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Analyzing Impact of Weather Forecasting Through Deep Learning in Agricultural Crop Model Predictions

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Abstract

Determining crop generation in-season is ending up progressively significant for agricultural producers to make informed crop management and financial decisions. Precisely forecasting crop yield in advance could extraordinarily beneficial for decision makers. In any case, the use of more weather-related parameters corresponding to crop models would improve the forecast efficiency. In this paper, we have considered several weather-related data to predict the crop production model using Adaptive Deep Neural Network Architecture. The crop models related data from Karnataka State Natural Disaster Monitoring Centre Data includes District Wise Monthly Actual Average Rainfall (mm) data, Temperature data, Relative humidity data, Agricultural data are gathered from three districts of Karnataka such as Bangalore, Belgaum, Bellary. The presented crop production model is dealt with the crops like Rice, Wheat, Jowar, Bajra, Maize, Ragi, and some other cereals and Pulses. The proposed model is designed to predict the future crop models based on the previous year's weather-related data. So, the prediction of future crop models based on the weather-related data would enable the farmers to take necessary steps for precaution or they can stop cultivation for any particular crops.

Keywords: ADNN, Crop models, Karnataka, Cereals, pulses

1. INTRODUCTION

India's most important is agriculture and its economy relies on the farming of the nation. The agriculture carries with it various issues, for example, agriculture generation and food security, water and soil asset protection, constraining the effect of cultivating on the nature of our environment [1]. The precipitation considerably affects agriculture. Consequently, early expectation of precipitation is significant for the better development of the economy, however it's a difficult challenge on the planet from past years [22]. Different types of techniques utilized for prediction, for example, Artificial Neural Network (ANN), Support Vector Machine (SVM), Regression investigation, and clustering and so on. Despite the fact that Artificial Neural Networks (ANNs) are utilized over huge range in remote detecting to anticipate vegetation parameters and crop yield and are commonly used to manage non-linear models, their practical application has a few challenges, for example, determination of the number and size of hidden layers, learning rate, the requirement for a huge preparing dataset and the issue of over fitting. Remote detecting was first connected to straightforwardly gauge crop creation utilizing relapse conditions [2].

Since the utilization of remotely detected data to legitimately gauge crop yield is flawed, an information absorption technique that satellite information is utilized to align parameters of crop development model has been created [3]. Notwithstanding, an information absorption strategy causes an excessive amount of confounded adjustment of a few models (crop development and radiative exchange) and requires field information of examination station. Consequently, demonstrating the harvest yield estimation for extensive stretch and over a wide territory has enormous difficulties.

Support Vector Machines (SVMs) are additionally being utilized in Precision agriculture (PA) and can possibly resolve the issue of over fitting when dissecting high-dimensional information, for example, hyper spectral imaging information [4].

In India, Pakistan, Bangladesh the yield was sorted them into three primary seasons are arranged in to rabi, Kharif, and zaid or zayad [5]. Machine Learning (ML) strategies accomplishes extraordinary outcomes in different fields, endeavors to apply propelled ML models, for example, support vector machine (SVM) [6], Bayesian systems [7] and random forest, strikingly expands the expectation accuracy. Be that as it may, ML-based designs for forecast have a few impediments in model settings.

Deep learning is an algorithm of machine learning utilizing the neural system (NN) with various layers. The essential profound learning device utilized in this work is Convolutional Neural Networks (CNNs). CNNs comprise a standout amongst the most dominant procedures for displaying complex procedures and performing design acknowledgment in applications with enormous measure of information, similar to the one of example recognition in images [8, 9]. Deep learning refers to an accumulation of machine learning algorithm which embraces 'profound' model design for information disclosure. At the end of the day, the information will be changed in either a straight or a nonlinear way on different occasions before inferring the yield [10]. Deep learning method, for example, RNN, was increasingly reasonable for arrangement getting the hang of demonstrating, is presented in crop ailment expectation [11, 12].

Deep learning has the ability to concentrate key highlights from the information for estimation; it very well may be required to have less reliance on the input information. Along these lines, even in regions where information obtaining is constrained, profound learning can be relied upon to give great quality estimation of crop yield [13]. Several Weather forecasting methods are used to predict the crop yield have discussed in next section of the document.

2. RELATED WORKS

Mumtaz Ali et al [14] have designed the multi-stage probabilistic machine learning. The multi-organize half and half Markov Chain Monte Carlo (MCMC)- Cop-Bat-OS-ELM model uses online-consecutive extraordinary learning machines coordinated with Markov Chain Monte Carlo (MCMC) based bivariate-copula and the Bat calculation was utilized to consolidate huge precursor precipitation (t–1) as the model's indicator in the preparation stage. The multi-organize, hybridized MCMC-Cop-Bat-OS-ELM model was prevalent apparatus for determining month to month rainfall.

