Crop Yield Prediction Using Profound Brain Organizations

U. Amulya [1], T. Jayasri [2], Sk. Heena [3], P.Anitha[4], P. Kiran[5]

[1, 2,3,4,5] Department of Computer Science and Engineering,
[1, 2, 3, 5] QIS College of Engineering and Technology, Ongole-523272, Andhra Pradesh, India
[4]Engineering and Technology Program, GVPCDPGC(A)
[1]amulya.u@qiscet.edu.in, [2] jayasri.t@qiscetedu.in, [3] heena.sk@qiscet.edu.in,
[4] anitha501p@gvpcdpgc.edu.in, [5] kiran.palakeeti@qiscet.edu.in
Corresponding Author Mail: qispublications@qiscet.edu.in

Article Info
Page Number: 479 - 487
Publication Issue:
Vol 70 No. 2 (2021)

Article History
Article Received:
05 September 2021
Revised: 09 October 2021
Accepted: 22 November 2021
Publication: 26 December 2021

Abstract

The complex character of crop development is influenced by a variety of factors, including genetics, the environment, and their interactions. Large data sets and powerful algorithms are both necessary for accurate yield prediction because it involves figuring out the functional relationship between yield and numerous competing elements. The 2018 Syngenta Crop Challenge asked participants to make predictions about the yield performance for 2017 using a variety of significant datasets that Syngenta released. These datasets listed the genotype and yield performance of 2,267 corn hybrids grown at 2,247 different locations between 2008 and 2016.A deep neural network (DNN) strategy was developed by one of the winning teams using cutting-edge modelling and resolution techniques. Including a Predicted values of 12%, our analysis showed boosted forecast accuracy. The validation dataset that determines whether or not the storm instrument is aligned with the annualized return and halves of the standard deviation. If the climate estimates were still the best, the RMSE might be trimmed to 11% of the average yield or 46% of the beta value. The trained DNN model was also modified for feature selection, which was effective in reducing the input space without noticeably lowering prediction accuracy. Our numerical results indicate that this model fits much poorer than other powerful techniques like Lasso, flat neural networks (SNN), even decision tree (RT). According to the study, non-genetic factors may have a larger detrimental impact on crop performance.

Keywords: Machine learning, crop recommendation, and agriculture.

I. INTRODUCTION

About 58 percent of the people in our country make their living mostly from agriculture [14],[15]. The use of farmland for non-agricultural purposes and farmer suicides were both on the rise in 17 states, in a economic poll released in 2016–17. In order to ensure that their fields preserved by the next generation, 48% of farmers were moved to urban areas. One reason for this is that farmers frequently select crops that do not yield well on a particular soil or are planted at the wrong time of year [9]. The farmer may have purchased the land from another party, so the decision was made without any prior information. It could be difficult for a family to make ends meet if this money is their only source of income. Case studies in developing countries are hampered by researchers' difficulty to get valid and reliable data. Using machine learning models that have been trained to take important economic and environmental elements into account in order to make forecasts and provide counsel on crop sustainability, an approach has been developed to tackle the problem.

Environment is considered in the suggested system. The system helps determine soil parameters including soil type, pH, and nutrient content as well as weather factors like rainfall, temperature, and condition to assist the user in selecting the best crop. If the farmer selects the right crop, he will also receive a forecast of the yield. Create an accurate and reliable crop sustainability model based on the distinct soil type and climatic conditions for each state. Farmers should be advised on the best crops to grow in the region to minimize losses. Based on the crop statistics from the previous year, create a profit analysis for each type of crop. Machine learning, an application of artificial intelligence that enables systems to learn and adapt automatically without the need for explicit programming by a developer, is used by the suggested system. This improves the software's accuracy as it doesn't require human intervention. Many scientists are working on this issue to help farmers in making the decisions stated below, which take into account a number of aspects, including physical, environmental, and economic considerations.

