DEEP SCALED CONJUGATE GRADIENT ALGORITHM FOR FORECASTING OF A TURMERIC YIELD IN TELANGANA

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Abstract: Traditional crop grown in India is turmeric which is most sacred spice of Indian market as well as in the international market. India is the world's major producer and exporter of turmeric which contributes more than 51 per cent of the global market. The total area under farming and production of turmeric has a rising trend in the country. To help the stake holders and the farmers by accurate forecasting using an efficient method, traditionally the linear methods like statistical analysis and to overcome the drawbacks of the linear methods the non linear methods line Artificial Neural Network methods are used further more to get more accurate forecasting of yield here the Deep Neural Network i.e., Deep Scaled Conjugate Gradient algorithm (with two hidden layers) is used for more accuracy.

Keywords: Deep Neural Networks.

Introduction: cultivation of Turmeric takes place at 1300 meters above the sea level. It grows in irrigated land and should have good rain, black, black clayey looms and red soils having natural drainage. Crops cannot withstand water logging or alkalinity. Turmeric is mostly cultivated in tropical area and subtropical area where it requires hot, moist climate, 1000-2000 mm rainfall and fairly light soil. Temperature required varying from 20 to 30 degrees centigrade and has a greater impact on crop growth. Normally the turmeric crop when cultivated mostly farmers need to store turmeric rhizome properly so that the curcumin content of the rhizome which shows the quality of the turmeric for that accurate forecasting is the most essential thing needed to plan and store efficiently. Here we introduced a new approach in which we have extended the existing Scaled conjugate gradient algorithm in its deeper form by increasing number of hidden layers to two and we name it as Deep Scaled Conjugate gradient algorithm.

Data Collection:

The appropriate data of Turmeric is obtained from different sources. The crop yield related data are collected from the Ministry of Agriculture, Government of Telangana and other online sources of Government of Telangana. The meteorological data are collected from the official website of the Indian Meteorological Department and other online sources. The rain is average monthly rainfall, max is maximum temperature in the month, min is minimum temperature in a month, hum is average monthly humidity in percentage, slp is mean sea level pressure in hPa, we is mean wind speed in km/h, maxws is maximum sustained wind speed in km/h and days is number of days of rain occurred in the month.

Year	Production in tones	Area in Hectare	Yield in Kg/Ha
2000	92	188	436
2001	135	278	464
2012	65	331	614
2013	96	348	539
2014	118	338	666
2015	87	219	604

Table 4.2. Sample data of the yield since 2000 to 2016 of Turmeric in Telangana

Methodology: Deep Scaled Conjugate Gradient feature extraction is training of a deep neural network. In this experiment we have used both single and multilayer feed forward network. It is not surprising that increase in no of feature improves recognition efficiency. Using Scaled Conjugate Gradient algorithm the Hessian matrix of error equation is always positive over all iterations. But in all other algorithms mentioned above this thing is not guaranteed. This property of SCG algorithm increases learning speed reliably in successive iteration.

 $E(\widetilde{w} + \Delta \widetilde{w}) = E(\widetilde{w}) + E'(\widetilde{w})^T \Delta \widetilde{w} + \Delta \widetilde{w}^{E''}(\widetilde{w}) \Delta \widetilde{w}$

Suppose the notations are used as $A = E'(\widetilde{W})$ and $H = E''(\widetilde{W})$. Weight vector in nth iteration may be mentioned as \widetilde{w}_n H is the Hessian matrix and A is the local gradient vector.

At starting of training in first iteration $p1 = r1 = -E'(\widetilde{W}_1)$ is assumed. The algorithm may be summarized as below.

- a) Initialization of parameters like σ , p, r in first iteration.
- b) Calculation of second order parameters like s,x and $\boldsymbol{\sigma}$
- c) Check whether Hessian matrix H is positive definite or not
- d) If false adjust the value of s by increasing λ and recalculate s again.
- e) Calculate ρ and readjust the value of λ
- f) Calculate step size
- g) If error > minimum error limit go to next iteration.
- h) Accept the weight vector for test.

After training with Deep scaled conjugate gradient algorithm the fitting network formed is neural network .

Data Simulation results using Deep scaled Conjugate gradient algorithm.

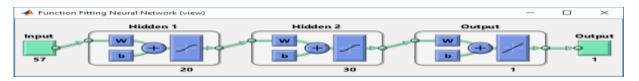


Fig : Neural Network with various size of layers having, 57 inputs and then a hidden layer of size 20 and then 30 and an output layer of size 1.

Internal Network					
ligorithms					
Training: Scaled	om (divideran I Conjugate Gri Squared Error	idient (trainseg)			
rogress					
Epoch: 0		11 iterations	1000		
Time:	contractor of the	0:00:00	C. Varianti		
11/00/00/00/00/00/00/00/00/00/00/00/00/0	.98e+10	1.88e+07	0.00		
Gradient: 8 Validation Checks:	.00e+10 0	4,78e+08	1.00e-06 6		
lats					
Performance	(plotperform	2			
Training State	(plottrainstats)				
Error Histogram (ploterrhist)					
Regression	(plotregress)	on)			
Fit (plutfit)					
Plot interval:		1 epc	ochs		
Opening Regre	ssion Plot				
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Fig: Training of Turmeric Yield forecasting on Deep ANN model using Deep Scaled Conjugate Gradient training method

The Algorithm takes 11 iterations to complete the training of the deep scaled conjugate gradient algorithm which will result in generation of mean square error and the regression values .

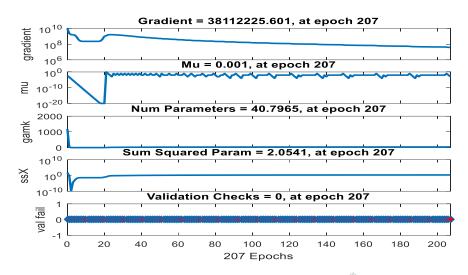


Fig: Gradient in Deep Scaled Conjugate gradient method

In the above figure the gradient variations are exhibited using Deep Scaled Conjugate gradient method

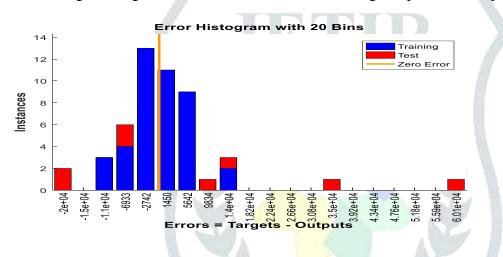


Fig: Error Histogram with Zero error

Table: Deep SCG generated values MSE, Regression and Iterations Double Hidden Layer

Algorithm	MSE	Regression	Iterations
SCG Hidden Layer =2	0.1461	0.8539	11

Deep Scaled conjugate gradient algorithm reduces the mean square error which is 0.1416 and the regression value using that data is achieved R = 0.8539 which is far better from the linear method and the general non linear methods like ANN so the deeper version the scaled conjugate gradient algorithm with two hidden layers will give better results while forecasting of crop yield. This execution was done using the Code in Mat lab.

Conclusions:

The increase in number of hidden layers i.e. by introducing the deeper form of the existing Neural Networks here we tried with two hidden layers in Scaled conjugate Gradient algorithm if we go on

increasing the number of hidden layers the efficiency of algorithm increases will give good results when compared with traditional linear methods and non linear ANN methods. By introducing the Deep learning concept the processing data will result in better forecasting.

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