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27th October 2021

Jointly Organized by

Department of Biological Science, Physical Science and Computational Science

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ABOUT THE INSTITUTION

A nations's growth is in proportion to education and intelligence spread among the masses. Having this idealistic vision, two great philanthropists late. S.P. Nallamuthu Gounder and Late. Arutchelver Padmabhushan Dr.N.Mahalingam formed an organization called Pollachi Kalvi Kazhagam, which started NGM College in 1957, to impart holistic education with an objective to cater to the higher educational needs of those who wish to aspire for excellence in knowledge and values. The College has achieved greater academic distinctions with the introduction of autonomous system from the academic year 1987-88. The college has been Re-Accredited by NAAC and it is ISO 9001 : 2015 Certified Institution. The total student strength is around 6000. Having celebrated its Diamond Jubilee in 2017, the college has blossomed into a premier Post-Graduate and Research Institution, offering 26 UG, 12 PG, 13 M.Phil and 10 Ph.D Programmes, apart from Diploma and Certificate Courses. The college has been ranked within Top 100 (72nd Rank) in India by NIRF 2021.

ABOUT CONFERENCE

The International conference on “Emerging Trends in Science and Technology (ETIST-2021)” is being jointly organized by Departments of Biological Science, Physical Science and Computational Science - Nallamuthu Gounder Mahalingam College, Pollachi along with ISTE, CSI, IETE, IEE & RIYASA LABS on 27th OCT 2021. The Conference will provide common platform for faculties, research scholars, industrialists to exchange and discus the innovative ideas and will promote to work in interdisciplinary mode.

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LIST OF ARTICLES

Wireless Sensor Network System For Clever Vegetation-IoT Using Convolutional Neural Network

Mrs.R.Vidhu[1], Dr.S.Niraimathi[2]

ABSTRACT: Internet of Things (IoT)-based automation of agricultural events can change the agriculture sector from being static and manual to dynamic and smart, leading to enhanced production with reduced human efforts. Wireless Sensor Network (WSN) and Precision Agriculture (PA) are the main drivers of automation in the agriculture domain. It uses specific sensors and software to ensure that the crops receive exactly what they need to optimize productivity and sustainability. PA includes retrieving real data about the conditions of soil, crops and weather from the sensors deployed in the fields. High-resolution images of crops are obtained from satellite or air-borne platforms (manned or unmanned), which are further processed to extract information used to provide future decisions.In this paper, a review of near and remote sensor networks in the agriculture domain is presented along with several considerations and challenges. This survey includes wireless communication technologies, sensors, and wireless nodes used to assess the environmental behaviour, the platforms used to obtain spectral images of crops, the common vegetation indices used to analyse spectral images and applications of WSN in agriculture. As a proof of concept, we present a case study showing how WSN-based PA system can be implemented. We propose an IoT-based smart solution for crop health monitoring, which is comprised of two modules. The first module is a wireless sensor network-based system to monitor real-time crop health status. The second module uses a low altitude remote sensing platform to obtain multi-spectral imagery, which is further processed to classify healthy and unhealthy crops. We also highlight the results obtained using a case study and list the challenges and future directions based on our work.

Keywords: smart agriculture; precision agriculture; vegetation index; Internet of Things

1. Introduction

The worldwide populace is anticipated to contact 9.6 billion by 2050 that represents a major issue for the agribusiness business [1]. Regardless of common difficulties like outrageous climate conditions, unfortunate environmental change, and its effect on cultivating, the resulting interest for food has been progressively immovable. We should fulfill these expanding requests; therefore, researchers have begun researching savvy IoT advances for Agriculture (Vegetation-IoT) [2]. Such advances will empower the agribusiness business to further develop usefulness, beginning from enhancing the utilization of manure to expanding the productivity of cultivating. Our target for Vegetation-IoT is to foster a structure for observing the harvest field with the assistance of sensors