RELATEDWORKS

Due to cultivation, we ranked plants by decision tree having to learn ID3 (Iterative Dichotomize 3) and artificial neural network K Nearest Neighbor Regression [9] approaches. Plant traits were examined using both the random forest method and Big ML [10]. To lessen the effects of water stress, a set of judgment criteria was developed using machine learning techniques [11]. To produce real-time predictions concerning agricultural expenses, intelligent technologies and machine learning techniques have been applied [5]. The many machine learning techniques used in agricultural production systems were summarized in this paper [8]. Additionally, using AI-based technologies, crop management guidance was given. Deep learning methods can increase crop yield [12][19]. Based on the current monthly weather, this work [2] provides an efficient yield forecast algorithm. The above predictive mechanism is devised via generic repressors and a modest statistical model. Using machine learning and data mining tools, farmers can select crops using soil qualities, a specific geographic region, sowing time, and environmental circumstances [3]. Utilizing regression analysis, the soil data set is examined [4]. To generate plant suggestions based on the underlying soil data, five different algorithms were used in this work [6]. Support Vector Machine, Bagged Tree, Adaboost, Naive Bayes, the Artificial Neural Networks are some five techniques. To get even more comprehensive data, the ensemble technique is frequently used. Radars are used in precision agriculture to locate bugs on coconut palms [7]. The students used CHAID, K-Nearest Neighbor, Naive Bayes, and Random Tree in a prediction model with a majority decision scheme.

PROPOSED SYSTEM ARCHITECTURE

The studies we propose carefully consider environmental and soil factors. This is due to the fact that some soil types are better suited to producing crops than others, and productivity will decrease if the weather is unfavorable. Figure 1 shows how the proposed system functions in general. We look for relationships among the data set's various attributes.

Acquisition of the Training Data Set:

The studies we propose carefully consider environmental and soil factors. This is due to the fact that some soil types are better suited to producing crops than others, and productivity will decrease if the weather is unfavorable. Figure 1 shows how the proposed system functions in general. We look for relationships among the data set's various properties.

Utilizing the cultivation cost, market price, standard pricing, and yield statistics, profit is computed. Having the study's profit may help with crop forecasts. By subtracting the profit particular to each nation by each cultivation in that region, the profit margin for entities that raise no or no harvests is calculated. To ensure that the overall prediction is unaltered, the zero and 0 yield values are now changed to -1. The data set must first be coded for the neural network to operate correctly. Prior to being utilized by machine learning algorithms, the data must be parsed. Preprocessing eliminates outliers, false positives, and missing data. Values are a topic. Values from the data collection are stored in strings. Prior to entering this data it in to a neural network, it will be molded into integers. Further information defect occurs once plants are weeded per the nutrient status and the nutrients in their soil. If the soil lacks the nutrients the plants need, training a plant requires far less time. Before training algorithms for machine learning such as synapses and regressions, the accumulated data is preprocessed.

LINEAR INCREASE

The y-red value for each crop is derived using yield, moisture, weather, pH, and linear regression. The crops are quickly listed in order of their linear regression model's your value, starting with the crop with the highest your value. The Keras module streamlines the neural network creation process. The long-term survival of various crops is predicted using a sequential model with three input layers and fifteen output layers.

