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Experimental Analysis of UAV Networks Using Oppositional Glowworm Swarm Optimization and Deep Learning Clustering and Classification

M.S. Minu[1,*], S.S. Subashka Ramesh[2], R. Aroul Canessane[3], Muhammad Al-Amin[4], Rejwan Bin Sulaiman[5]

[1,2]Department of Computer Science and Engineering, SRM Institute of Science and Technology, Ramapuram, Chennai, India.
[3]Department of Computer Science, Sathyabama Institute of Science and Technology, Chennai, Tamil Nadu, India.
[4]Department of International Relations, Sichuan University, Chengdu, China.
[5]Department of Computer Science and Technology, Northumbria University, London, United Kingdom.
msminu1990@gmail.com[1], subashka@gmail.com[2], aroulcanessane@gmail.com[3], alamin2022@stu.scu.edu.cn[4], rejwan.sulaiman@northumbria.ac.uk[5]

Abstract: Unmanned aerial vehicles (UAVs) have recently attracted numerous regards from researchers and academics. The UAV is useful in heterogeneous applications such as transportation, disaster monitoring, surveillance, etc. Because UAVs have limited internal energy, clustering can effectively balance energy consumption and load. On the other hand, scene classification on high-quality remote sensing photos captured by UAVs is difficult for UAV networks. This paper provides an Oppositional Glowworm Swarm Optimization with Deep Learning Enabled Clustering with Classification (OGSODL-CC) scheme for UAV networks in this regard. The proposed OGSODL-CC model primarily aims to cluster UAVs for energy efficiency and classification. The OGSODL-CC algorithm learns how to maximize its fitness from residual power, trust, and distance to neighbours. The scene classification model includes NASNet feature extraction and the SoftMax classifier. Many scenarios are enacted, and the results are evaluated in several regards to demonstrate the enhanced outcomes of the OGSODL-CC algorithm. The experimental results revealed that the OGSODL-CC model outperformed the previous techniques.

Keywords: Opposition Based Learning; SoftMax Classifier; Scene Classification; Clustering of Metaheuristics; Decision Range; OGSODL-CC algorithm; Unmanned Aerial Vehicles; Deep Learning Enabled Clustering with Classification.

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1. Introduction

Recently, unmanned aerial vehicles (UAV) have received considerable attention and are employed in transportation, agriculture defence, search and rescue, surveillance, and monitoring [1]. Such vehicles might cover broad fields in the area [2]. Monitoring and coordinating systems are necessary to enable the transportation system to specify the path and efficiently utilize the asset [3]. Also, The UAV technique is called a network of UAVs. It accomplishes sensing and actuating equipment to collectively implement the complex process. Coordination and cooperation among the networks of UAV swarms assist in completing complex missions across a wide region. Making decisions for the next position arises at several stages of transmission. Almost all communication between the vehicles and the control centre occurs in the air [4-5].

Several researches demonstrate and present a workable answer to the routing problem. By using the presented method, routing occurs in the cluster, and it is a fundamental mechanism for cluster transmission [6]. Several techniques are utilized to improve

[*]Corresponding author.

the network throughput, where UAV applications expand widely [7]. It affects the total efficiency of the process. Various techniques and approaches are developed for an optimum solution for UAV swarms. With this approach, network capacity can be enhanced by increasing the rate of the spatial multiplex. Due to technological advances, the communication ratio and spectrum deployment are emphasized. In recent years, several researchers have attempted to resolve the UAV swarm problem with various techniques; however, it remains a challenge. Various studies have investigated the cellular network of UAVs [8-9]. It can be essential for centralizing the control because of the higher intelligence level of UAVs [10]. Fig. 1 illustrates the structure of cluster-based UAVs.