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(for light, stickiness, temperature, soil dampness, and so forth) and arranging the water system framework. Remote Sensor Network (WSN), a fundamental structure block for Vegetation-IoT [3], plan a strong enormous scope autonomous checking and control network by arbitrarily deploying an enormous number of little sensor gadgets, otherwise called hubs, having correspondence and registering capacities. All gadgets are associated through remote channels to finish their jobs and learn cooperatively.A undeniable level structure of a WSN-based Vegetation-IoT is depicted in Fig. 1, where various Sensor Nodes (SNs) are conveyed for a few parts of horticulture, from steers management to hardware activity. All the information from SNs are gathered by the sink hub through remote information trade interfaces even with arbitrary spatial positions and extensive developments. The information is regularly moved to the centre organization through various entryways, for example, a Base Transceiver Station (BTS) for additional preparing, information examination, which, thusly, might actually computerize the whole Vegetation-IoT framework. Such computerization instrument is additionally upheld by a helpful correspondence arrangement and bunch development between the hubs dependent on the application necessities. We foster a particularly natural component to embed human-level knowledge in the Vegetation-IoT.

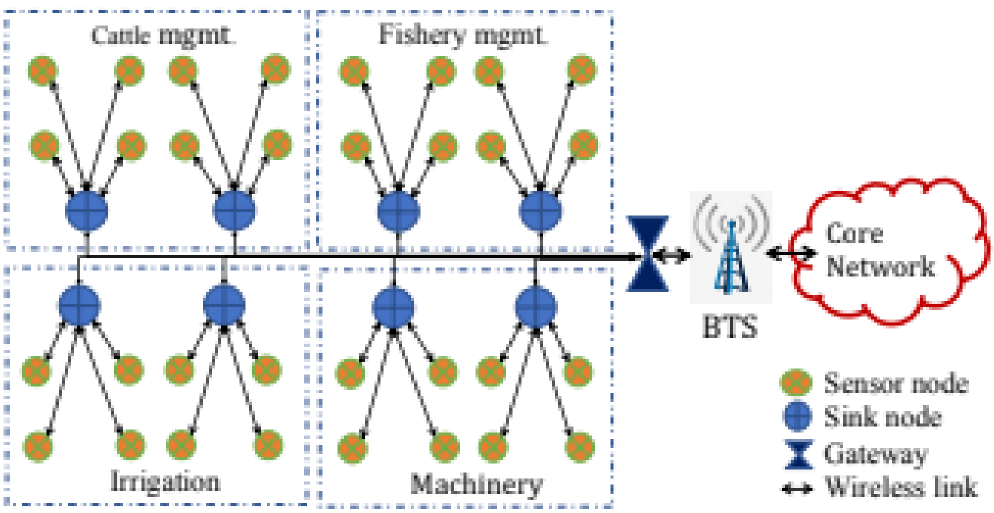

Figure 1: A theoretical perspective on the WSN system for clever Vegetation-IoT

It is trying to arrange the hubs in the Vegetation-IoT to accomplish powerful distribution of assets, for example, network band-width and energy of the WSN [4]. Presentation of Distributed Artificial Intelligence (DAI) for circulated wise preparing has as of now conquer the shortcoming of conventional unified learning engineering. Accordingly, in light of Distributed Problem Solving (DPS) approach, we propose a Multi-Agent System (MAS) to misuse the knowledge and adaptability. The new MAS, fundamentally similar common WSN, approach examines insight in the conduct coordination and community oriented works among various specialists [5].

In the proposed model, the different sensors have gone about as multi-specialists, and hence the DPS for DAI approach has been utilized to upgrade the helpful organizing thought. To take care of the issue of effective hub assignment for WSN in Vegetation-IoT and acknowledge ideal asset portion with low energy utilization and low intricacy, the WSN dependent on DAI is to be dissected and concentrated hypothetically. We initially plan an asset distribution model of WSN dependent on multi-specialists. From that point onward, we form a streamlining issue for the cycle of asset assignment; the proposed Back Engendering Neural Network (BPNN) in the neural networkhas been embraced to foster a target capacity and track down an ideal asset allotment plot. The idea of the bunching [6]–[8] is depicted as comparable items that fulfill the target capacity can be gathered into a group, and the articles between various groups should be totally different. In light of it, our methodology separates the asset assignment measure into two stages: intercluster development followed by an intra-group arrangement. In view of the organization status of the group, the Cluster Head (CH) is chosen among the bunches that work with the portion of the relating assets. The CH distribution to the assets will be performed first, trailed by a self-evaluation, and contrasting whether the current energy is higher than the objective energy limit. This distinguishes whether it is the assignment to be prepared or the following phase of asset portion is to be performed.