Mumtaz Ali et al [15] have proposed a committee extreme learning machine (Comm-ELM) model in regard to a board of trustees particle swarm optimization adaptive neuro fluffy derivation framework (Comm-PSO-ANFIS) and committee multiple linear regression (Comm-MLR) model connected to forecast month to month institutionalized precipitation file (SPI). Comm-ELM can be effectively connected for SPI guaging, in spite of the fact that there was a critical variety as far as the model estimating exactness among the exhibition of these models with and without periodicity.

Sujan Ghimire et al [16] have proposed a self-adaptive differential Evolutionary ELM (i.e., SaDE-ELM) , The technique uses a swarm-based Ant Colony Optimization (ACO) highlight choice to choose the most significant indicators for GSR, and the SaDE-ELM was then benchmarked with nine unique information driven models: an essential ELM, hereditary programming (GP), online consecutive ELM with fixed (OS-ELM) and fluctuating (OSVARY-ELM) input sizes, and hybridized model including the molecule swarm streamlined fake neural system model (PSO-ANN), hereditary calculation upgraded ANN (GA-ANN), PSO-bolster vector machine model (PSO-SVR), hereditary calculation improved SVR model (GA-SVR) and the SVR model enhanced with network seek (GS-SVR). The SaDE-ELM was favored instrument over the essential ELM and the hybridized form of ANN, SVR and GP model.

Dunnan Liu et al [17] have proposed a circulated burden forecasting strategy dependent on neighborhood climate data. In this methodology, estimating models have been chosen from burden forecasting model base, which incorporates neural system, autoregressive coordinated moving affirms age model, autoregressive and moving normal, dim model, etc.

Dominique Brunet et al [18] have presented a generalized distance transform (GDT) which was smoother than the established DT. This change can be utilized to characterize a summed up Hausdorff metric and it's progressively powerful to commotion while protecting every single metric property.

Jorge Angel Gonzalez Ordiano et al [19] have exhibited a technique which uses a uninhibitedly accessible dataset just as an efficient pre-processing and information mining system to make a progression of basic information driven guaging models. The plan has a speculation limit and along these lines can be utilized for various sorts of time arrangement just as various information mining procedures. Jose R et al [20] have depicted an anticipating structure to investigate data from a lattice of numerical climate forecasts (NWP) connected to both breeze and sun oriented vitality. The approach joins the angle boosting trees calculation with highlight designing methods that concentrate the greatest data from the NWP framework.

3. PROPOSED AGRICULTURAL CROP PRODUCTION MODEL

The proposed model is advised to predict the future approaching crop models based on the antecedent year’s weather connected data. So, the forecast of approaching crop models based on the weather related data would facilitate the farmers to acquire all-important steps for safeguard or they can stop cultivation for any particular crops. Therefore, the proposed crop production model can be comprised of two main stages, particularly, Data collection stage and, Future Crop Prediction stage. In the Data collection stage, a range of weather related data’s are collected for 20 districts of Karnataka. As, the proposed crop production model is analyzed with the crops like Rice, Wheat, Jowar, Bajra, Maize, Ragi, and some added cereals and Pulses; therefore, the historical crop data including the analyzed crops are also gathered. Finally, in the prediction stage, the future crop production is predicted using Adaptive DNN classifier. The stages of proposed crop production model are detailed in the upcoming sections. Moreover, the Structure of presented Crop Production Model is shown in the below figure 1.

3.1 Data Collection Stage

Information Collection assumes a crucial job in the enhancement of forecast precision. In information collection stage, the weather associated data includes the District Wise Monthly Actual Average Rainfall (mm) data, temperature data, relative humidity data from 20 districts of Karnataka and the data composed from the Karnataka State Natural Disaster

Monitoring Centre. Based on these data, the future crop production data is forecasted.