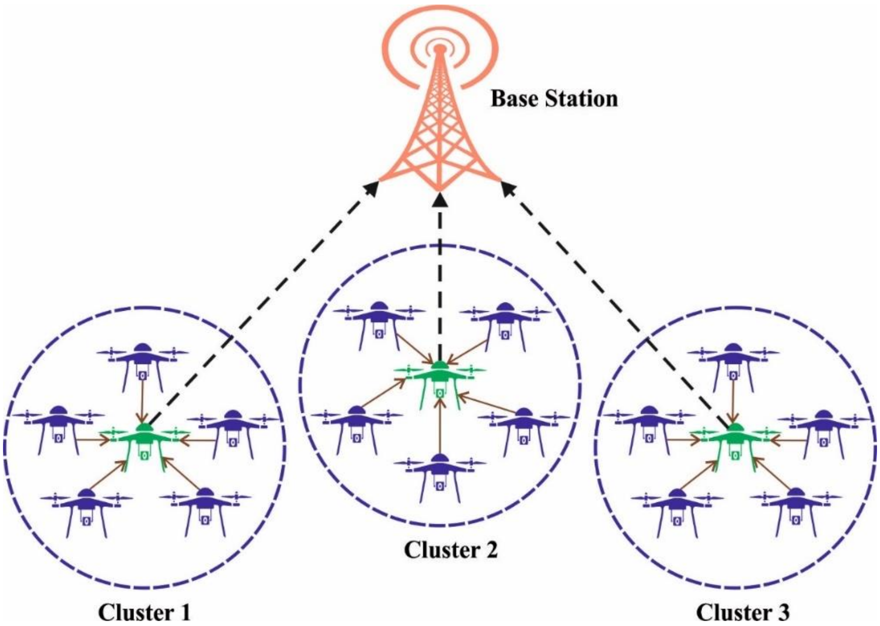

Figure 1: Cluster-based UAV

Transmission likelihood in cellular networks validated by UAVs that employ UEs in clusters was analysed using a signal-to-interference-plus-noise (SINR) ratio. Lin et al. [12] presented the utilization of hybrid compressed sampling with exacting and greedy techniques. The energy-optimum architecture uses an improved sequential scheduling strategy for the least expensive flow problem modelling. The greedy technique depended on the presented balance feature parameter containing data sparsity and distance in CH to a common node. A method of gathering hierarchical data was executed to improve node clustering efficacy.

In [13], a novel ID-based encryption-dependent information aggregate verification method named IBE-AggAuth was introduced for UAVCN. During the presented method, every type of data in distinct UAVs is verified by batch confirmation rather than “one-by-one” confirmation. In particular, it shows that an elliptic curve-based computationally Diffie-Hellman presumption obtained through the arbitrary oracle technique was essential to the existence-unforgeable security of the IBE-AggAuthapproach against the adaptive selected message and ID attack (EUF-CMA).

Mustafa Hilal [14] extracted features of several kinds of UAVs with full polarization. Afterwards, the communication with local agents (CLA) approach was utilized to overcome the difficulty of achieving target-trained instances in the real electromagnetic environment. In [15], a coalition game theoretical structure was presented for clustering UAVs as a coalition from a distributed autonomous approach dependent upon collective and movement statistics. The presented game permits the UAV with similar sets as feasible as one coalition in any constraints like cluster size and diameter.

This study presents an Oppositional Glowworm Swarm Optimization with Deep Learning Enabled Clustering with Classification (OGSODL-CC) scheme for UAV networks. The proposed OGSODL-CC model majorly intends to cluster the UAVs for energy efficiency and classification. At the primary level, the OGSODL-CC model derives the definition of fitness metrics from three different parameters: residual power, trust, and distance to neighbours. Besides, the presented scene classification model comprises NASNet feature extraction and softmax classifier. Enhanced outcomes must be shown to prove the worth of the OGSODL-CC method, and the results of various simulations executed are examined from various angles.

2. The Proposed Model

This research presented a novel OGSODL-CC technique to cluster the UAVs for energy efficiency and classification in the UAV network. Initially, the OGSODL-CC model derived a fitness function comprising three diverse input variables: residual power, trust, and distance to neighbours. Moreover, the presented scene classification model comprises NASNet feature extraction and softmax classifier.

2.1. Design of OGSO Algorithm

GSO is an intelligent swarm optimization approach which is exploited according to the luminescent feature of fireflies. In the presented technique, a glowworm (GW) swarm has been disseminated from the solution space and Fitness Function (FF) of every location of GW. The effective GW demonstrates the highest brightness, and its optimal position comprises the highest FF rate.