Considering restricted energy just as life pattern of the hubs in a bunch, the distance among hubs and energy utilization are characterized utilizing wellness capacities. All the more explicitly, two neural organization based streamlining calculations are utilized to improve asset assignment, which will at long last find the ideal hub arrangement. For this, we build up an asset designation model of WSN dependent on DAI. The advanced conditions are the setup of sensor hubs and the hub inclusion, which are characterized as the wellness work. The oddity of the proposed model lies in the execution of Bayesian Neural Network (BNN) in BPNN for Vegetation-IoT applications. The current works on IoT and WSN essentially centeraround systems administration and calculations utilizing distinctive improvement methods.

I. Related Works

There are many exploration results on asset portion techniques in WSN. Presentation of grouping can successfully decrease energy utilization of the framework just as equilibrium the organization load. Creators in [7] utilized basic fake fish school and subterranean insect state calculation for asset portion of WSNs, and furthermore streamlined the grouping interaction. Creators in [9], [10] likewise utilized grouping to further develop the LEACH-CS calculation and proposed a low-energy versatile bunching asset allotment convention, which depends on market instrument. The market system plot pointed toward expanding benefit to acknowledge disseminated asset assignment through the arrangement and change of specialists. Thinking about the QoS, creators have received a brought together asset distribution strategy in [11], [12] to limit the designated energy utilization. In [13], an asset distribution model dependent on a lining network was set up. The consistent state examination of the model was utilized to track down an ideal asset portion plot. These techniques chiefly consider issue according to the viewpoint of lessening network energy utilization. In any case, as the quantity of clients develop that requests diverse QoS necessities of various clients. Thusly, a more unique and effective asset allotment system should be set up. To expand use of assets, creators booked the errands sensibly as indicated by the QoS of various clients to apportion them to various hubs in [14]. Even with the heterogeneity of WSN, reference [15] receives the asset portion strategy dependent on heterogeneous factual QoS to change the objective into the augmentation of organization throughput. A few scientists utilize shrewd calculations to enhance the presentation of asset allotment. In [16], Genetic Algorithm (GA) is utilized to enhance the design of sensor hubs, where the hub inclusion is characterized as wellness work. The wellness work comprises task transmission time and energy utilization. An asset portion calculation dependent on Binary Particle Swarm Optimization (BPSO) is embraced in [14] to streamline the hub setup and asset booking of WSNs. To confirm the plausibility of the plan, distinctive topological constructions and move capacities are broke down and talked about. In [17], the creator utilized neural organization to further develop BPSO to enhance the asset designation interaction of WSNs and altogether enhance the union speed. Considering a genuine WSNs working climate is constant and dynamic. Creators in [18] proposed a specialist based WSN asset portion structure.

Since the specialist is liable for information assortment, combination and dispersion in the organization, a precise area data and reaction season of the specialist will influence the postponement and work effectiveness of the whole organization [19]. Reference [20] embraced a specialist based Fuzzy Group Optimization calculation (FGO) to lessen energy utilization and delayed the existence pattern of hubs in the WSNs. In [21], creators decrease the quantity of sensors to be chosen utilizing Multiplayer Perceptron (MLP), Support Vector Machine (SVM) and Naive Bayes for expanding WSN lifetime.

II. CNN and Vegetation application

Notwithstanding, the utilization of CNN to UAV symbolism for planning vegetation properties stays uncommon because of different difficulties. These incorporate (1) the intricacy of normal vegetation shelters, (2) the requirement for spatially unequivocal and broad reference information for preparing and approval and (3) that planning approaches are not committed to portray single pictures, yet to find and describe explicit highlights inside pictures. 1) Complexity of normal vegetation coverings: CNN are regularly utilized in order undertakings (Krizhevsky et al. 2012; Hu et al. 2015; Wcaldchen and Mcader 2018, Wagner et al. 2019).

