI but instead of VGT NDVI for operational crop management and yield prediction. The researchers utilized paired readings from the two sensors even during overlap period once both communications satellites remained operational. This overlap period, which extends out from conclusion of October 2013 towards the close of May 2014, coincides to the period during which North African countries evaluate crop progress (from January to May) and provide timely yield projections for the major agricultural crops. Rather than examining product agreement, as is common in satellite merchandise inter-comparison research findings, the objective of this investigation is to make sure that the data obtained from PROBA-V can be securely utilized to help substitute that of SPOT-VGT organizationally and flawlessly, and to also assess the potential difficulties connected with this transformation of source of data from of the customer viewpoint. The authors focus on the NDVI statistic that is used for national yield forecasting in Moroccan, Algerian, and Tunisian.

E. Myers [13] evaluated the influence of the time-series end date and scanning frequency on their capacity to correlate VI with maize yield utilizing continuous, high-resolution (3-m GSD) multispectral satellite data.

This research contributes to the existing piece of research on using Cubesats as well as harmonized sensor data for crop prediction, contrasts different avenues for gap-filling and designed to detect green-up date and time in VI time series, as well as makes a significant contribution to research progress into temporal imaging prerequisites for environment monitoring by examining the relationships among both yield comparison precision and satellite re-entry. Prior to examining VI-yield correlations, the authors discovered that reconfiguring plot-average GNDVI time-series at respective corresponding green-up dates provided the most consistent results across different time-series end dates. For gap-filling but also smoothing GNDVI time-series data, two alternatives were to coefficient of determination to a temporal shape description or to do local fitting with the Flexfit technique.

III PROPOSED METHODOLOGY

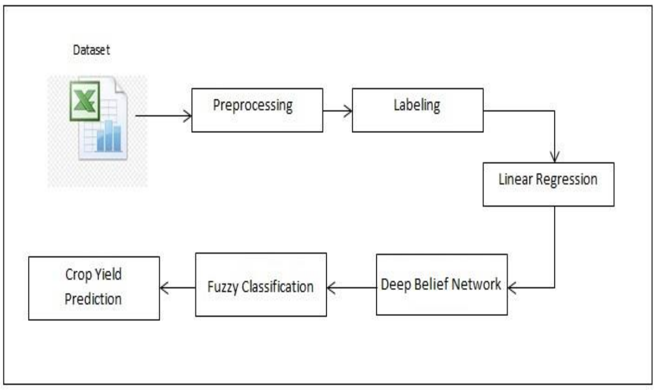

Figure 1: System Overview Diagram

The system overview diagram presented in figure 1 above depicts the proposed methodology for leveraging Deep Belief Networks to allow a crop production forecast strategy. The prediction system was introduced by the use of a strategy, the stages of which are detailed below.

Step 1: Dataset collection, preprocessing and Labeling – The crop yield prediction algorithm was shown using a dataset obtained from the URL. https://github.com/VaibhavSaini19/Crop-Yield-Prediction-using-ML. This dataset will be utilized to compute agricultural output and will be fed into the proposed technique.

The resulting dataset is fed into the proposed method for making projections. The dataset is firmly incorporated into a worksheet format, which the software accesses using the pandas library. The python code can use this library to interface the workbook files.

The dataset has a diverse variety of characteristics, but only a few are considered for our technique because then they can assist us produce a precise prediction. The metrics obtained include farm area, yield, temperatures, rainfall, moisture, soil type, type of crop, and district. These are the essential qualities; the others are superfluous and are deleted. These qualities are critical in affecting the forecast and have resulted in higher in output that may be highly useful.

The user interface is used to enter the farm details before giving the program input in the format of the farms characteristics. The characteristics or attributes that are contained in the dataset, and selected for the purpose of predicting the yield are taken as an input through the use of the tkinter based Graphical user interface.

Step 2: Linear Regression – In this step of the procedure, the preceding phase of the method provides input data of a double dimension list. This list comprises the attributes that have already been preprocessed and labelled. To do the regression on all these parameters, the linear regression approach is applied.