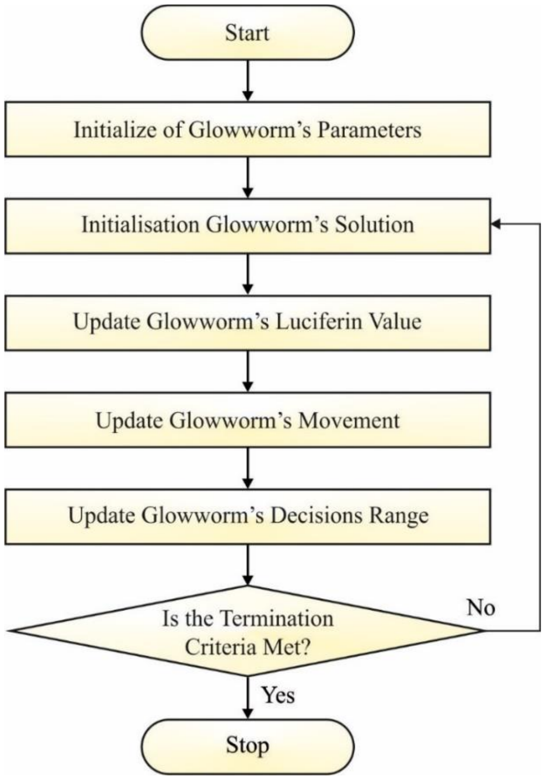

Figure 2: Flowchart of GSO technique

At the same time, the decision radius was controlled once GW travelled towards similar fluorescence in a decision domain. After attaining a higher iteration value, every GW is situated in the optimum location:

- Glowworm location
- Fluoresce in concentration
- Decision domain radius
- Neighbor set
- Moving possibility

Considering a concentrated enhancement strategy, the subsequent equation describes the fluorescence.

$$l_a(z) = (1 - \alpha)l_a(r - 1) + \beta f(x_a(z)), \qquad (1)$$

Now α shows the fluoresce in volatilization coefficients, $l_a(f)$ represents the fluoresce from the attentiveness of i^{th}GW at time f, β embodies the fluoresce in development factor, $f(x)$ indicates FF, and $x_a(r)$ symbolizes the position of GWa at f time [16],

$$N_a(t) = \{b: \|x_b(r) - x_a(z)\| < r_d^a; l_a(z) < l_b(z)\}, \qquad (2)$$

Here, characterizes the radius of the decision field of a^{th}GW at the moment f, $N_a(f)$ signifies the neighbouring group of a^{th}GW at time r and $r_d^a(r)$that is offered as:

$$r_d^a(z+1) = \min\{r_s, \max\{r_d^a(z) + \gamma(n_a - |N_a(z)|)\}\}, \quad (3)$$

In which, γevidences the importance of domains of choice, r_s characterizes the radius of GW, and n_i represents the neighbouring threshold. The dynamic potential of advanced technology is displayed as:

$$p_{ab}(r) = \frac{l_b(z) - l_a(z)}{\sum_{k\in N_z} l_k(z) - l_a(r)}, \quad (4)$$

In the equation, $p_{ab}(z)$ characterizes the possibility of GWa travel to the GWb at r time as follows. Fig. 2 illustrates the flowchart of the GSO technique [17].

$$x_a(z+1) = x_a(z) + s\left(\frac{x_v(z) - x_a(z)}{\|x_b(z) - x_a(z)\|}\right), \quad (5)$$

Opposition-based Learning (OBL) was widely applied by improved resolution rates for heuristic optimization modules using a practical optimization approach.

The effective performance of OBL contributed to assessing opposite and existing populations from similar generations to recognize optimum candidate solutions. The OBL model is effectively applied in dissimilar meta-heuristics to enhance the convergence speed. It could be demonstrated in the following equation.

Assume $N \in N[a,b]$stands for a true quantity. Opposite to the quantity N^0 is shown as follows

$$N^o = a + b - N \quad (6)$$

When the query area has d measurements, the clarification is expanded as follows:

$$N_i^o = a_i + b_i - N_i \quad (7)$$

Now $(N_1, N_2, .. N_d)$ indicates the d-dimension searching space and $N_i[a_i, b_i], i = 1,2,..,d$. OBL method was applied from the initiation procedure of the GSO technique and for each iteration from the application of the jumping rate.

2.2. Application of OGSO Algorithm for Clustering

In this study, the OGSO algorithm has been derived for effectual choice of CHs. The OGSODL-CC model attains FF by using three input parameters: distance to neighbours, energy to CH choice, and trust level.

