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Crop Yield Prediction by Modified Convolutional Neural Network and Geographical Indexes

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Abstract: Agriculture is the main sector of employment in India. One of the major causes for the continuing downfall in agricultural trends is cultivation of crops that are not suitable with the environmental factors like soil and weather conditions. A recommendation system can provide suggestions for a crop that can be cultivated based on spatial conditions. The research focus on to build a recommendation system that can collect raw data for environmental factors like NDVI, SPI parameters from satellite images. The collected data then will be forwarded where this data is processed. In this paper modified convolutional neural network was proposed which takes spatial features as input and trained by back propogation, this reduce error of prediction as well. Experiment was done real dataset from authentic geo-spatial resources. Results are compared with some previous existing methods and it was obtained that proposed modified CNN model was better on various evaluation parameters.

Index Terms— Crop yield prediction, Data mining, machine learning, Vegetation Index.

I. INTRODUCTION

In agriculture, decision-making processes often require reliable crop response models. Agricultural management specialists need simple and accurate estimation techniques to predict crop yields in the planning process. Over the last few decades, statistical methods have traditionally been used for predictions and classifications. Some of the common traditional statistical techniques used for predictions and classifications are multiple regression, discriminate analysis, logistic regression etc. Most of the researchers have employed regression models for prediction purposes in various disciplines. Due to the nature of linear relationship in the parameters, regression models may not provide accurate predictions in some complex situations such as non linear data and extreme values data. As regression models need to fulfill the regression assumptions and multiple co-linearity between independent and dependent variables, it causes regression models to be inefficient.

Nearly two-third of India population directly depends on agriculture for its livelihood. In spite of the fact that large areas in India have been brought under irrigation, only one-third of the cropped part is in fact irrigated. The productivity of agriculture is very low. [2] So as the demand of food is increasing, the researchers, farmers, agricultural scientists and government are trying to put extra effort and techniques for more production. And as a result, the agricultural data increases day by day. As the volume of data increases, it requires involuntary way for these data to be extracted when needed. Still today, a very few farmers are actually using the new methods, tools and technique of farming for better production.

Recommender systems are one of information filtering systems forecasting the items that may be additional interest for user within a big set of items on the basis of user's interests. Recommender systems are considered as a filtering and retrieval technique developed to alleviate the problem of information and products overload. Collaborative filtering is the most popular and successful method that recommends the item to the target user. This paper proposes a new collaborative filtering approach for recommender system, which have been studied in dynamic environment. By developing an improved collaborative filtering recommender system based on proposed algorithms, will be useful in the agricultural field.

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II. Related Work

Abhishek Pandey et. al. [2] work employed two types of Artificial Neural Networks i.e., a Generalized Regression Neural Network (GRNN) and a Radial Basis Function Neural Network (RBFNN) to predict the yield of potato crops, which have been sown differently (flat and rough). Crop parameters like leaf area index, biomass and plant height were used as input data, while the yield of potato fields as output dataset to train and test the Neural Networks. Both GRNN and RBNN predicted potato crop yield accurately. However based on quick learning capability and lower spread constant (0.5), the GRNN was found a better predictor than RBFNN. Furthermore, the rough surface field was found more productive than flat field.

E. Manjula et. al. [3] research proposes and implements a system to predict crop yield from previous data. This is achieved by applying association rule mining on agriculture data. This research focuses on creation of a prediction model which may be used to future prediction of crop yield. This paper presents a brief analysis of crop yield prediction using data mining technique based on association rules for the selected region i.e. district of Tamil Nadu in India. The experimental results shows that the proposed work efficiently predict the crop yield production.

Yuzugullu, O., et al. [4] proposed the X-band Co-polar SAR for rice growth monitoring. The Biologische Bundesanstalt, Bundessortenamt und CHemische Industrie (BBCH) scale assignment was implemented for achieving the plant growth forecasting. The developed paddy rice yields were explored by TerraSAR-X Co-polar SAR information. Then the identical classes were prearranged by K-means algorithm, utilized in polarimetric feature vector space and collected of backscattering intensities and polarimetric phase variations. After, the clustering method according to the temporal separability of explanatory parameters was performed to classify the identical groups. The misclassification between two distinctive growth phases was eliminated by the growth trend based update approach. However, the determination of the detailed growth phase of rice fields was required.