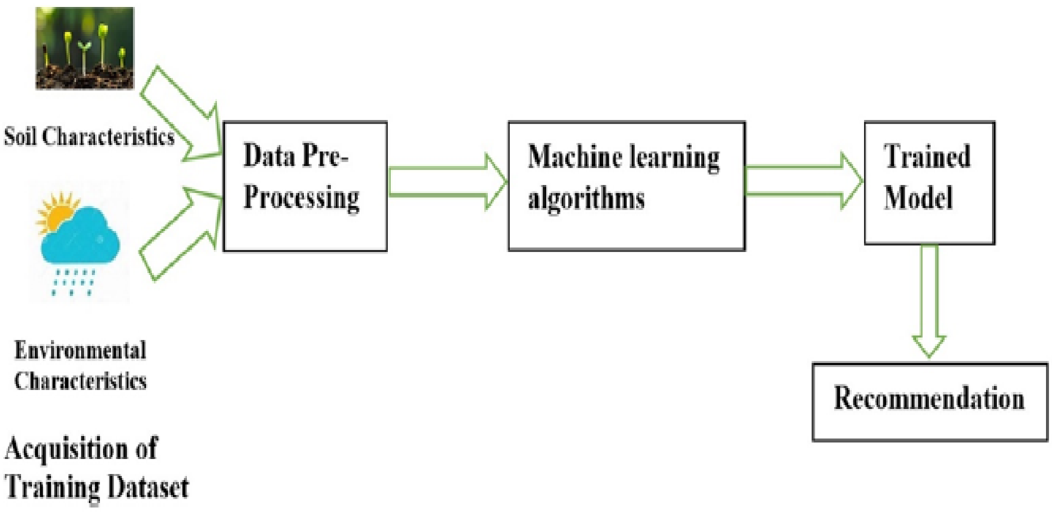

Fig 1: Crop Recommendation System

II CONCLUSION AND RESULTS

Tensor flow, a free and open-source scripting tool, was then used to create the two deep neural networks in Python (Abadi et al., 2016). In assertion, the flat neural network (with a single hidden layer of 300 neurons), the least absolute shrinkage and selection operator (LASSO), and the regression tree were rehired as auxiliary comparison models (Breiman, 2017). These three models were segregated into two, prefiguring yield and dictating yield, to permit for fair comparisons. They made yield predictions based on changes in their results. In order to assure fair comparisons, each of these models was constructed in Python as efficiently as feasible and put through the identical software and hardware testing process. The regression tree's hyper parameters were as follows. Two and unearthed that the most correct estimates were made for rates in the range of 0.1 and 0.3. The tree's maximum depth was set at 10 to prevent over fitting.

```
In [15]: profit_data
Out[15]:
```

	state	crop	profit
0	Andhra Pradesh	Rice	6.385184e+04
1	Andhra Pradesh	Jowar	1.097407e+04
2	Andhra Pradesh	Bajra	7.414478e+03
3	Andhra Pradesh	Maize	3.136984e+04
4	Andhra Pradesh	Ragi	5.636376e+03
5	Andhra Pradesh	Wheat	1.000000e+00
6	Andhra Pradesh	Barley	-1.000000e+00
7	Andhra Pradesh	Gram	5.058972e+03
8	Andhra Pradesh	Tur	1.000000e+00
9	Andhra Pradesh	Groundnut	1.017747e+04
10	Andhra Pradesh	Mustard	1.000000e+00
11	Andhra Pradesh	Soyabean	7.632153e+03
12	Andhra Pradesh	Sunflower	9.739718e+03
13	Andhra Pradesh	Cotton	1.000000e+00
14	Andhra Pradesh	Jute	-1.000000e+00
15	Andhra Pradesh	Mesta	1.609931e+03
16	Andhra Pradesh	Sugarcane	8.931305e+05
17	Arunachal Pradesh	Rice	9.995866e+02
18	Arunachal Pradesh	Jowar	-1.000000e+00

Fig. 2: state-by-state crop profit

```
[7.01187226]
['Barley', 'Bottle Gourd']
[-13.77759935]
[-0.81033561]
[-5.14828826]
[-2.21432874]
[-4.81342706]
[-59.60942137]
[-2.84073175]
[-75.81061724]
[0.69908353]
['Barley', 'Bottle Gourd', 'Groundnut']
[0.70479237]
['Barley', 'Bottle Gourd', 'Groundnut', 'Jowar']
[0.61912891]
['Barley', 'Bottle Gourd', 'Groundnut', 'Jowar', 'Khesari']
[-9.91352688]
[-0.28529204]
[-1.7600131]
[4.11882972]
['Barley', 'Bottle Gourd', 'Groundnut', 'Jowar', 'Khesari', 'Orange']
[-262.25858254]
[8.45690409]
['Barley', 'Bottle Gourd', 'Groundnut', 'Jowar', 'Khesari', 'Orange', 'Potato']
[2.20757848]
['Barley', 'Bottle Gourd', 'Groundnut', 'Jowar', 'Khesari', 'Orange', 'Potato', 'Raddish']
[-4.04423303]
[0.71076754]
['Barley', 'Bottle Gourd', 'Groundnut', 'Jowar', 'Khesari', 'Orange', 'Potato', 'Raddish', 'Sannhamp']
[-0.77569453]
[-54.22040544]
[-17.77020347]
[-24.76243297]
ACCURACY SCORE:- 88.26342114086883 %
```

Fig.3: Regression model outcomes

```
In [55]: print ('Recommended crop for the month of '+NumtoMonth[month]+' in '+state+' is/are: \n'+final_crop)

         Recommended crop for the month of May in Bihar is/are:
         Potato,Bottle Gourd,Orange,Barley,Raddish,Sannhamp,Jowar,Groundnut,Khesari

In [ ]:
```

Fig.4: Recommend crop

```
173  0.536654  0.242637  0.167341   0.201528  0.163237  0.181734  0.068485
174  0.428104  0.075437  0.008961   0.209194  0.432152  0.157399  0.039976
175  0.523158  0.221789  0.238394   0.327195  0.251305  0.164559  0.104569
176  0.482467  0.185739  0.208894   0.164559  0.030575  0.024127  0.002197

In [62]: Soil=input()
         Month=input()
         State=input()

         Alluvial
         March
         Punjab

In [63]: # df

In [64]: # df[df['State']==State]['State_code']
```