Distance to neighbours. There should be as little space as possible between each car in the CH you choose during the intra-cluster transmission procedure, sensor vehicle energy utilization, and CH communication. Keeping vehicles as far apart as possible can lessen the strength of communication inside a cluster.

$$f_1 = \sum_{j=1}^{m} \frac{1}{l_j}\left(\sum_{i=1}^{l_j} dis(CH_j, s_i)\right) \quad (8)$$

Trust factor (TF): Initially, the entire vehicle was described as TF is one. Whenever the car does an unconventional job and is labelled a malevolent vehicle, the value of TF is dropped due to the aberrant forecasting component.

$$f_2 = \sum_{j=1}^{m} \frac{1}{m}(TF_j) \quad (9)$$

Energy: It can be a count of power utilization, namely CHs to RE of CHs. Meanwhile, the CH utilizes minimal power usage, namely process, sense, and broadcast procedure with maximum RE, which is collected as minimal power to weight. As a result, the selectivity of CH increases as the power ratio decreases.

$$f_3 = \sum_{j=1}^{m} \frac{E_c(CH_j)}{E_R(CH_j)} \quad (10)$$

Minimizing the desired function's linear transformation throughout this procedure is critical. This led to the following implementation of the potential power function in a SHPC-SEMD fashion:

$$Minimize\ Potiential\ energy\ function = \alpha_1 \times f_1 + \alpha_2 \times f_2 + \alpha_3 \times f_3 \quad (11)$$

Where $\alpha_1 + \alpha_2 + \alpha_3 = 1, \alpha_2 \geq (\alpha_1 + \alpha_3). Also\ 0 < f_1, f_2, f_3 < 1$.

Algorithm 1: Pseudocode of GSO Algorithm

Initializing m dimension
Initializing of n glowworm
Consider s as step size
Assume $x_i(t)$ signifies glowworm location i at time t
Send out agents at random
$deploy - agents\_randomly$;
for $i = 1$ to n do $I_i(0) = \ell_0$
$r_d^i(0) = r_0$
Consider maximum iterations= max_$iter$;
set $t = 1$;
while $(t \leq \max\_iter)$ do:
{
for all glowworms i do:
$I_\mathrm{i}(\mathrm{t}+1) = (1-\rho) * I_\mathrm{i}(\mathrm{t}) + \gamma * F(\mathrm{x_i}(\mathrm{t}+1))$;
for every glowworm i do:
{
$N_i(t) = \{j : d_{ij}(t) < r_d^i(t); I_i(t) < I_j(t)\}$;
for every glowworm j do:
$p_{ij}(t) = \frac{I_j(t) - I_i(t)}{\Sigma m \in N_i(t) I_p(t) - I_i(t)}$;
$j = choose\_glowworm(\vec{p})$;
$x_i(t+1) = x_i(t) + s * \left(\frac{x_j(t) - x_i(t)}{\lVert x_j(t) - x_i(t) \rVert}\right)$
$r_d^i(t+1) = \min\left\{r_s,\ \max\left\{0, r_d^i(t) + \beta(n_t - \lvert N_i(t) \rvert)\right\}\right\}$;
}
$t \leftarrow t + 1$;
}

2.3. Scene Classification Model

For effectual categorization of scenes, the proposed OGSODL-CC model derives a scene classification model involving two major steps, namely NasNet-based feature extraction and SM classifier. The NASNet Mobile model is a recently established DL model with 53,26,716 parameters. It demonstrates excellent dependability. The building block of the NASNet architecture is the block, and a set of blocks are collectively combined into a cell.

The factorization of the system into units, as well as the splitting of the system into blocks, constitutes the method of searching space used by the NASNet. The type and number of blocks or cells are not predetermined [18]. But they should be enhanced for the selected dataset [19].

The probable function of the block encompasses separable convolution, convolution, average pooling, identify map, max pooling, and so on [20]. The block can map two inputs into output feature mapping [21-22]. The network progression is concentrated on three features: cell stack height (N), cell infrastructure (F), and the number of primary layer filters (F).

SM layer is considered an outstanding technology for demonstrating categorical distribution. The SM function, mainly utilized in the output layer, is a normalized exponent of the output value [23-24]. This function is distinguishable and signifies a specific possibility of the output. Furthermore, the exponential element raises the maximal value probability:

$$o_i = \frac{e^{z_i}}{\sum_{i=1}^{M} e^{z_i}}, \tag{12}$$

In which z_i represent the output i beforehand the SM, M indicates the overall amount of output nodes and 0_i denotes the SM output number i.