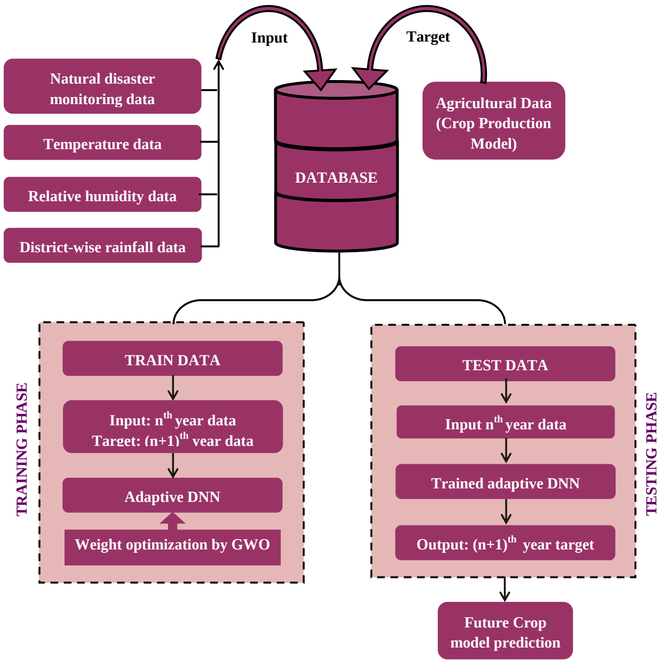

Fig 1: Structure of proposed Crop Production Model

3.2 Future Crop Prediction by Deep Neural Network (DNN)

A deep neural system (DNN) is a artificial neural system (ANN) with numerous hidden layers of units between an income and outcome layers. Deep learning methods are very compelling when the amount of accessible examples in the midst of the preparation stage is tremendous. Therefore, the proposed crop production model is defined with DNN based approach. During the training of traditional DNN, the weights of the neurons are refreshed in every cycle till the error amongst output and input is not within tolerance. This is time consuming. To enhance traditional DNN, we have introduced adaptive DNN for predicting the future crops based on numerous quantity of weather related data's. In adaptive DNN, an optimization algorithm Grey Wolf Optimization is used for acquiring the optimal set of weights to be used in the interconnection links.

The working procedure of proposed Adaptive DNN for forecasting the crop production model is categorized into two phases. Like traditional DNN's, the proposed Adaptive DNN also involves the training process in the first phase and the second phase is involved of the testing process. From above fig 1, it is clear that, the input is nth year weather related data including District wise Monthly Actual Average Rainfall (mm) data, temperature data, relative humidity data and Natural Disaster Monitoring Centre data from 20 districts of Karnataka and the Target data as crop production data of (n+1)th year of corresponding districts. Based on the input and target data, the training process is done using Adaptive DNN.

GWO calculation is used here to successfully choose an interconnection loads ideally between the connections associating the neurons of DNN for to empower quicker preparing of the classifier organize

Generally, the training process is repeated until the proposed classifier is trained with the data's provided. Here, in adaptive DNN, the training process is speeded up with the aid of Grey Wolf Optimization (GWO) algorithm. GWO algorithm is utilized here to effectively select an interconnection weight optimally between the links connecting the neurons of DNN for to enable faster preparing of the classifier organize. The design of Proposed Deep Neural Network Architecture is shown in the below fig 2.

Let $\left[R_m\right]$ be the incoming data where $1 \le m \le M$ 'C' be the outcoming data. Here, an input $\left[R_m\right]$ is weather related data including the District wise Monthly Actual Average Rainfall (mm) data, temperature data, and relative humidity data of any set of $\left(n\right)^{th}$ year data. Output, 'C' is the agricultural crop production model for crops like Rice, Wheat, Jowar, Bajra, Maize, Ragi, and some other cereals and Pulses of $\left(n+1\right)^{th}$ year. For example, if we have historical weather related data from 2010 to 2017, the future crop data from 2011 to 2018 can be obtained based on previous historical data (i.e. data before 2010) including both weather related and crop dataset.

The summed up model of the neural system can be shown as ' for outcoming of the whole system and ' for yield of concealed layer. In DNN, there are progressively shrouded layers, the individual component sources of info are increased by loads in the principal concealed layer. Moreover, the individual previously shrouded component yields are duplicated by another arrangement of loads in the second concealed layer, etc.

In DNN, there are increasingly shrouded layers, the individual component information sources are duplicated by loads in the principal concealed layer. In like manner, the individual initially shrouded component yields are duplicated by another arrangement of loads in the second concealed layer, etc.

The summed up model of the neural system can be shown as 'C' for outcome of the whole network and 'C_H' for outcoming of hidden layer. In DNN, there are more hidden layers, each incoming data's are multiplied by weights in the first hidden layer. Likewise, the individual first hidden element outputs are multiplied by another set of weights in the second hidden layer and so on.

In the initial hidden layer, the weighted estimations of input are inserted to the summing capacity with the inclination of the neuron as in equation (1):

$$C_{H\_1}(x=1,2..,K)=\left(\sum_{m=1}^{M} w_{xm}\, R_m\right)+b_x \qquad (1)$$

steady esteem goes about as predisposition, is the interconnection weight between the info and concealed layer with and speaking to the quantity of information and shrouded hubs in the principal concealed layer.