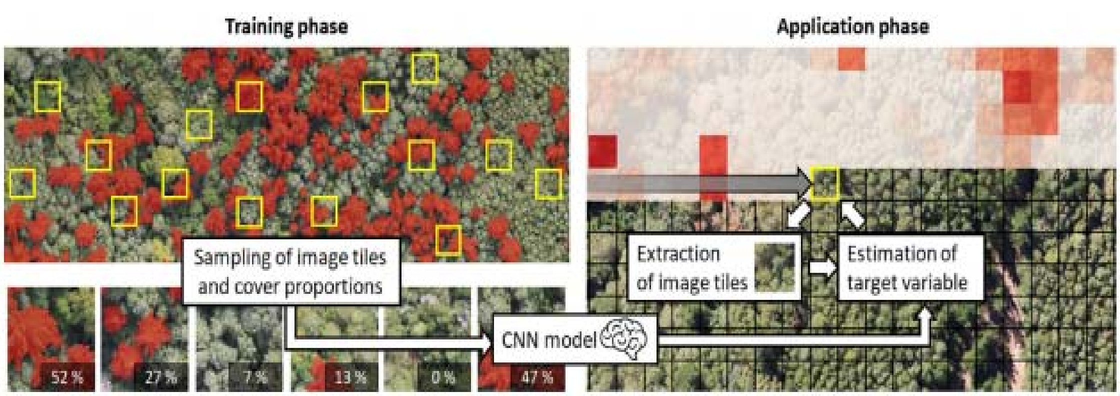

Fig 2: Convolutional Neural Networks have effectively been effectively applied in vegetation related applications, for instance, the picture based discovery of plant sicknesses, plant phenotyping (Ubbens and Stavness 2017) and picture based recognizable proof of plant species (see for example Pl@ntnet, Flora Incognita, Joly et al. 2016)

In any case, as a reaction to steady changes of ecological elements, vegetation coverings regularly include comparing continuous changes in species cover, local area organization or shelter properties (Foody et al. 1992;

Schmidtlein and Sassin 2004; Rocchini et al. 2013). Besides, pixels may contain more than one vegetation type, even in extremely high goal information. In this way, vegetation frequently will in general be all the more properly depicted by nonstop measurements (for example the inclusion of an animal varieties [%]) and a powerful and adaptable planning approach ought to in a perfect world portray the objective variable utilizing a ceaseless scale instead of discrete classes. 2) Reference information accessibility: The prescient exactness of CNN ordinarily profits by huge amounts of preparing information (otherwise called names). However, in most far off detecting applications reference information are by and large a scant ware because of the expense of ground-based testing and troubles in getting to destinations. Besides, the utilization of field information might be weakened by the failure to precisely adjust the geolocation of field-based perceptions with far off detecting symbolism and examining inclination coming about because of ground-based cover gauges (Lunetta et al. 1991; Leps and Hadincov a 1992; Valbuena et al. 2010; Kaartinenet al. 2015; Leit~ao et al. 2018). One option is to utilize spatially unequivocal perceptions from UAV symbolism. This is attainable if previous ground-based examples are accessible to help the visual outline of the objective shelters or if the objective variable is the front of an effortlessly distinguished species or vegetation type (Vanha-Majamaa et al. 2000; Luscier et al. 2006; Lisein et al. 2015; Kattenborn et al. 2018, 2019). 3) Location and portrayal of highlights inside pictures: Originally, CNN approaches were created to examine pictures where the objects of interest cover a generous piece of the picture and the whole picture is alloted to a class (Krizhevsky et al. 2012). Conversely, a utilization of CNN in vegetation distant detecting should empower to find vegetation highlights inside the orthoimagery and show comparing spatial slopes. An answer for this issue is to apply CNN to similarly dispersed tiles separated from the orthoimagery.