3. Results and Discussion

In this section, the verification of experiments of the OGSODL-CC algorithm is executed, and the results are examined under several rounds of execution [25]. Table 1 and Fig. 3 illustrate a brief energy consumption (ECM) assessment of the OGSODL-CC model updated using modern techniques [26]. The experimental outcome demonstrated that the OGSODL-CC technique has outshined the various techniques with minimal ECM values. For the sample, with 100 rounds, the OGSODL-CC model has attainable minimal ECM of 17.95mJ while the T2FL, KH, MPSO, and TIFL models have attained higher ECM of 24.33mJ, 27.13mJ, 30.72mJ, and 35.51mJrespectively [27-29]. Moreover, with 500 rounds, the OGSODL-CC method has obtainable lesser ECM of 96.16mJ while the T2FL, KH, MPSO, and TIFL approaches have gained higher ECM of 108.13mJ, 123.29mJ, 133.66mJ, and 143.64mJ correspondingly [30].

Table 1: Energy Consumption Analysis of OGSODL-CC Technique with Recent Algorithms

Rounds	OGSODL-CC	T2FL Algorithm	KH Algorithm	MPSO Algorithm	TIFL Algorithm
100	17.95	24.33	27.13	30.72	35.51
200	38.70	48.27	59.05	60.24	65.83
300	57.45	69.02	79.00	88.18	94.56
400	74.21	79.40	97.75	105.33	114.91
500	96.16	108.13	123.29	133.66	143.64

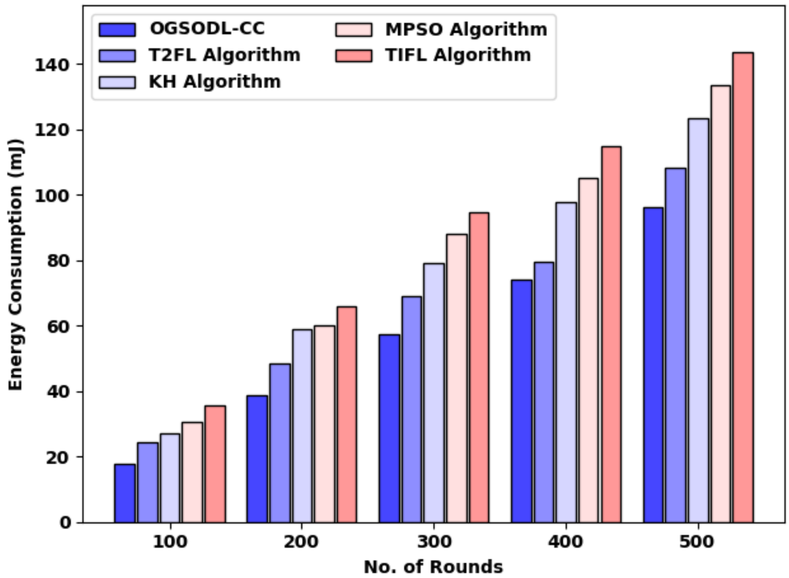

Figure 3: ECM evaluation of OGSODL-CC model with recent procedures

Table 2 and Fig. 4 exemplify a quick end-to-end delay (ETED) inspection of the OGSODL-CC model with up-to-date approaches [31]. The experimental outcome indicated that the OGSODL-CC system outperformed the other methods with minimal ETED values [32]. For the sample, with 100 rounds, the OGSODL-CC approach has accessible reduced ETED of 1.11sec whereas the T2FL, KH, MPSO, and TIFL techniques have attained maximal ETED of 1.60sec, 2.03sec, 2.13sec, and 2.25sec correspondingly [33-36].

Table 2: End-to-End Delay Analysis of OGSODL-CC Technique with Recent Algorithms

Rounds	OGSODL-CC	T2FL Algorithm	KH Algorithm	MPSO Algorithm	TIFL Algorithm
100	1.11	1.60	2.03	2.13	2.25
200	1.68	2.29	2.49	2.90	3.67
300	2.13	2.84	3.18	3.97	4.70
400	2.72	3.53	4.18	6.23	5.80
500	3.83	4.87	5.58	6.42	6.94