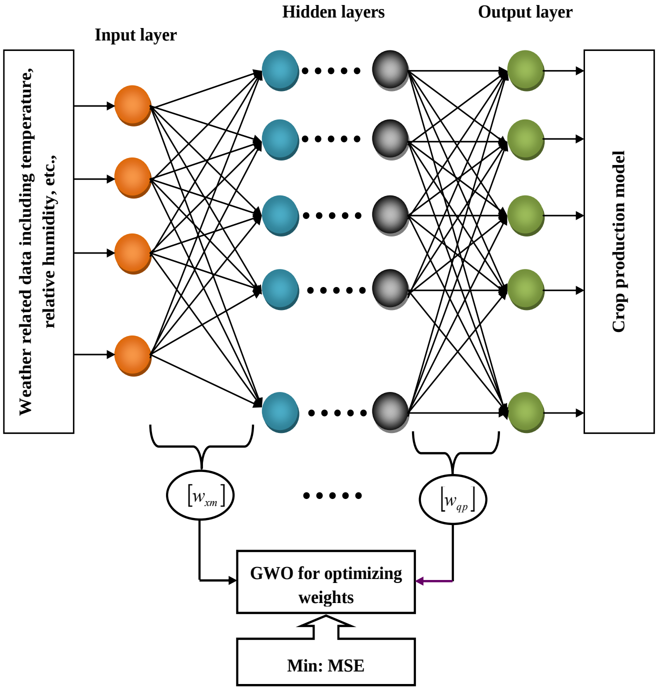

Fig 2: Proposed Design of Deep Neural Network Architecture

The initiation work which is the yield of the primary concealed layer is given as, Where, b_x steady esteem goes about as predisposition, w_{xm} is the interconnection weight between the income and hidden layer with M , K and denotes the No. of incoming and hidden nodes in the first hidden layer.

The initiation function which is the outcome of the first hidden layer is,

$$F\left(C_{H\_1}(x)\right)=\frac{1}{\left(1+e^{-C_{H\_1}(x)}\right)} \tag{2}$$

Where, $F(\cdot)$ is the sigmoid initiation function

Therefore, operation of y^{th} hidden layer can be generalized as,

$$C_{H\_y}(p)=\left(\sum_{z=1}^{K} w_{pz}F\left(C_{H\_(y-1)}(z)\right)\right)+b_p \tag{3}$$

Where b_p is the bias of p^{th} hidden node, w_{pz} is interconnection weight between the $(y-1)^{th}$ hidden layer, $(y)^{th}$ hidden layer with K hidden nodes.

The initiation function that is an output of the y^{th} hidden layer is given below,

$$F\left(C_{H\_y}(p)\right)=\frac{1}{\left(1+e^{-C_{H\_y}(p)}\right)} \tag{4}$$

concealed layer is again increased with the interconnection loads (for example weight between the shrouded layer and yield layer) and after that summed up with the inclination

At the outcoming layer, the outcoming of y^{th} hidden layer is again multiplied with the interconnection weights (i.e. weight between the y^{th} hidden layer and outcoming layer) and after summed up with the bias (inclination)(b_q) as,

$$C(q)=F\left(\sum_{p=1}^{K} w_{qp}\, f\left(C_{H\_y}(p)\right)+b_q\right) \tag{5}$$

Where w_{qp} denotes the interconnection weight at the y^{th} hidden layer and outcoming layer having p^{th} and q^{th} nodes respectively. The initiation function at the outcoming layer work as the result of the total model.

Presently, the system outcome is appeared differently in relation to the objective and distinction (for example error) is acquired to streamline the system output. The error estimation is as in equation (6)

$$\varepsilon=\frac{1}{M}\sum_{m=1}^{M}\left(Actual\,(C_m)-\Pr edicted\,(C_m)\right)^2 \tag{6}$$

Where, $\Pr edicted\,(C_m)$ is represents the evaluated network output , $Actual\,(C_m)$ denotes actual output. The error must be limited for getting optimal network structure. Thus, the weight esteems must be balanced until the mistake gets diminished at each cycle. Here, weights of ‘ y ’ number of hidden layers are selected optimally using GWO algorithm.

3.2.1 Weigh Selection by (GWO) Grey Wolf Optimization Algorithm

The grey wolves satisfactorily encase a Canidae's piece Precursors and are regarded as the Peak Predators offering their area at the fortitude's food sequence. They constantly show exacting social prevailing pecking order. The heads speak to a male and a female, set apart as alpha, which is in charge of settling on choices about chasing, dozing place, time to wake, etc. The decisions arranged by the alpha are allowed onto the gathering. The Beta and delta pass on to the second and third grade in the extraordinary orchestrate of the dark wolves. They are, essentially, integral wolves that enough bargain various help to the alpha in the choice creating or comparing bunch introduction. The rest of the wolves are spoken to by omega, which is the smallest division of the dark wolf gathering. In GWO process the following (improvement) is coordinated by α , β , δ and ω

Here, the anticipated strategy utilizes gray wolf optimization algorithm for the powerful forecasting of future crop generation. The well Ordered procedure of gray wolf optimization algorithm is referenced underneath,

Step 1: **Solution Encoding**

To optimize the weights of DNN, GWO algorithm basically generates a results based on the arbitrary population that is equal to the size of weights required. To determine the optimal result rapidly, 10 solutions will be created randomly during every iterations and it is compared with the previous best solution (weight matrix). Among all solutions, an optimal solution is selected and stored if it is better than other solutions. Moreover, the coefficient vectors $b, B, and\ D$ are also initialized. Here, the solution can be figured as follows.

$$[W_j] = \begin{bmatrix} w_{xm}(1) & w_{pz}(1) & \dots & w_{qp}(1) \\ w_{xm}(2) & w_{pz}(2) & \dots & w_{qp}(2) \\ \vdots & \vdots & & \vdots \\ w_{xm}(n) & w_{pz}(n) & \dots & w_{qp}(n) \end{bmatrix} \quad (7)$$

Where, w_{xm} is the weight matrix of incoming layer to first hidden layer; w_{pz} is the weight matrix of input to $(y-1)^{th}$ hidden layer to $(y)^{th}$ hidden layer and w_{xm} the weight matrix of $(y)^{th}$ hidden layer to output layer. Also, j and n represents the iteration and the number of solutions generated for each iteration.