Shastry, A., et al. [5] proposed crop yield prediction through parameter based model. In this approach, the crop yield was derived through attributes. The fuzzy logic, adaptive Neuro fuzzy inference system and multiple linear regression techniques were proposed for predicting the wheat yield. This prediction was obtained based on biomass, extractable soil, water, radiation and rain which are utilized as different input parameters. The pre-processing was performed in the database by removing the outliers, redundant, inconsistent and missing values. The prediction of wheat yield was effectively achieved, but the mean squared error rate of this approach was moderately high.

Natarajan, R., et al. [6] proposed sugarcane yield classification technique based on the hybrid method. A novel hybrid technique based on fuzzy cognitive map learning algorithm was proposed for sugarcane yield classification. The hybrid algorithm (FCM-DDNHL-GA) was developed through integrating the features of data drivel nonlinear Hebbian learning algorithm and genetic algorithm. This algorithm was improved for different soil and weather features. The accuracy of the classification and inference abilities of this hybrid learning algorithm was evaluated and compared to the machine learning algorithms. However, the performance of evolutionary computation for classification was required further improvement for agricultural monitoring applications.

II. Proposed Methodology

In order to make a general model which work on various available data Indices a whole work is classify into two steps first was to pre-process data as per input environement than second was Modified convolutional neural network. In this work MCNN is used as the learning model where input data was processed by fig. 1 steps. While MCNN is shown in Fig. 2, where each block diagram was explained by the various section.

