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Evaluation of the Factors Affecting the Efficiency of Some Modified Firefly Algorithms

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ABSTRACT

Firefly Algorithms (FA) is one of the nature-inspired metaheuristic algorithms used in solving modern global optimization problems. Several Modified Firefly Algorithms (MFA) have been developed to overcome the lapses of the standard FA, however, critical factors which determine the performance of these MFA have not been adequately evaluated. This research evaluates the critical factors which determine the efficiency of four MFAs: Chaotic, Parallel, Binary, and Gaussian in the classification of mammographic test. Eighty-four mammographic data samples were obtained from the Wisconsin Breast Cancer Database. Simulation experiments were carried out by applying Chaotic, Parallel, Binary, and Gaussian Firefly algorithms on the data samples. The outcome of the experiments was subjected to principal component analysis by computing the mean and standard deviation of variables. The variables were normalized and correlation metric computed. Eigen values of correlations and sum of squares were used to arrive at percentage of variance. The percentage of variance form the basis for estimating the level of contribution of three critical factors: Light Intensity (LT), Distance Dependence (DD), and Randomization Term (RT) on the performance of the selected MFAs. The performance of Chaotic, Parallel, Binary, and Gaussian factors algorithms was evaluated based on Percentage of Variance. The percentage of variance for Chaotic Firefly algorithm based on LI, DD, and RT were 88.20, 11.24, and 0.56%, respectively, while the corresponding values for Parallel Firefly algorithm were 86.20, 11.79 and 2.00%, respectively. Furthermore, the percentage of variance for Binary Firefly algorithm based on LI, DD, and RT were 85.21, 13.01, and 2.00%, respectively, while the corresponding values for Gaussian Firefly algorithm were 67.81, 29.25 and 2.94%, respectively. Light Intensity was discovered to be the most critical factor while Chaotic Firefly algorithm was the most effective Modified Firefly Algorithm.

Key words: Firefly, Binary, Gaussian, parallel, Chaos, PCA, Light Intensity, Randomness, Eigenvalue, optimization.

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1. INTRODUCTION

Optimization is the process of using a parameter in a function to make a better solution. This process may involves algorithm such as deterministic or stochastic algorithm. Deterministic algorithm is quite efficient in finding local optimal because it follows a rigorous procedure, and its path and values of both design variables and the functions are repeatable (Farahani *et al.,* 2011).Stochastic algorithms often have a deterministic and a random componentswhich are divides into heuristic and meta-heuristic. In heuristic algorithm, the quality solutions for tough optimization problems can be found, but there is no guarantee the solution is optimal (Nadhirah *et al.,* 2004). Meta-heuristic algorithm is better than heuristic because the search process is randomization and local search as well as provides acceptable solution (Yang, 2010). Nature-inspired meta-heuristic algorithms such as firefly algorithm are becoming powerful in solving modern global optimization problems and its superiority over the traditional algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Ant Bee Colony (ABC) was confirmed (Yang, Ukasik and Salawormiz, 2009). Firefly algorithm is a nature-inspired metaheuristic approach based on the behavior of fireflies (Olusi et al., 2025). The Firefly algorithm is well known for its efficiency in solving optimization problems, including feature selection, where irrelevant or redundant features are discarded to improve the performance of models (Olusi et al., 2021).
Thus, this study evaluates the performance of modified fireflies algorithm by determining the most critical factor which affect the efficiency of binary, gaussian, parallel and chaos modified firefly techniques.

2. LITERATURE REVIEW

2.1 Firefly Algorithm
Firefly is characterized by their flashing light produced by biochemical process bioluminescence from light producing organs called lantern (Iztok *et al.,* 2013). The function of the flashing light is to attract partners (communication) or attract potential prey and as a protective warning toward the predator. Firefly is attracted toward the other firefly that has brighter flash than itself. The attractiveness is depended with the light intensity (Yu, Yang and Su, 2013). Intensity of light is the factor of the other fireflies to move toward the other firefly. It varies at the distance from the eyes of the beholder. The light intensity is decreased as the distance increase (Yang, 2010). Firefly algorithm has two important variables; light intensity and attractiveness (Tilahun and Ong, 2012).