Step2: **Evaluate fitness**

Calculate the fitness action of $[W_j]$ is based on the equation (8) shown in below and that gives a best outcome. The fitness of solutions at j^{th} iteration is obtained as,

$$Fit\ [W_j] = \min(MSE) \quad (8)$$

Step3: **Determine W_α , W_β and W_δ based on fitness**

Presently, we determine the dissimilar consequence based on the fitness value. The initial finest fitness consequences is W_α, the secondary finest fitness consequences W_β and the third finest fitness explanation W_δ.

Step 4: **Solution update**

We assume that the alpha, beta, and delta contain the improved actualities about the plausible position of the prey so as to recreate accurately the following exercises of the dark wolves. Due to the result, we collect the essential three best arrangements (for example best three weight grid) achieved as of not long ago and power the further inquiry loads (counting the omegas) to alter their circumstance alongside the circumstance of the best pursuit loads. For emphasis, the inventive weight $W(j+1)$ is unsurprising by the formulae given below,

$$W(j+1) = W(j) - \vec{B}.(\vec{H}) \quad (9)$$

$$\vec{H} = | \vec{D} \cdot W(j+1) - W(j) | \quad (10)$$

Here, the newer weights $W(j+1)$ is calculated based on the initial finest fitness consequences W_α, the secondary finest fitness consequences W_β and the third finest fitness value W_δ. This can be represented as follows:

$$W(j+1) = \frac{W_1 + W_2 + W_3}{3} \quad (11)$$

Where

$$\begin{cases} W_1 = W_\alpha - \vec{B}_1.(\vec{H}^\alpha),\ W_2 = W_\beta - \vec{B}_2.(\vec{H}^\beta),\ W_3 = W_\delta - \vec{B}_3.(\vec{H}^\delta) \\ \vec{H}^\alpha = | \vec{D}_1 \cdot W_\alpha - W |,\quad \vec{H}^\beta = | \vec{D}_2 \cdot W_\beta - W |,\quad \vec{H}^\delta = | \vec{D}_3 \cdot W_\delta - W | \end{cases} \quad (12)$$

Where j symbolize the iteration number, $\vec{B} = 2\vec{b}r_1 - \vec{b}$ and $\vec{D} = 2r_2$ symbolize the coefficient vector, $\vec{b}$ is straightly reduced from 2 to 0, $r_1 and\ r_2$ symbolize the arbitrary vector [0, 1]. It very well may be recognized that the last loads would be in a self-assertive position prearranged a circle which is exact by the situation of alpha, beta, and delta in the research break. It likewise implied by alpha, beta, and delta assess the area of the prey and beneficial wolves modernize their area arbitrarily in the district of the prey. Examination and usage are explicit by methods for the versatile estimations of $\vec{b}\ and\ \vec{B}$.The versatile estimations of confinement $\vec{b}\ and\ \vec{B}$ permit GWO to easily changeover amidst examination and usage. By withdrawing $\vec{B}$, half of the emphases are committed to the examination $|\vec{B}| < 1)$ and the extra parts are dedicated to the show. Joining the air, the resulting conditions are misused recognition as a main priority the end target to give arithmetical portrayal.

Step 5: **Fitness Evaluation**

The new search weights of fitness is evaluated by using equation (9) and then store the best result for optimal weight matrix of Adaptive DNN.

Step 6: **Stopping criteria**

Replicate pace 2 to 5, anticipating an improved wellness or most prominent measure of emphases are accumulating. Gotten from over pronounced method achieve the best weight network.

Once the finest weight matrix is obtained, the ADNN is trained and can be generalized to predict future crops for newer weather-related dataset. Therefore, the finest weight matrix is applied for the proposed future crop prediction model using Adaptive DNN for testing newer input weather related data's to predict the future crop models.

4. RESULTS AND DISCUSSION

The experimental outcomes achieved for the proposed method is examined obviously in this section. An Adaptive Deep Neural Network Architecture is proposed for the climate-based crop production models. The exhibited algorithm is prepared by using MATLAB programming and the experimentation is finished using a game plan of having 4 GB RAM and 2.10 GHz Intel I-3 processor.