Fig.5: Producing data for the predictor

```
In [68]: pred = model.predict_proba(Choices)
         df2 = pd.DataFrame(pred, columns=["Rice","Wheat","Cotton","Sugarcane","Tea",→"Coffee","Cashew","Rubber","Coconut","O:
         print(df2)
         df2.shape

       Rice   Wheat    Cotton  Sugarcane       Tea    Coffee    Cashew  \
0  0.495499  0.2027  0.236318   0.184892  0.043014  0.035415  0.004605

     Rubber   Coconut  Oilseed      Ragi    Maize  Groundnut    Millet  \
0  0.002973  0.005234  0.06702  0.087935  0.13789   0.075435  0.125787

     Barley
0  0.043136
Out[68]: (1, 15)
```

Fig.6: Values for predicting crop sustainability

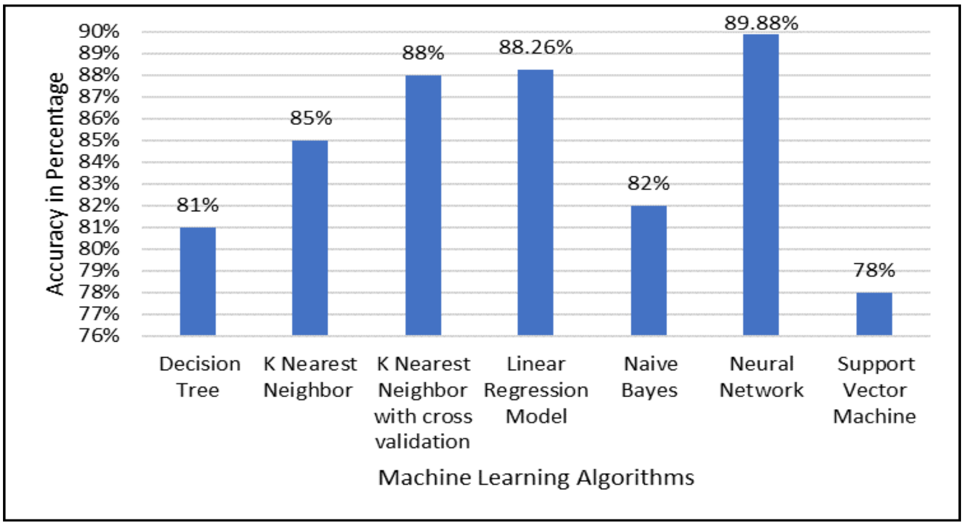

Fig. 7: Analyzing the suggested system in comparison to several statistics methods

TABLE 1: Dependability For CROPS RECOMMENDED

S.No	Algorithms	Accuracy
1	Decision Tree	81%
2	K Nearest Neighbour	85%
3	K Nearest Neighbour with cross validation	88%
4	Linear Regression Model	88.26%
5	Naive Bayes	82%
6	Neural Network	89.88%
7	Support Vector Machine	78%

VI. FUTURE SCOPE AND CONCLUSION

The prototype has data access that ordinary peasants do not, which lowers crop failure and boosts output. They yet don't experience any financial problems. Web and cellular apps may be able to provide rural households with advice on how to cultivate crops more adeptly and productively, depending on specific theories.

REFERENCES

[1] R. Kumar, M. P. Singh, P. Kumar, and J. P. Singh, "Crop Select ion Method to maximize crop yield rate using machine learning technique", 2015 International Conference on Smart Technologies and Management for Computing, Communication, Controls, Energy, and Materials (ICSTM), Chennai, 2015, pp.138-145, DOI: 10.1109/ICSTM.2015.7225403.

[2] H. Lee and A. Moon, "Development of yield prediction system based on real-time agricultural meteorological information", 16t h International Conference on Advanced Communication Technology, Pyeongchang, 2014, pp. 1292-1295, DOI: 10.1109/ICACT.2014.6779168.

[3] T.R. Lekhaa, "Efficient Crop Yield and Pesticide Prediction for Improving Agricultural Economy using Data Mining Techniques", International Journal of Modern T rends inEngineering and Science (IJMTES), Volume 03, Issue10, 2016.

[4] Jay Gholap, Anurag Ingole, Jayesh Gohil, Shailesh Gargadeand Vahida Atar, " Soil Data Analysis Using Classification Techniques and Soil Attribute Prediction", International Journal of Computer Science Issues, Volume 9, Issue 3,2012.