III. Advanced Resource Allocation Scheme In Intra-Cluster Based On PSO-BPNN

To understand the ideal asset distribution in the framework bunch and further develop the existence pattern of the organization, we will enhance the set target work in this part. Neural networks have been end up being viable in approximating the necessary precision of estimation capacities [14], be that as it may, BPNN is broadly utilized practically speaking. We will utilize the neural organization to assess the target capacity and track down the best asset allotment methodology. In our execution, BPNN is made out of a three-layer network structure, which has a component of mistake input, and has moderate intermingling issue. Hence, we receive Particle Swarm Optimization (PSO) calculation to further develop the learning velocity of BPNN. The stream outline portrayed in Figure 2 is portrayed as follows:

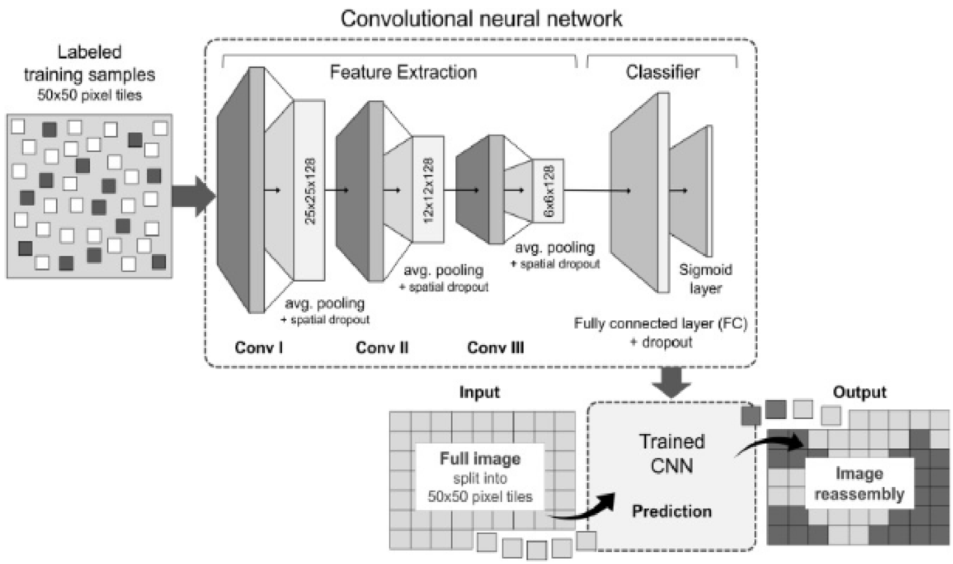

Fig 3: Illustration of the CNN engineering and the order interaction. The organization was prepared with physically named tests with a tile size of 50 × 50 pixel. The prepared classifier was then applied on entire recurrent photos, which were likewise parted into 50 × 50 pixel tiles. The classifier predicts the yield for each single tile and reassembles them to the first picture size.

Stage 1-The preparation test set of BPNN is started dependent on target works that are detected by the heterogeneous hubs, hub number and their spatial sending. The cycle begins at t = 0ms during the preparation of the example information regarding their underlying developments.

Stage 2-Based on the preparation test set of BPNN, the first information is then standardized. The standardization interaction is utilized for normalizing numerical displaying of the technique alongside other parametric conditions.

Stage 3-The model presently executes Particle Swarm introduction utilizing the standardized information planned on to trainingsample information of the goal work. This fills in as the preoptimization stage, where the information are produced dependent on unique bunching and standardized in like manner.

Stage 4-Here, the model is making a wellness work dependent on the standardized and prepared goal and cost capacities. This progression will act as the underlying advancement stage which conveys further the target capacities dependent on the BPNN yields.

Stage 5-In this stage, in light of the past wellness work yields, the ideal wellness work is ordered to refresh the molecule position and speed noted from the spatially dispersed hubs.

Stage 6-This is the first step of the proposed model, where the ideal number of cycles is determined dependent on the BPNN-PSO approach. In the event that the ideal number of cycles isn't reached, molecule wellness is again determined and continues for improvement.

Stage7-As soon as the ideal number of emphasess is accomplished during agreeable correspondence among the Vegetation-IoT hubs, the information stockpiling for iterative calculations come into the image, which empowers setting up the new preparing set for the next time occurrence.