For calculating the presentation of the presented production model, monthly average rainfall in mm is obtained from the year of 1980-2017. Second, monthly minimum and maximum range of temperature is gathered from the year of 2012-2016. Third, the relative humidity range values are gathered monthly wise from the year of 2012-2016. Finally, the crop data are obtained from the year of 1980-2012. Above mentioned every data are collected for 20 districts of Karnataka. The effectiveness of crop production model is evaluated based on error function.

4.1. Performance Analysis for Crop Production Model.

The performance measures of the presented Adaptive Deep Neural Network (ADNN) and SSO-ANN [21] for predicting the crop model is appeared in this section with different existing techniques. The evaluation is made in the premise of permitting 80% of tests for preparing method and staying 20% examples for the testing procedure. The Correlation coefficient, Mean Score Error, Root Mean Square Deviation (RMSD), Mean and STD esteems for various crop models of Bangalore are happens for presented method is organized beneath the table.1, From the table.1 obviously our proposed Adaptive Deep Neural Network (ADNN) methodology reduces the Root Mean Score Error (RMSE) and Mean Score Error (MSE) while comparing DNN systems. The effectiveness of our showed methodology is gained from different yield models of various districts of Karnataka, for instance, Bangalore, Belgaum and Bellary.

The table.4 and table.5 has Correlation coefficient, Mean Score Error, Root Mean Square Deviation (RMSD), Mean and STD measures of various crop models for the presented techniques OFF method DNN. The error rate of our proposed method ADNN is low compared to SSO-ANN and DNN.

Table 1: Co-efficient, MSE, RMSE, Mean and STD for ADNN and SSO-ANN

Bangalore										
	ADNN					SSO-ANN				
Crop Models	Correlation Coefficient	MSE	RMSE	Mean	STD	Correlation Coefficient	MSE	RMSE	Mean	STD
Rice	0.999993	43.28	6.57	1542.14	1844.25	0.999993	43.28	6.57	1542.1	1844.25
Jowar	0.867	67.29	8.20	1.16	8.45	0.867	67.29	8.20	1.16	8.45
Bajra	0.999948	15.76	3.97	299.55	356.96	0.999948	15.76	3.97	299.5	356.9
Maize	1	82.45	9.08	5599.93	13526.57	1	82.45	9.08	5599.9	13526.57
Ragi	0.999975	66.96	8.18	1002.33	1171.22	0.999975	66.96	8.18	1002.3	1171.2
Total cereals+ MM	0.999979	75.48	8.68	1195.88	1404.13	0.999979	75.48	8.68	1195.8	1404.13
Total Pulses	0.99982	64.53	8.03	377.51	440.24	0.99982	64.53	8.03	377.51	440.24
Wheat	0.999744	63.00	7.93	99.72	358.53	0.999744	63.00	7.93	99.72	358.53

Table 2: Co-efficient, MSE, RMSE, Mean and STD for ADNN and SSO-ANN

Belgaum										
	ADNN					SSO-ANN				
Crop Models	Correlation Coefficient	MSE	RMSE	Mean	STD	Correlation Coefficient	MSE	RMSE	Mean	STD
Rice	0.999975	42.46	6.51	803.4	961.23	0.999978	50.19	7.08	803.17	957.01
Jowar	0.999881	66.06	8.12	480.0	545.15	0.999873	70.60	8.40	479.48	544.90
Bajra	0.999873	13.39	3.65	194.1	227.89	0.999798	23.98	4.89	195.20	227.02
Maize	0.999986	85.48	9.24	1502.9	1727.84	0.999982	99.12	9.95	1505.7	1727.58
Ragi	0.99959	69.82	8.35	238.0	286.02	0.999512	79.94	8.94	240.17	285.23
Total cereals+ MM	0.999954	75.83	8.70	829.9	944.20	0.999942	96.84	9.84	830.16	942.90
Total Pulses	0.999118	65.86	8.11	170.0	196.76	0.998571	102.6	10.13	171.37	193.67
Wheat	0.999908	63.86	7.99	537.2	609.08	0.999854	102.7	10.13	539.56	608.17

The table.3 has Correlation coefficient, Mean Score Error, Root Mean Square Deviation (RMSD), Mean, STD measures of various crop models for the proposed method ADNN a. The error rate of our proposed method ADNN is low compared to SSO-ANN.

From the above diagrams and tabulation, it obviously demonstrates that our proposed ADNN approach anticipated the crop models effectively while contrasting and other existing SSO-ANN approach.

What's more, it additionally limits the error rate while contrasting and other existing method.