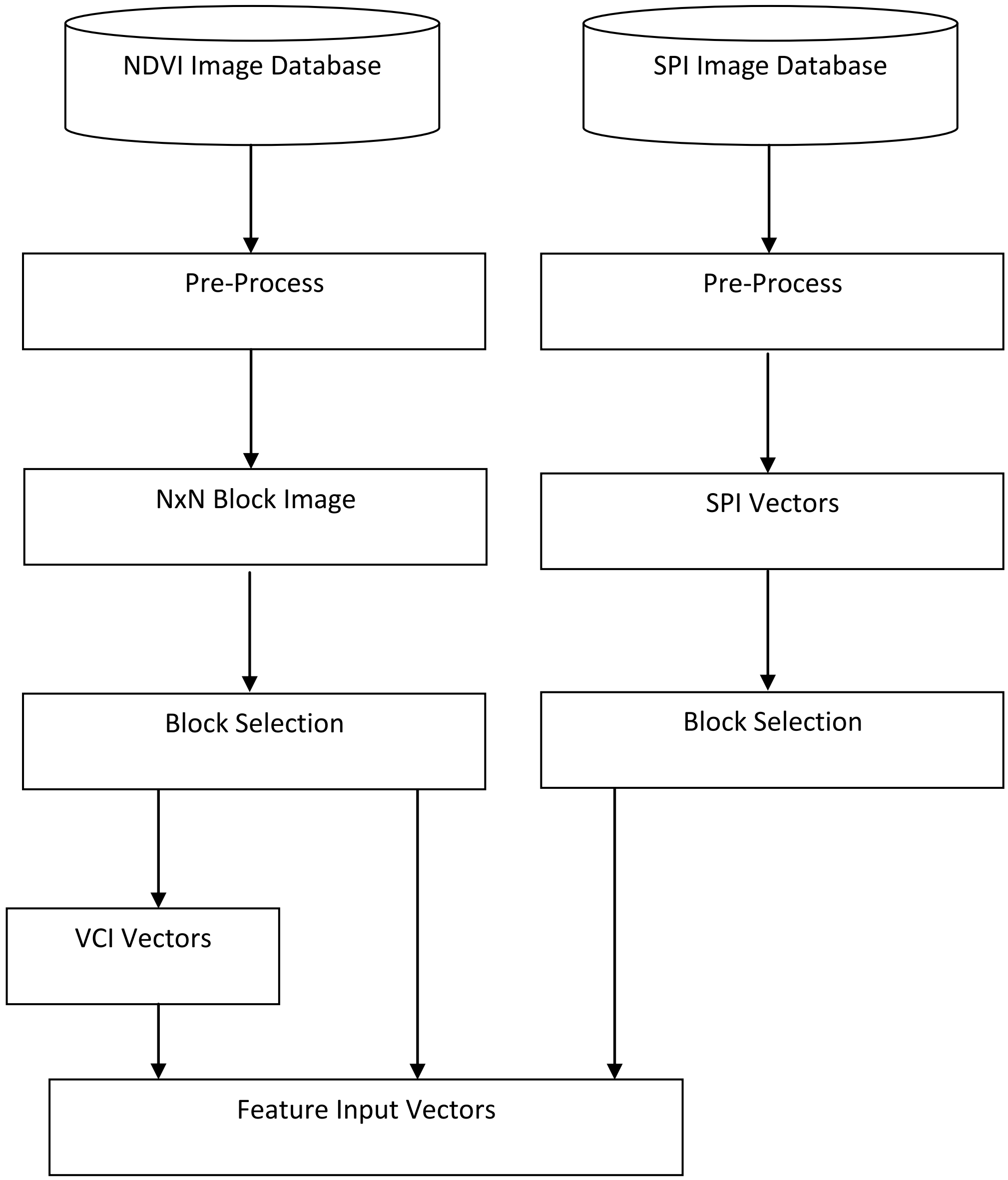


Fig. 1 Block diagram of proposed Feature Collection.

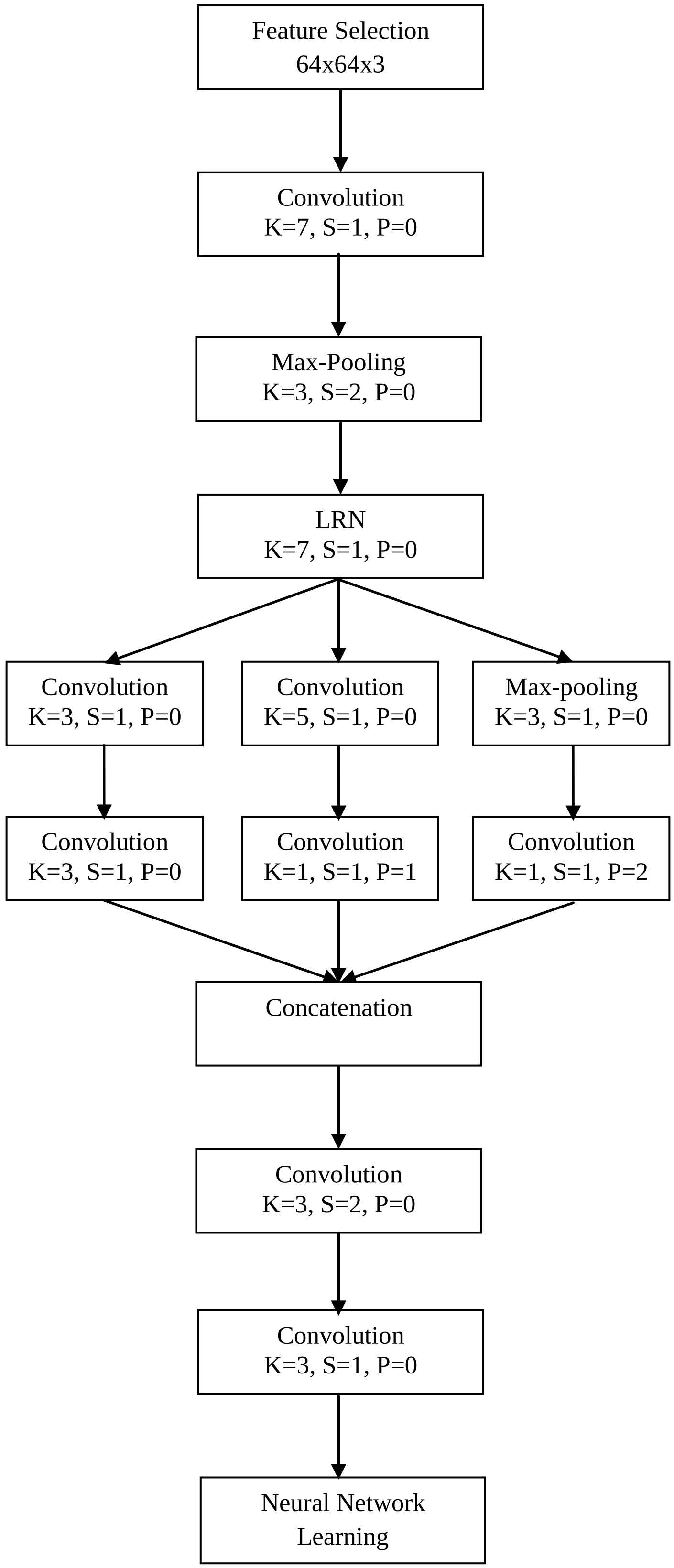
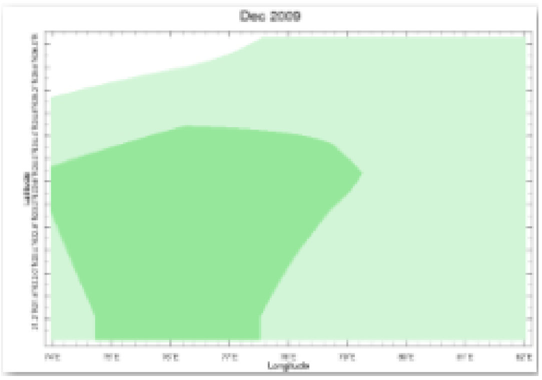