A consistent regression between an independent and a dependent parameter is established using linear regression. These values are indicated by the x [] and y [] lists, with x designating the independent variable and y signifying the dependent variable. This is mathematically illustrated in Equation 1.

Y=Mx + B ________________________ (1)

The degree of regression is calculated by multiplying the magnitude of b, which is the intercept, by an undetermined quantity of m, which would be the gradient. To get these outcomes, the dependent and independent values, which are variables such as temperature, precipitation, and humidity, are employed. These attributes are supplied in the form of an array X [] from the original preprocessed and labeled dataset for intercept and slope evaluation that use the equations 2 and 3 below. And the parameters entered by the user for the field attributes are treated as a Y [] list to be entered into to the equations stated below.

__________________ (2)

______________________ (3)

Where:

x = Independent variable (user input)

y = Dependent variable (Dataset values)

M = Slope or Gradient (how steep the line is)

B = the Y Intercept (where the line crosses the Y axis)

N= Size of the array

Y=Intercept value

Because once values have indeed been assessed, they may be used in equation 1 to compute the value of the dependent variable. This is performed by considering the system's input from the user for a specific attribute. The quantities of the independent variables are provided, and the associated y values are generated using regression. These numbers are subsequently included into the crop yield prediction method.

Step 3: Deep Belief Network – This is perhaps the most important and difficult stage of the process. This is the point where the yield is predicted. The labeled and preprocessed list is used as an input in this stage of the approach to evaluate the hidden state and output neurons. The qualities obtained before for achieving linear regression were utilized as input for this step of the method. This is advantageous since it allows for accurate and quick crop yield prediction.

This component receives a preprocessed and labeled list of the dataset's required properties as input for assessing the hidden and output layers. Deep Belief Networks operate on three layers: input layers, hidden layers, and output layers. For a specific district, the input parameters of the selected variables, temperature, rainfall, area, yield, moisture, type of soil, and crop, are presented and used to estimate crop yield.

These values are merged with the provided random weights to create the five hidden layers. The bias weights are combined with both the two weights for every quality. The Relu activation function is being used to evaluate the five hidden layers. The acquired hidden values are sent to the output layer, which calculates the output error probability.

The hidden layer values, and also the weights and bias weights, are used to produce the output layer values. These figures, along with the two target variables T1 of 0.01 and T2 of 0.99, are utilized in equation 4 to calculate the error probability rate given beneath.

$$Error\ Probability = \sum \frac{1}{2} \text{-----} \quad (4)$$

Where,

T = Target Values

O_L = Output Layer Values

The error probability estimate mentioned above is then appended to the end of the row in the district's double dimension list. This is repeated for each quality. The resultant list is ordered in ascending order of the error probability rate, with the higher numbers indicating the least amount of mistake. The dependability of the produced probability, which will be used in the next phase of the classification procedure, is inversely proportional to the error probability percentage. The technique of hidden layer evaluation is demonstrated in Algorithm 1.

ALGORITHM 1: Hidden Layer Estimation

```
//Input: Pre-processed List  PR_L, Weight set W_S= { }
//Output: Hidden Layer value list H_LV
hiddenLayerEstimation (PR_L, W_S),index=0
Start
H_LV =Ø { Hidden Layer value]
  for i=0 to size of PR_L
      ROW= PR_L [i]
        for j=0 to size of ROW
              X=0
          for k=0 to N [ Number of Neurons]
                ATR=ROW[j]
                X = X + (ATR* W_S[index])
                index++
          end for
        H_LV= reLUmax(0, X)
    end for
```

14: ***end for***

15: return H_{LV}

16: Stop

Step 3: Fuzzy Classification – The error probability list acquired in the previous stage is used as an input for fuzzy classification in this phase of the technique. This list has already been sorted in ascending order, and its length has already been computed and divided by 5. This number is used to categorize the list into five unique groups, with fuzzy crisp values of VERY LOW, LOW, MED, HIGH, and VERY HIGH. These sections are similarly scored on a scale of 1 to 5.