Stage 8-As soon as the capacity improvement happens during dynamic grouping, the BPNN cost capacities are refreshed and comparing ideal wellness capacities are determined. In view of this cycle, the best asset allotment plan is persistently refreshed and executed concerning time. The proposed BPNN training method is briefly described as follow:

Algorithm 1: Training of BPNN for asset portion

```
Input : X; Y 1*l framework
Output : X; Y 1*l network
for I = 1 to l do
for j = 1 to l do
C[i,j] = 1;
end
end
while C[i,j] <= !l
i(i = 1; 2; :::; k) do
C[i,j] =1;
loop from 1 to k;
forbj
m = m[i]+1;
for l = 1 to m do
 e = !eF + !aC;
end
end
end
```

CNNs are made out of three primary segments: convolutional layers, pooling layers and completely associated layers (Voulodimos et al., 2018). The initial two segments are answerable for programmed highlight extraction by applying countless various channels on the info information. This interaction of highlight extraction is performed on numerous levels, whereby the yield of each level is the contribution to the accompanying. From one level to another, the removed highlights expansion in intricacy - from rather basic highlights (for example edges) on the most reduced level to more intricate highlights on the most elevated level (Gu et al., 2018).

By passing enormous amounts of named preparing information through the organization, the model progressively figures out how to perceive the applicable highlights, which are important to recognize classes. For the programmed grouping of woody vegetation, we fostered a CNN comprising of three convolutional layers and one completely associated layer.

Every one of the three convolutional layers was sifted with 128 portions of size 3×3. Normal pooling with a 2×2 channel was performed on each convolutional layer. Other than the ordinary dropout on the completely associated layer (dropout rate = 0.7), we moreover applied spatial dropout (Tompson et al., 2014) on each convolutional layer (dropout rate = 0.3). This was for our situation more fruitful in forestalling overfitting and further developing speculation. Dropout was applied on the preparation set as it were. We added a sigmoid capacity to the last layer, which is liable for the parallel characterization. The ideal design of the CNN was resolved through a heuristic experimentation measure. We carried out the CNN utilizing the R-bundle "R Interface to keras" (Chollet and Allaire, 2017) and TensorFlow backend.

IV. CONCLUSION

Convolutional Neural Networks regression models are a powerful tool to harness high resolution data acquired to predict vegetation patterns. In many cases, where spectral information is scarce or does not help in identifying the given vegetation or species, spatial patterns can be essential. This cutting-edge technique, in concert with hyper spectral remote sensing in a multi-temporal setting will pave the way toward unprecedented accuracy in future vegetation mapping. At the same time, CNN alone will revolutionize the way we use high resolution spatial imagery. The high predictive accuracies obtained in our case studies using low cost RGB sensors highlights the potential application for a wide range of users. We conclude that combining UAV and CNN will provide ground-breaking opportunities for applied vegetation mapping. Moreover, satellite images are already approaching the high spatial resolutions relevant for the methods tested in this contribution, opening up a wealth of further applications.

REFERNCES

[1] United Nations Food and Agriculture Organizarion, ”How to Feed the World in 2050”. http://www.fao.org/fileadmin/templates/wsfs/docs/expert / paper/How to Feed the World in 2050.pdf

[2] O. Elijah, T. A. Rahman, I. Orikumhi, C. Y. Leow and M. N. Hindia, ”An Overview of Internet of Things (IoT) and Data Analytics in Agriculture: Benefits and Challenges,” in IEEE Internet of Things Journal, vol. 5, no. 5, pp. 3758-3773, Oct. 2018.

[3] N. Ahmed, D. De and I. Hussain, ”Internet of Things (IoT) for Smart Precision Agriculture and Farming in Rural Areas,” in IEEE Internet of Things Journal, vol. 5, no. 6, pp. 4890-4899, Dec. 2018.

[4] H. P. Gupta, P. K. Tyagi and M. P. Singh, ”Regular Node Deployment for k -Coverage in m -Connected Wireless Networks,” in IEEE Sensors Journal, vol. 15, no. 12, pp. 7126-7134, Dec. 2015.

[5] M. G. Kibria, K. Nguyen, and G. P. Villardi, et. al, “Big Data Analytics, Machine Learning, and Artificial Intelligence in Next-GenerationWireless Networks,” IEEE Access, vol. 6, pp. 32328-32338, 2018.