[5] S. R. Rajeswari, ParthKhunteta, Subham Kumar, Amrit RajSingh, Vaibhav Pandey, "Smart Farming Predict ion using Machine Learning", International Journal of Innovative Technology and Exploring Engineering, 2019, Volume-08, Issue-07.

[6] Z. Doshi, S. Nadkarni, R. Agrawal, and N. Shah,"AgroConsultant : Intelligent Crop Recommendation System Using Machine Learning Algorithms", Fourth Int ernational Conference on Computing Communication Control and Automation (ICCUBEA), Pune, India, 2018, pp. 1-6, DOI:10.1109/ICCUBEA.2018.8697349.

[7] S. Pudumalar, E. Ramanujam, R. H. Rajashree, C. Kavya, T.Kiruthika and J. Nisha, "Crop recommendation system for precision agriculture," Eighth International Conference on Advanced Computing (ICoAC), 2017, pp. 32-36, DOI:10.1109/ICoAC.2017.7951740.

[8] Konstantinos G. Liakos, PatriziaBusato, Dimitrios Moshou, Simon Pearson and DionysisBochtis, “Machine Learning in Agriculture: A Review”, Article on sensors, 2018, pp 1 - 29,doi:10.3390/s18082674.

[9] M. T. Shakoor, K. Rahman, S. N. Rayta and A. Chakrabarty,"Agricultural product ion output predict ion using Supervised Machine Learning techniques”, 1st International Conference on Next Generation Computing Applications (Next Comp),Mauritius, 2017, pp. 182-187, DOI:10.1109/NEXTCOMP.2017.8016196.

[10] Marion Olubunmi Adebiyi, Roseline OluwaseunOgundokunand Aneoghena Amarachi Abokhai, "Machine Learning-BasedPredict ive Farmland Optimization and Crop Monitoring System",open-access article distributed Volume 2020, pp 1-12,ht tps://doi.org/10.1155/2020/9428281

[11] DimitriadisSavvas and Christos Goumopoulos. “ Applyingmachine learning to extract new knowledge in precisionagricultureapplicat ions”, 2008 P anhellenic Conference onInformatics, IEEE, (2008), pp:100-104.

[12] N. Kussul, M. Lavreniuk, S. Skakun, and A. Shelestov,"Deep Learning Classificat ion of Land Cover and Crop Types Using Remote Sensing Data”, IEEE Geoscience and Remote Sensing Let ters, vol. 14, no. 5, pp. 778-782, May 2017, DOI:10.1109/LGRS.2017.2681128.

[13] Kevin Tom Thomas, Varsha S, Merin Mary Saji, LishaVarghese, Er. Jinu Thomas, “ Crop Prediction Using Machine Learning”, International Journal of Future Generation Communication and Networking Vol. 13, No. 3, (2020), pp.1896–1901.

[14] www.india.gov.in/topics/agriculture

[15] www.ibef.org/indust ryagriculture-india.aspx

[16] ht tps://data.gov.in/g

[17] ht tps://www.kaggle.com/notebook

[18] Chandy, Abraham. "Pest Infestat ion Ident ificat ion inCoconut Trees Using Deep Learning." Journal of Art ificialIntelligence 1, no. 01 (2019): 10-18.

[19] Vijayakumar, T., and Mr R. Vinothkanna. "Mellownessdetect ion of dragon fruit using deep learning strategy." Journal ofInnovative Image Processing (JIIP) 2, no. 01 (2020): 35-43.

[20] R. Pryzant, S. Ermon, and D. Lobell, “Monitoring Ethiopian Wheat Fungus with Satellite Imagery and Deep Feature Learning,” presented at the IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), pp. 1524–1532, Honolulu, HI, USA, 2017.

[21] Q. Yang, et al., “Deep convolutional neural networks for rice grain yield estimation at the ripening stage using UAV-based remotely sensed images,” Field Crops Research, vol. 235, no. 1, pp. 142–153, April 2019.

[22] J. Long, et al., “Fully convolutional networks for semantic segmentation,” Presented at the IEEE Conf. on Computer Vision Pattern Recognition, pp.3431–3440, Boston, MA, USA, 2015.

[23] A. Krizhevsky, I. Sulskever, and G. E. Hinton, “ImageNet classification with deep convolutional neural networks,” Proc. of the 25th International Conference on Neural Information Processing Systems, vol. 1, pp. 1097 – 1105, 2012.