This component of the algorithm also considers user input, and the corresponding district is discovered in the clusters for its labeled location. Once the location of the input region has been established, it is computed by splitting the number of clusters by 5, and the resultant value is coupled with the regression value for the corresponding region found in the previous steps. As a result, a diversity of variables are created, which are then sorted for classification and ratio evaluation. To achieve the yield, the best outcome for the predictions is selected from the list and displayed to the user through the use of the interactive graphical interface.

IV RESULT AND DISCUSIONS

The described technique for crop yield forecasting was accomplished using the python programming language. For the implementation of the suggested approach, the Spyder IDE was utilized. The installation computer has 6GB of RAM and 1TB of hard disk space, and it is driven by an Intel Core i3 CPU. The pandas library is being used to allow the dataset to be interfaced with java code in a spreadsheet format.

An in-depth examination of the forecasting approach for the occurrence of any mistakes has been obtained through experimental testing. The error evaluation determines the precision of the forecast, which may be very useful in determining the precision of the crop yield forecasting method. To calculate the error of the proposed prediction method, the RMSE or Root Mean Square Error performance assessment approach was used.

The RMSE approach determines the error between two or more relevant and dependent variable using two or more relevant and consistent parameters. Our technique employs two factors: predicted crop yield predictions and realized crop yield predictions. The error was calculated using the equation indicated in equation 5 underneath.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(x_{1,i} - x_{2,i}\right)^2}{n}} \quad \text{\_ (5)}$$

Where,

- Summation

$(x_1 - x_2)^2$ - Differences Squared for the addition in between the expected crop yield predictions and the obtained crop yield predictions n - Number of samples or Trails

No. of Trials	No of Expected Crop Yield Predictions	No of Obtained Crop Yield Predictions	MSE
1	11	10	1
2	2	2	0
3	13	12	1
4	5	5	0
5	8	7	1
6	1	1	0
7	9	9	0
8	8	7	1
9	4	4	0
10	10	10	0

Table 1: Mean Square Error measurement

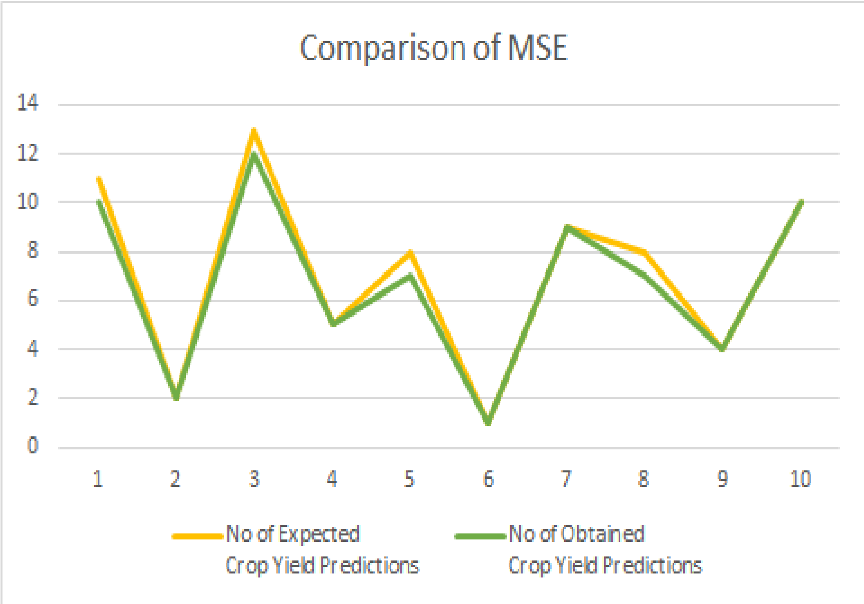

Figure 2: Comparison of MSE in between No of expected Crop Yield predictions V/s No of obtained Crop Yield rate predictions

The experimental technique and its outcomes are provided in table 1 above. The data obtained in the table are utilized to generate a line graph, as illustrated in figure 2 above. We may conclude from an in-depth examination of the visually depicted and tabular results that the error attained in this approach for crop yield prediction is negligible. To calculate MSE, or Mean Square Error, a series of ten experimental trials with variable input were undertaken.