Table 3: Co-efficient, MSE, RMSE, Mean and STD for ADNN and SSO-ANN

Bellary										
	ADNN					SSO-ANN				
Crop Models	Correlation Coefficient	MSE	RMSE	Mean	STD	Correlation Coefficient	MSE	RMSE	Mean	STD
Rice	0.999993	55.13	7.42	1661.5	1870.5	0.999993	57.10	7.55	1660.6	1867.7
Jowar	0.999938	80.45	8.96	658.04	757.0	0.999936	77.08	8.77	656.78	755.53
Bajra	0.99996	32.61	5.71	346.43	395.02	0.999932	43.34	6.58	346.80	394.04
Maize	0.999979	81.77	9.04	1231.0	1420.8	0.999974	109.6	10.47	1233.1	1420.67
Ragi	0.999739	66.80	8.17	305.37	365.8	0.999685	87.26	9.34	306.78	365.19
Total cereals+ MM	0.999977	83.49	9.13	1194.14	1346.3	0.999971	101.9	10.09	1193.6	1345.21
Total Pulses	0.999574	69.35	8.32	251.84	284.2	0.999322	111.0	10.53	252.51	281.43
Wheat	0.999908	69.35	8.32	529.75	607.5	0.999857	117.7	10.85	531.32	606.03

Table 4: Co-efficient, MSE, RMSE, Mean and STD for DNN

DNN										
	Bangalore					Belgaum				
Crop Models	Correlation Coefficient	MSE	RMSE	Mean	STD	Correlation Coefficient	MSE	RMSE	Mean	STD
Rice	0.999993	52.88924	7.272499	1543.959	1843.532	0.999973	46.28265	6.803135	804.2217	960.1844
Jowar	0.754	72.9326	8.540059	2.890846	8.364025	0.999888	65.73521	8.107725	480.7692	543.822
Bajra	0.999964	16.60414	4.074818	300.5232	356.2631	0.999911	9.624431	3.102327	194.0938	227.1677
Maize	1	109.1834	10.44909	5604.171	13532.48	0.999982	102.3653	10.11757	1506.203	1726.802
Ragi	0.999967	92.48539	9.616933	1006.069	1170.4	0.99951	87.15475	9.335671	240.7931	284.0356
Total cereals+ MM	0.999978	96.70326	9.833781	1199.899	1402.98	0.999953	84.73337	9.205073	833.0077	942.5102
Total Pulses	0.999785	87.59226	9.359074	381.0602	439.5849	0.998902	79.50154	8.916364	172.5538	195.828
Wheat	0.999733	78.90305	8.882739	102.8171	357.3054	0.999898	71.41514	8.450748	539.3877	608.6593

Table 5: Co-efficient, MSE, RMSE, Mean and STD for DNN

DNN					
	Bellary				
Crop Models	Correlation Coefficient	MSE	RMSE	Mean	STD
Rice	0.999993	51.08313	7.147246	1660.374	1869.563
Jowar	0.999941	71.0112	8.426814	656.7676	755.546
Bajra	0.99997	14.72522	3.837346	344.3999	394.1406
Maize	0.999973	107.336	10.36031	1232.278	1420.297
Ragi	0.99967	90.92828	9.535632	306.0992	364.2618
Total cereals+ MM	0.999977	93.85051	9.687647	1195.16	1344.837
Total Pulses	0.999478	85.49652	9.246433	252.3985	283.754
Wheat	0.999898	76.92495	8.770687	529.8477	607.3312

5. CONCLUSION

In this paper, we have considered several weather-related data including the Karnataka State Natural Disaster Monitoring Centre Data, District wise Monthly Actual Average Rainfall (mm) data, temperature data, and relative humidity data, agriculture data are predicted from the five districts of Karnataka (i.e.) Bangalore, Belgaum, Bellary. We have introduced a new architecture named as Adaptive Deep Neural Network for prediction of crop models. The research is carried out over crops like Rice, Wheat, Jowar, Bajra, Maize, Ragi, and some other cereals and Pulses. The proposed future crop prediction model using ADNN is analysed with other existing approaches using traditional DNN and Modified ANN (Social Spider Optimization based ANN) in terms of various performance analytics measures. The result outcomes show steady improvement for the proposed ADNN based prediction model for all five districts when compared to the existing approaches, thus showing the effectiveness of our proposed future crop prediction model.

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REFERENCES

[1] Chandrasegar Thirumalai, K Sri Harsha , M Lakshmi Deepak ,K Chaitanya Krishna,” Heuristic Prediction of Rainfall Using Machine Learning Techniques”, *International Conference on Trends in Electronics and Informatics (ICEI),*2018

[2] David B. Lobell , David Thau , Christopher Seifert , Eric Engle , Bertis Little,” A scalable satellite-based crop yield mapper”, *Remote Sensing of Environment*, Volume 164, July 2015, Pages 324-333

[3] P.C. Doraiswamy, J.L. Hatfield , T.J. Jackson , B. Akhmedov , J. Prueger , A. Stern,” Crop condition and yield simulations using Landsat and MODIS”, *Remote Sensing of Environment*, Volume 92, Issue 4, 30 Pages 548-559, 2004

[4] Anna Chlingaryana, , Salah Sukkarieh , Brett Whelan,” Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review”, *Computers and Electronics in Agriculture*, Volume 151, Pages 61-69, August 2018,