Fig. 2 Represent Block Diagram of Proposed Work.

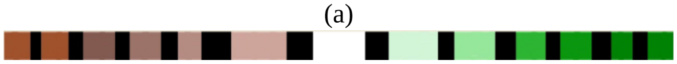
Pre-Processing:
Input image data need to be preprocessed first for transforming data as per proposed model. It involves activities like cleaning of data and convert in required environment format. Read a image means making a matrix of the same dimension of the image then fill the matrix correspond to the pixel value of the image at the cell in the matrix.

As images are taken from different sources so there dimension need to be bought at common scale. So image get resized in this step to same dimension, further matrix operation were run in a smooth way.

Index Vector:
In order to get index value from the image each image has its own color scale where pixel value corresponding to a specific color is replaced by its index value. This can be understand as let fig. 3 (a) has SPI index than all the dark green portion in the image is consider as the extremely wet region so if this dark green is represent by pixel value 65 than all the pixel value in the image of SPI where 65 value is present is consider as extremely wet region and SPI value for the cell is +1.2. In similar fashion other regions are also detect in the image. While NDVI image index value are obtained from its separate index as image color region of this image is different.



(a)



(b)

Fig. 3 Input data for getting SPI Vector, (a) SPI Image, (b) SPI scale.

Feature Selection: In this work three index are use as the training parameters first was NDVI, second was SPI and third was VCI. Use of three feature vector for training increase the accuracy of the resultant neural network. As this help in covering various other geographical parameters of the location. So a set of values for any geographical location at particular period of time this feature vector have three value set. This can be understand as if geographical location (x_i, y_i), than its corresponding feature vector for time instance t_i is [N_i, V_i, S_i]. While for same location but at time t_j it might be [N_j, V_j, S_j]. So for each year data input feature vector is three dimension vector where first and second dimension provide geographical position while third provide index vector for the same.

Modified Convolutional Neural Network
Convolutional Neural Networks (**ConvNets** or **CNNs**) are a category of Neural Networks that have proven very effective in areas such as image recognition and classification. LeNet was one of the very first convolutional neural networks which helped propel the field of Deep Learning. This pioneering work by Yann LeCun was named LeNet5 after many previous successful iterations since the year 1988 [3]. There have been several new architectures proposed in the recent years which are improvements over the LeNet.

Convolution: ConvNets derive their name from the "convolution" operator. The primary purpose of Convolution in case of a ConvNet is to extract features from the input image. Convolution preserves the spatial relationship between pixels by learning image features using small squares of input data. We will not go into the mathematical details of Convolution here, but will try to understand how it works over images. As discussed above, every image can be considered as a matrix of pixel values. Consider a 5 x 5 image block B whose pixel values are only 0 and 1. As input feature vector is passed from the canny algorithm that find edges in the images, so all edge portion is represent by 1 while non edge was represent by 0.

$$B=\begin{vmatrix} 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 & 0 \end{vmatrix}$$

$$F=\begin{vmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{vmatrix}$$

slide the orange matrix over original block image by 1 pixel called 'stride' represent as s and for every position, compute element wise multiplication and add the multiplication outputs to get the final integer which forms a single element of the output matrix. Note that the 3×3 matrix F act as filter or kernel, where size of filter depends on k. In this case padding value p=0 is consider.

$$\begin{vmatrix} 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 & 0 \end{vmatrix} \text{ X } \begin{vmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{vmatrix} = \begin{vmatrix} 4 & 3 & 4 \\ 2 & 4 & 3 \\ 2 & 3 & 4 \end{vmatrix}$$

Max-pooling: Pooling (also called subsampling or downsampling) reduces the dimensionality of each feature map but retains the most important information. Spatial Pooling can be of different types: Max, Average, Sum etc.