The empirical outcomes demonstrate that the prediction system's error is moderate and reasonable. The prediction error is typically detected in estimation techniques that conduct predictions on real-world data. Crop yield predictions are influenced by a variety of distinct circumstances.

The MSE and RMSE values of 0.632 and 0.4, correspondingly, obtained are quite good and demonstrate a reliable formulation of the crop yield prediction method. The suggested method outperformed the crop yield prediction approach through CNN as shown in [14]. Our method achieves a lower RMSE. Table 2 below shows a tabular comparison of the CNN based approach of [14] and the proposed DBN crop yield prediction methodology.

Performance Metric	Our Approach (DBN)	CNN based Crop Yield Prediction approach [15]
RMSE	0.632	0.81
MAE	0.4	4.25

Table 2: Comparison with [14]

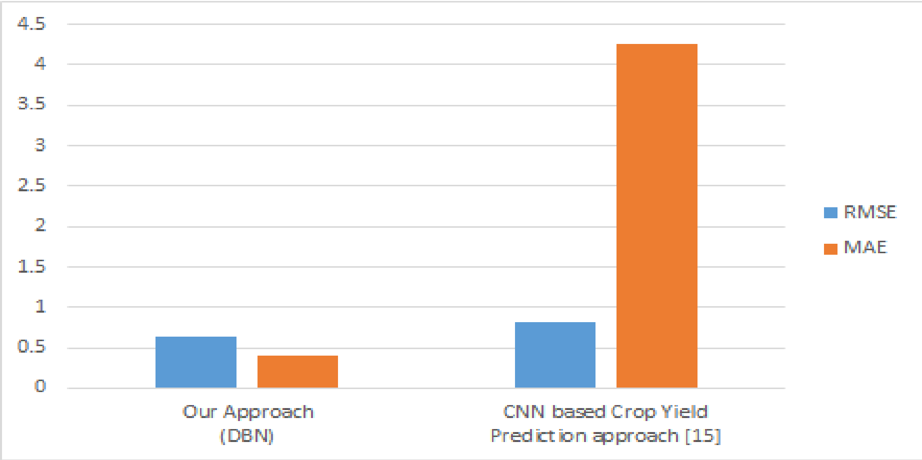

Figure 3: Comparison with crop yield prediction approach in [14]

The Deep Belief Network utilized in this research work dependably surpasses the CNN based crop yield prediction approach described in [14], as seen in Figure 3. This is owing to the DBN's extremely accurate implementation, which dramatically enhances prediction quality and reduces errors.

V CONCLUSION AND FUTURE SCOPE

The presented technique for the purpose of achieving accurate crop yield prediction through the implementation of deep learning methodologies has been presented in this research article. The crop yield prediction is performed using the dataset provided as an input as well as the user attributes of the field. The dataset along with the field parameters are provided as an input to the approach which effectively performs the preprocessing task that removes any redundant and contradictory data. The preprocessed data is sent along to the next phase of the technique, which involves labeling the information; the labeled information is then transferred on to the following step, which involves regression examination. For the assessment of the regression list, which accomplishes the regression and sends the outcome to the following stage for neuron generation, linear regression is utilized. To obtain the error probability in the characteristics, the Deep Belief Networks were developed using the ReLu activation function. The achieved error probability needs to be classified to achieve the outcomes. The classification approach of Fuzzy Classification has been utilized to classify the probability scores and achieve the precise crop production output. The approach has been evaluated for its error using the RMSE approach which has been contrasted with the conventional crop yield prediction approaches with highly satisfactory results.

The future research can be performed in the direction of achieving the crop prediction in a larger area such as a state or a country. The approach can be enhanced to be realized as a smartphone application for easier access to the farmers and the governmental agencies.

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