[6] H. P. Gupta, S. V. Rao, A. K. Yadav and T. Dutta, ”Geographic Routing in Clustered Wireless Sensor Networks Among Obstacles,” in IEEE Sensors Journal, vol. 15, no. 5, pp. 2984-2992, May 2015.

[7] Xiao H, Zhao X, Ogai H. ”A New Clustering Routing Algorithm for WSN based on Brief Artificial Fish-School Optimization and Ant Colony Optimization”, IEEJ Transactions on Electronics, Information and Systems, 2013, Volume 133, Issue 7, Pages 1339-1349.

[8] SahTyagi, S.K., Zhou, Y., Lin, T. et al. ”Realization of a computational efficient BBU cluster for cloud RAN”. J Ambient Intelligence and Humanized Computing (2018).

[9] Zimmerman A T, Lynch J P, Ferrese F T. “Market-based resource allocation for distributed data processing in wireless sensor networks,” ACM Transactions on Embedded Computing Systems, vol. 12, no.3, pp. 1-28, 2013.

[10] S. R. Pokhrel, S. Verma, S. Garg, A. K. Sharma and J. Choi, ”An Efficient Clustering Framework for Massive Sensor Networking in Industrial IoT,” IEEE Transactions on Industrial Informatics (2020).

[11] P. Goswami, et.al., “An Energy Efficient Clustering using Firefly and HML for Optical Wireless Sensor Network,” Optik, vol. 182, pp. 181-185, 2019.

[12] S. K. SahTyagi, T. Lin and Y. Zhou, ”Thermal-Aware Dynamic Computing Resource Allocation for BBU Pool in Centralized Radio Access Networks,” 2017 IEEE 85th Vehicular Technology Conference (VTC Spring), Sydney, NSW, 2017, pp. 1-5, doi: 10.1109/VTCSpring.2017.8108488.

[13] Victor Cionca , Ramona Marfievici , Roland Katona , Dirk Pesch . “JudiShare: Judicious resource allocation for QoS-based services in shared wireless sensor networks,” in Proc. 2018 IEEE Wireless Communications and Networking Conference (WCNC), IEEE, 2018.

[14] A. Mukherjee, P. Goswami, Z. Yan, L. Yang and J. J. P. C. Rodrigues, ”ADAI and Adaptive PSO-Based Resource Allocation for Wireless Sensor Networks,” in IEEE Access, vol. 7, pp. 131163-131171, 2019.

[15] Martins F V C , Carrano E G , Wanner E F , et al. “On a Vector Space Representation in Genetic Algorithms for Sensor Scheduling in Wireless Sensor Networks,” Evolutionary Computation, vol. 22, no. 3, pp. 361–403, 2014.

[16] WenzhongGuo ,Jie Li ; Guolong Chen , YuzhenNiu , Chengyu Chen. “A PSO- Optimized Real-Time Fault-Tolerant Task Allocation Algorithm in Wireless Sensor Networks,” IEEE Transactions on Parallel and Distributed Systems, vol. 26, no. 12, pp. 3236 - 3249, 2014.

[17] K. Anusha , G.I. Shamini . “Power and resource allocation using modified binary particle swarm optimization in neural network,” in Proc. 2016 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), IEEE, 2016.
[18] Fukuda H , Leger P. “An efficient agent location management for wireless sensor networks”, in Proc. International Conference on Distributed Computing in Sensor Systems, IEEE, 2015.
[19] GuoyingC , Yan W . “Multi-mobile Agent collaborative control data separation method in wireless sensor network,” Journal of ComputerApplications, vol.34, no.4, pp.910-915, 2015.
[20] Amrit Mukherjee, et.al., “Distributed Artificial Intelligence based Cluster Head power allocation in Cognitive Radio Sensor Networks”, IEEE Sensor Letters, pp.1-4, 2019.
[21] Abdulaziz Y. B., Ismail M. K., “Energy management in wireless sensor networks based on Naive Bayes, MLP, and SVM Classifications: A comparative study”, Journal of Sensors, Hindawi vol. 2016, Pages: 1-12, 2016.
[22] Legg S, Hutter M. “Universal Intelligence: A Definition of Machine Intelligence”, Minds & Machines, vol.17, no.4, pp.391-444, 2007.