In case of Max Pooling, define a spatial filter kxk window and take the largest element from the rectified feature map within that window. In practice, Max Pooling has been shown to work better. Here shifting was done as per stride value s and padding will be done as per p value.

$$\begin{vmatrix} 1 & 1 & 2 & 4 \\ 5 & 6 & 7 & 8 \\ 3 & 2 & 1 & 0 \\ 1 & 2 & 3 & 4 \end{vmatrix} \rightarrow \begin{vmatrix} 6 & 8 \\ 3 & 4 \end{vmatrix}$$

In above matrix let k=2, so window of 2x2 move around the image block. While s=1 and p=0.

ReLu: ReLU is an element wise operation (applied per pixel) and replaces all negative pixel values in the feature map by zero. The purpose of ReLU is to introduce non-linearity in our ConvNet, since most of the real-world data we would want our ConvNet to learn would be non-linear (Convolution is a linear operation – element wise matrix multiplication and addition, so we account for non-linearity by introducing a non-linear function like ReLU).

Steps of MCNN: Here whole model is divide into ten layes where first nine are various combination of convolution, ReLu and Max-pooling steps in each step fix set of stride, padding and window size fig. 2 represent all working steps. Out of the last ninth layer of MCNN was pass in the final or tenth layer which adjust the weight value as per softmax function.

Fully Connected Layer

The Fully Connected layer is a traditional Multi Layer Perceptron that uses a softmax activation function in the output layer (other classifiers like SVM can also be used, but will stick to softmax in this post). The term "Fully Connected" implies that every neuron in the previous layer is connected to every neuron on the next layer. I recommend reading this post if you are unfamiliar with Multi Layer Perceptrons.

The output from the convolutional and pooling layers represent high-level features of the input image. The purpose of the Fully Connected layer is to use these features for classifying the input image into various classes based on the training dataset.

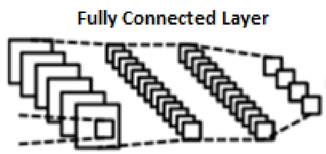


Fig. 3 Fully connected layer of modified convolutional network.

In order to understand above steps let us consider an example where Wij have some weight values. $H_j = \sum x_i \,.\, w_{ij} - \theta_j$, $1\leq\ i \leq n$; n is the number of inputs to node j, and θ_j is threshold for node j

$$Wij \quad = \begin{vmatrix} W_{11} & W_{12} & W_{13} \\ W_{21} & W_{21} & W_{21} \\ W_{31} & W_{31} & W_{31} \end{vmatrix}$$

Let input vector of three value which include values from NDI, VCI, SPI images are pass from the first layer of neural network. These values get multiply by above weight values.

Now this act as input $H1_{input}$ to next layer of hidden neurons. In this some biasing is also possible which was neglect in this example. So weight values of the neuron for next level is assumed as shown in below matrix.

$$W_{jk} \quad = \begin{vmatrix} W_{11} & W_{12} & W_{13} \\ W_{21} & W_{21} & W_{21} \\ W_{31} & W_{31} & W_{31} \end{vmatrix}$$

Where each value obtained from the previous weight matrix multiplication is passed through the soft-max function. Therefore small variation in the output value was done by this function.

$$SoftMax = e^{O_{ij}} \sum_{k=1}^{j} e^{O_k} ----eq(1)$$

So difference between the expected with obtained is consider as the error. This error need to be correct by adjusting the weight values of each layer. So here forward movement of the neural network is over and error back propagation starts.

$$\frac{\partial E_i}{\partial O_i} = \frac{\partial(-1 * ((y_i * \log(O_i) + (1 - y_i) * \log(1 - O_i)}{\partial O_i}$$

$$\frac{\partial E_i}{\partial O_i} = (-1 * ((y_i * \log(O_i) + (1 - y_i) * \log(1 - O_i) - eq(2)$$

In similar fashion other values can be calculate to find other set of derivatives. Here as per out value may vary.