[5] Dominique Courault,Valérie Demarez,Martine Guerif,Michel Le Page,Vincent Simonneaux,Sylvain Ferrant,Amanda Veloso,” Contribution of Remote Sensing for Crop and Water Monitoring” *Land Surface*

Remote Sensing in Agriculture and Forest, Pages 113-177, 2016

[6] Rakesh Kaundal, Amar S Kapoor , Gajendra PS Raghava," Machine learning techniques in disease forecasting: a case study on rice blast prediction", *BMC Bioinformatics*, 2006

[7] Yun Hwan Kim , Seong Joon Yoo, Yeong Hyeon Gu , Jin Hee Lim , Dongil Han , Sung WookBaik," Crop Pests Prediction Method using Regression and Machine Learning Technology: Survey", *IERI Procedia*, Volume 6, Pages 52-56, 2014

[8] Lee, S.H., Chan, C.S., Wilkin, P., Remagnino, P. 2015. Deep-plant: Plant identification with convolutional neural networks. 2015 *IEEE Intl Conf. on Image Processing*, pp. 452–456.

[9] Geoffrey Hinton, Li Deng, Dong Yu, George E. Dahl, Abdel-rahman Mohamed, Navdeep Jaitly, Andrew Senior, Vincent Vanhoucke, Patrick Nguyen, Tara N. Sainath, and Brian Kingsbury,"Deep neural networks for acoustic modeling in speech recognition", *IEEE Signal Processing Magazine*, Volume: 29, Issue: 6, 2012

[10] Cheng Fan , Fu Xiao , Yang Zhao," A short-term building cooling load prediction method using deep learning algorithms", *Applied Energy*, Volume 195, Pages 222-233, 1 June 2017,

[11] Wei Xu , Qili Wang, Runyu Chen," Spatio-temporal prediction of crop disease severity for agricultural emergency management based on recurrent neural networks", *GeoInformatica*, Volume 22, Issue 2, pp 363–381, 2018

[12] Kuwata, K., Shibasaki, R., 2015. Estimating crop yields with deep learning and remotely sensed data, *IEEE International Geoscience and Remote Sensing Symposium, (IGARSS)*, pp. 858–861, 2015

[13] Konstantinos P. Ferentinos," Deep learning models for plant disease detection and diagnosis", *Computers and Electronics in Agriculture*, Volume 145, Pages 311-318, 2018

[14] Mumtaz Ali, Ravinesh C. Deo, Nathan J. Downs, Tek Maraseni," Multi-stage hybridized online sequential extreme learning machine integrated with Markov Chain Monte Carlo copula-Bat algorithm for rainfall forecasting ",*Atmospheric Research* Volume 213, Pages 450-464, 2018

[15] Mumtaz Ali, Ravinesh C. Deo , Nathan J. Downs, Tek Maraseni," Multi-stage committee based extreme learning machine model incorporating the influence of climate parameters and seasonality on drought forecasting", *Computers and Electronics in Agriculture*, Volume 152, Pages 149-165, 2018

[16] Sujan Ghimire , Ravinesh C. Deo , Nathan J. Downs, Nawin Raj," Self-adaptive differential evolutionary extreme learning machines for long- term solar radiation prediction with remotely-sensed MODIS satellite and Reanalysis atmospheric products in solar-rich cities", *Remote Sensing of Environment*, Volume 212, Pages 176-198, 2018

[17] Dunnan Liu, Long Zeng, Canbing Li, Kunlong Ma, Yujiao Chen, Yijia Cao, "A Distributed Short-Term Load Forecasting Method Based on Local Weather Information", *IEEE Systems Journal* ,Volume: 12, Issue: 1, 2018

[18] Dominique Brunet , David Sills," A Generalized Distance Transform: Theory and Applications to Weather Analysis and Forecasting", *IEEE Transactions on Geoscience and Remote Sensing*, Volume: 55, Issue: 3, 2017

[19] Jorge Ángel González Ordiano ,Simon Waczowicz , Markus Reischl ,Ralf Mikut, Veit Hagenmeyer," Photovoltaic power forecasting using simple data-driven models without weather data", *Computer Science - Research and Development*, Volume 32, Issue 1–2, pp 237–246, 2017

[20] Jose R. Andrade and Ricardo J. Bessa ," Improving Renewable Energy Forecasting with a Grid of Numerical Weather Predictions", *IEEE Transactions on Sustainable Energy* ,Volume: 8, Issue: 4, Oct. 2017.

[21] L. Naveen and H.S Mohan, "High-Resolution Weather Prediction Using Modified Neural Network Approach Over the Districts of Karnataka State", *International Conference on Computer Networks and Communication Technologies*, pp. 125-143, 2018.

[22] L. Naveen and H S Mohan, "Atmospheric Weather Prediction Using Advanced Techniques: A Survey", Proceedings of the *Third International Conference on Computing Methodologies and Communication, IEEE*, pp. 440-446, 2019.