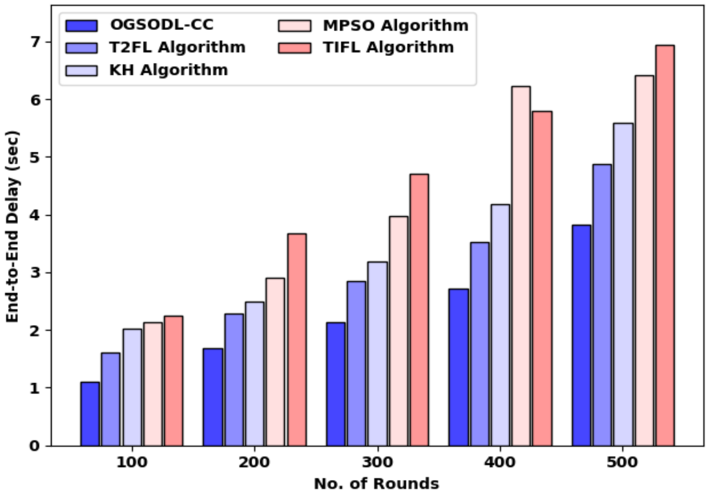

Figure 4: ETED Evaluation of OGSODL-CC Model with Recent Procedures

Furthermore, after 500 iterations, the OGSODL-CC method provides the lowest ETED of 3.83s, while the T2FL, KH, MPSO, and TIFL procedures all achieve higher ETEDs of 4.87s, 5.58s, 6.42s, and 6.94s, correspondingly [37-41].

A detailed throughput (THRP) evaluation of the OGSODL-CC method with existing methods is executed in Table 3 and Fig. 5. The experimental values implied that the OGSODL-CC method has improved THRP values over the existing models.

Table 3: Throughput Evaluation of OGSODL-CC Method with Recent Procedures

Rounds	OGSODL-CC	T2FL Algorithm	KH Algorithm	MPSO Algorithm	TIFL Algorithm
100	1008	978	966	941	905
200	985	945	903	846	785
300	927	893	861	766	705
400	890	864	787	709	623
500	867	803	711	636	570

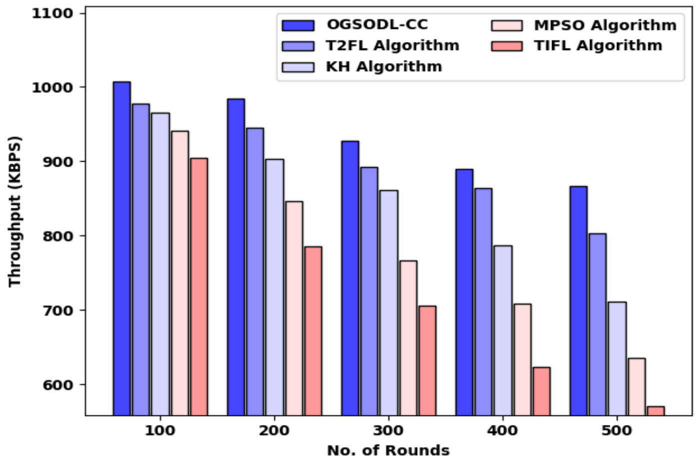

Figure 5: Throughput analysis of the OGSODL-CC method with recent algorithms

For instance, with 100 rounds, the OGSODL-CC model has gained an increased THRP of 1008kbps while the T2FL, KH, MPSO, and TIFL models have attained reduced THRP of 978kbps, 966kbps, 941kbps, and 905kbps respectively. Furthermore, with 500 rounds, the OGSODL-CC approach has developed a higher THRP of 867kbps, whereas the T2FL, KH, MPSO, and TIFL techniques have attained reduced THRP of 803kbps, 711kbps, 636kbps, and 570kbps correspondingly [42-47].

Fig. 6 provides a detailed comparative study of the OGSODL-CC method with recent methods in terms of $accu_y$. According to the data provided by PlaceNetas well, VGG-VD19 models have reached minimal values of $\mathrm{accu_y}$. In addition, the VGG-VD16, VGG-S, VGG-M, and VGG-F models have attained slightly improved values of $\mathrm{accu_y}$, Followed by the CaffeNet, AlexNet, DL-MOPSO, and C-PTRN models, have reached equitable performance with closer $accu_y$values. Results from the OGSODL-CC model, on the other hand, have been effective, with a maximum $accu_y$ of 99.18% [48-53].