$$\frac{\partial O_i}{\partial H_i} = \frac{\partial\left(e^{O_{ij}} \sum_{k=1}^{j} e^{O_k}\right)}{\partial H}$$

$$= \frac{(e^{O_{H1}} \times (e^{O_{H2}} + e^{O_{H3}}))}{(e^{O_{H1}} + e^{O_{H2}} + e^{O_{H3}})} eq(3)$$

For each input to neuron let us calculate the derivative with respect to each weight. Now let us look at the final derivative

$$\sum_{i=1:n} \frac{\partial H_i}{\partial W_{i(j,k)}} = \frac{\partial(\mathrm{h_{i(ouput)}} * W_{i(j,k)})}{\partial W_{i(j,k)}} - -eq(4)$$

Now by using chain rule final derivates were calculate for the same. Here multiplication of each derivative was done in following way:

$$\frac{\partial E_i}{\partial W_i} = \frac{\partial E_i}{\partial O_i} * \frac{\partial O_i}{\partial H_i} * \frac{\partial H_i}{\partial W_i} - -eq(5)$$

So overall ∂W_i can be obtained by getting value of weight from above equation, here all set of weight which need to be update are change by below matrix values.

$$\partial W_i = \begin{bmatrix} \frac{\partial E_1}{\partial W_{1,1}} & \frac{\partial E_2}{\partial W_{1,2}} & \frac{\partial E_3}{\partial W_{1,3}} \\ \frac{\partial E_1}{\partial W_{2,1}} & \frac{\partial E_2}{\partial W_{2,2}} & \frac{\partial E_3}{\partial W_{2,3}} \\ \frac{\partial E_1}{\partial W_{3,1}} & \frac{\partial E_2}{\partial W_{3,2}} & \frac{\partial E_3}{\partial W_{3,3}} \end{bmatrix}$$

- So error corresponds to the input data was estimate by differencing desired output obtain from output layer.

$$e_k(n) = d_k(n) - y_k(n)$$

- The ebpnn weight updation was done by above matix of ∂W_i

$$w_{ij} = w_{ij} + \Delta w_{ij}$$

- So end of above iteration steps over when error obtained from the output layer get nearer to zero or some constant such as 0.001.

Testing of EBPNN

Testing of trained neural network obtained from above steps are processed by passing testing input images of NDVI, SPI. Finally feature vectors were pass in the trained EBPNN which gives crop yield predicted value. This crop yield predicted value are compared on various parameters to find the fitness of the proposed work.

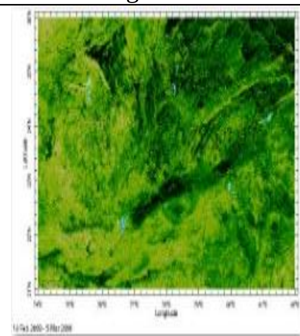
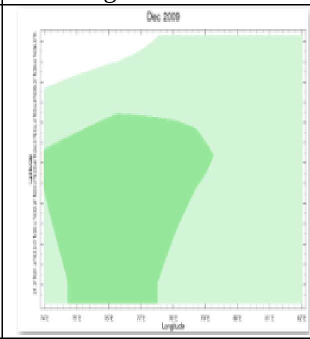
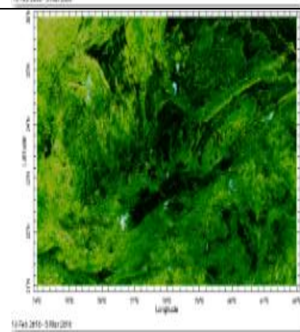
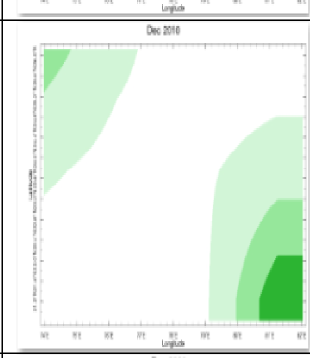
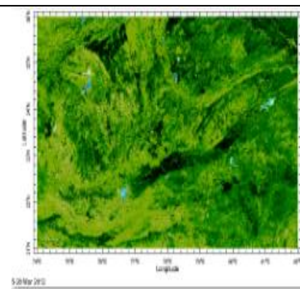
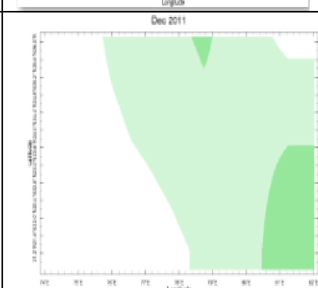
III. Experiment and Results

In order to conduct experiment and measure evaluation results MATLAB 2012a version software is use. This section of paper show experimental setup and results. Experiment was done on machine having configuration of 4 GB RAM, with sixth generation intel I3 processor.