[24] X. Liu, et al., “AgeNet: deeply learned regressor and classifier for robust apparent age estimation,” Presented at the Proc. of IEEE Int. Conf. on Computer Vision, pp. 258–266, Santiago, Chile, 2015.

[25] K. Kuwata, and R. Shibasaki, “Estimating crop yields with deep learning and remotely sensed data,” Presented at the IEEE Int. Geoscience and Remote Sensing Symp. (IGARSS), pp. 858–861, Milan, Italy, 2015.
[26] C. Bi, and G. Chen, “Bayesian networks modelling for Crop Diseases,” Computer and Computing Technologies in Agriculture IV, Springer Berlin Heidelberg, pp. 312–320, 2010.
[27] J. You, et al., “Deep Gaussian process for crop yield prediction based on remote sensing data.,” Proc. of 31st Conf. on Association for the Advancement of Artificial Intelligence, pp. 4559–4565, San Francisco, California, USA, 2017.
[28] L. Hongyi, Y. Zhang, et al.., “A PCA and neural networks-based method for soil fertility evaluation and production forecasting,” IEEE Int. Conference on Computer Science and Automation Engineering (CSAE), pp. 35–38, Zhangjiajie, China, July 2012.
[29] P. Sharma, et al., “Prediction of Potato Late Blight Disease based upon weather parameters using Artificial Neural Network Approach”, Presented in the 2018 9th International Conference on Computing, Communication and Networking Technologies (ICCCNT), pp. 1–13, Bangalore, India.
[30] M. Lavreniuk, N. Kussul, et al., “Deep learning crop classification approach based on sparse coding of time series of satellite data,” Presented at the 2018 IEEE Int. Geoscience and Remote Sensing Symposium, pp. 4812–4815, Valencia, Spain.
[31] P Ramprakash, M Sakthivadivel, N Krishnaraj, J Ramprasath. ”Host-based Intrusion Detection System using Sequence of System Calls” International Journal of Engineering and Management Research, Vandana Publications, Volume 4, Issue 2, 241-247, 2014
[33] N Krishnaraj, S Smys.”A multihoming ACO-MDV routing for maximum power efficiency in an IoT environment” Wireless Personal Communications 109 (1), 243-256, 2019.
[34] N Krishnaraj, R Bhuvanesh Kumar, D Rajeshwar, T Sanjay Kumar, Implementation of energy aware modified distance vector routing protocol for energy efficiency in wireless sensor networks, 2020 International Conference on Inventive Computation Technologies (ICICT),201-204
[35] Ibrahim, S. Jafar Ali, and M. Thangamani. "Enhanced singular value decomposition for prediction of drugs and diseases with hepatocellular carcinoma based on multi-source bat algorithm based random walk." Measurement 141 (2019): 176-183. https://doi.org/10.1016/j.measurement.2019.02.056
[36] Ibrahim, Jafar Ali S., S. Rajasekar, Varsha, M. Karunakaran, K. Kasirajan, Kalyan NS Chakravarthy, V. Kumar, and K. J. Kaur. "Recent advances in performance and effect of Zr doping with ZnO thin film sensor in ammonia vapour sensing." GLOBAL NEST JOURNAL 23, no. 4 (2021): 526-531. https://doi.org/10.30955/gnj.004020 , https://journal.gnest.org/publication/gnest_04020
[37] N.S. Kalyan Chakravarthy, B. Karthikeyan, K. Alhaf Malik, D.Bujji Babbu,. K. Nithya S.Jafar Ali Ibrahim , Survey of Cooperative Routing Algorithms in Wireless Sensor Networks, Journal of Annals of the Romanian Society for Cell Biology ,5316-5320, 2021
[38] Rajmohan, G, Chinnappan, CV, John William, AD, Chandrakrishan Balakrishnan, S, Anand Muthu, B, Manogaran, G. Revamping land coverage analysis using aerial satellite image mapping. Trans Emerging Tel Tech. 2021; 32:e3927. https://doi.org/10.1002/ett.3927

[39] Vignesh, C.C., Sivaparthipan, C.B., Daniel, J.A. et al. Adjacent Node based Energetic Association Factor Routing Protocol in Wireless Sensor Networks. Wireless Pers Commun 119, 3255–3270 (2021). https://doi.org/10.1007/s11277-021-08397-0.

[40] C Chandru Vignesh, S Karthik, Predicting the position of adjacent nodes with QoS in mobile ad hoc networks, Journal of Multimedia Tools and Applications, Springer US,Vol 79, 8445-8457,2020