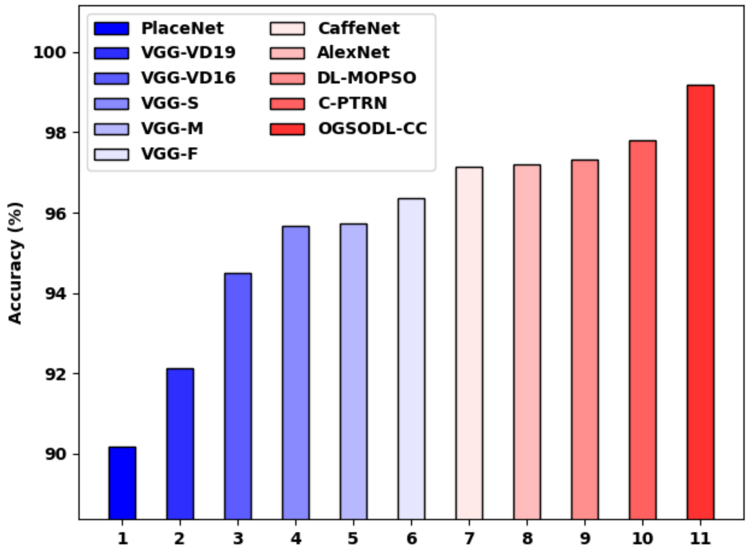

Figure 6: Accuracy analysis of the OGSODL-CC method with recent procedures

Fig. 7 offers a detailed analysis by comparison of the OGSODL-CC algorithm with recent techniques in terms of$prec_n$, $reca_l$, and F_{score}. The figure reported that the GoogLeNet-RBFNN and CA-ResNet-BiLSTM models had reached minimum values of $prec_n$, $reca_l$, and F_{score}. Moreover, the CA-GoogLeNet-LSTM, VGG-RBFNN, GoogLeNet, and CA-ResNet-LSTM models have attained slightly improved values of $prec_n$, $reca_l$, and F_{score}, Afterward, the VGGNet, CA-VGG-BiLSTM, CA-GoogLeNet-BiLSTM, CA-VGG-LSTM, and C-PTRN approaches have reached reasonable performance with closer $prec_n$, $reca_l$, and F_{score} Values. At last, the OGSODL-CC methodology has resulted in an ineffectual outcome with maximum $prec_n$, $reca_l$, and F_{score} of 99.07%, 99.27%, and 99.29% [54].

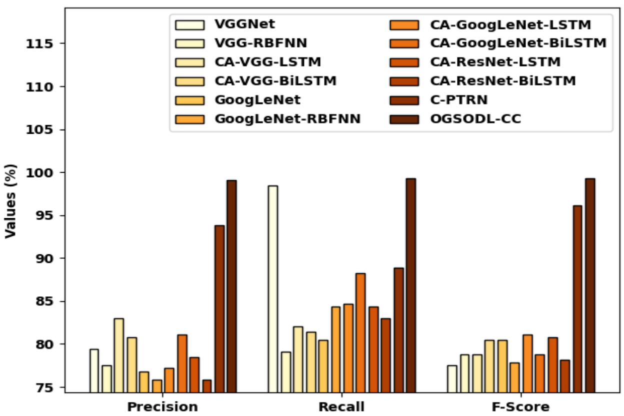

Figure 7: Comparative analysis of OGSODL-CC technique with recent algorithms

After observing the detailed experimental outcomes, it can be stated that the OGSODL-CC approach has produced the best performance compared to the alternative options. The experimental outcomes exhibit the betterment of the OGSODL-CC method compared to the current methods. Thus, the OGSODL-CC model can be employed to enhance the overall performance of the UAV networks.

4. Conclusion

This study suggests a new OGSODL-CC approach for clustering unmanned aerial vehicles (UAVs) in the UAV network with the purpose of improving energy efficiency and categorization. In the beginning, the OGSODL-CC model was able to derive a fitness function that was composed of three different input factors. These variables were residual power, trust, and distance to local neighbours. Additionally, the NASNet feature extraction and softMax classifier are both components of the scene classification model that has been described there. In order to demonstrate the improved results that may be achieved through the application of the OGSODL-CC technique, a large number of simulations are executed, and the results are analysed from a variety of perspectives. This was proved by the results of the studies, which showed that the OGSODL-CC model performed far better than the newest techniques. Therefore, the OGSODL-CC model is a practical option that can be utilised to improve the overall performance of the UAV networks. In order to further improve the UAV networks, it is possible to incorporate models for the accumulation of information and the compression of data.

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