Dataset

Experiment is done on real dataset having values of the SPI from https://iridl.ldeo.columbia.edu/maproom/Global/Precipitation/SPI.html. While NDVI value obtained from http://iridl.ldeo.columbia.edu/SOURCES. Each source image are extract on the longitude parameters 21N-26N 60, and Latitude parameters 74E-82E, where selected region is one of state Madhya Pradesh in India. While average of different crop yields are obtained from http://www.mospi.gov.in/statistical-year-book-india/2016/177. Groud truth values are also considered from the same site http://www.mospi.gov.in for testing of trained models.

Table 1 Dataset NDVI and SPI Values.

	NDVI Image	SPI Image
2009		
2010		
2011		

Results

Results are compare with the previous work (SNN) Spiking neural network in [1] which is term as previous work in this paper.

Table 1: RMSE value comparison of Previous work with proposed work different sets.

Values	**RMSE**		
	SNN	**EBPNN**	**MCNN**
2012	2509.4	943.7	1274.9
2013	1401.1	1188.1	480.6
2014	1615.3	1631.8	1396.4

It has been observed by table 1 that proposed work ***GA+EBPNN*** of crop yield prediction using multiple feature work well as compare to the previous method adopt in [1] and EBPNN. Here RMSE value of proposed work is low as compare to spiking neural network model. In this work use of TLBO algorithm for reducing input feature data increase the value of accuracy as well.

Table 2: Relative error value comparison of Previous work with proposed work different sets.

Values	**Relative Error**		
	SNN	**EBPNN**	**MCNN**
2012	19.1075	7.1858	9.7079
2013	10.8299	9.1835	3.7151
2014	11.5063	11.3895	9.8465

It has been observed by table 2 that relative error of proposed work of crop yield prediction work is less as compared to the previous method adopt in [1]. One more important factor is observed that by change in climate production of crops are also raise. Above table shows that combination of two soft computing technique from genetic and neural network has reduce Relative error value.

Table 3: Yield in Tones value comparison of Previous work with proposed work different sets.

Values	**Yield in Tones Values**			
	Ground Truth	**SNN**	**EBPNN**	**MCNN**
2012	13133	10624	12196	12186
2013	12937	11536	11786	12608
2014	14182	12550	12567	12786

It has been observed by table 3 that relative error of proposed work of crop yield prediction value is much near to the ground truth value as compared to the previous method adopt in [1]. As dimension reduction done by TLBO good set of cluster center were selected and reduce the confusion of neural network while training.

Table 4: Training time value comparison of Previous work with proposed work different sets.

Iterations	**Training Time in seconds**		
	SNN	**EBPNN**	**MCNN**
10	29.36	15.23	15.03
20	42.58	26.98	21.36
40	74.46	48.23	32.89

.It has been observed by table 4 that training time required for error back propagation neural network is comparatively low because of less number of neuron in input layer as compare to spiking neural network used in previous work [1]. Here input layer in the EBPNN is depend on number of feature used while in case of spiking neural network number of neuron in input layer depend on training block size. While in case of MCNN it was assumed that finding cluster center is a kind of pre-processing step before the input in the neural network training. So base on that execution time of proposed work was low as compared to other existing methods.

V. References

Crop yield data is highly dynamic and chaotic in nature and has large size of data. This paper is an attempt to see how spatial data solution can be utilized in the field of yield prediction. Artificial Neural Network (ANN) on Map-Reduce framework is implemented for prediction of crop suggestion. Here CNN is used with various aptial feature like NDVI, SPI and VCI for prediction of crop yield was done. In this paper a modified convolutional neural network with the use of back propagation technique was used which is an error correction technique so this leads to high accuracy in the predicted results. An attempt is made to suggest best suitable crop and its information based on farmer's location with current climate condition tends to increase the yield of crops. It was obtained that proposed work has reduced the relative error by 16.17% as compared to SNN, while RMSE also get reduced by 16.25%. In this work average training time for prediction of crop yield was decreased by 23.39%. Here overall accuracy of the propose work was also improved.

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