This algorithm is based on a physical formula of the light intensity I that decreases with the increase in the square of the distance r^2 (Iztok *et al.,* 2013). Firefly algorithm uses the three rules according to (Raed *et al.,* 2017) as stated: A firefly is attracted to other fireflies regardless of their sex, because all fireflies are unisex. Attractiveness is proportional to their brightness, thus for any two flashing fireflies, the less bright one will move towards the brighter one (both attractiveness and brightness are decreasing as the distance between the two fireflies' increases, if no one is brighter than a particular firefly, then it moves randomly). The brightness or light intensity of a firefly is determined by the objective function of the optimization problem. According to Yang (2010), the light intensity thus attractiveness is inversely proportional with the particular distance r from the light source. Thus the light and attractiveness is decrease as the distance increase;

$$l_{(r)} = I_0 e^{-\gamma r^2} \tag{1}$$

where I = light intensity
I_0 = light intensity at initial or original light
γ = light absorption coefficient
r = distance between fireflies i and j

The singularity at $r=0$ in the expression $1/r^2$ is avoided by combining the effects of the inverse square law and an approximation of absorption in Gaussian form.The attractiveness β of fireflies is proportional to their light intensity $I(r)$.Therefore, equation similar to equation (1) can be defined, in order to describe the attractiveness β as shown in equation (2).

$$\beta = \beta_o e^{-\gamma r^2} \tag{2}$$

where β_o is the attractiveness at $r = 0$. The light intensity I and attractiveness β are directly proportional as seen by another fireflies and β is that attractiveness. The distance between two fireflies *i* and *j* is expressed as the Euclidean distance by the base firefly algorithms as shown in equation (3).

$$r_{i,j} = \left|x_i - x_j\right| = \sqrt{\sum_{k=1}^{d}\left(x_{i,x} - x_{j,x}\right)^2} \tag{3}$$

where *d* denotes the dimensionality of the problems. Firefly *i* is attracted towards the more attractive firefly *j.* The movement of firefly *i* and firefly *j* is defined as equation (4).

$$\Delta x_i = \beta_0 e^{-\gamma r_{i,j}^2}\left(x_j^t - x_i^t\right) + \propto \text{Ƶ}_i, \qquad x_i^{t+1} + \Delta x_i \tag{4}$$

Binary firefly algorithm uses a binary encoding of the candidate solutions, an adaptive light absorption coefficient γ for accelerating the search within the population (Falcon, Almeida and Nayak, 2011). The binary firefly algorithm are similar to standard firefly except changes in the direction of movement of the fireflies which separate the hyper plane into two. According to Raed *et al*. (Raed *et al*., 2017). Gaussian firefly algorithm makes use of vector of random walks drawn from a Gaussian distribution. Gaussian firefly algorithm can get rid of being trapped in several local optimum because of directed movement of firefly. A random walk is a process that consists of a series of the consecutive random step (Farahani *et al.,* 2011). This algorithm applies three behaviors to improve performance of firefly algorithm which are; adaptive step length, directed movement towards global best and social behavior of fireflies that changes position based on Gaussian distribution (Yang, 2010).

Parallel firefly approach is used to create a distributed firefly algorithm. The number of fireflies will be distributed into N-subordinates while the main firefly will be in charge of information exchange during the operation (Gabriel *et al.,* 2010). A modified parallel graphical processing unit was proposed by (Husselmann *et al*., 2012). The standard benchmark functions were taken for comparison with classical firefly. The results of the parallel FA were more accurate and faster but this was valid only for multimodal functions.

Chaos is a deterministic, random-like process found in nonlinear, dynamical system, which is non-period, ergodic, non-converging and bounded that it depends on its initial condition and control parameters (Ming, Juan and Huanwen, 2004)).

Chaotic algorithm uses chaotic sequences to fine tune the α and γ. In these algorithms, due to the non-repetition and ergodicity of chaos, it can carry out overall searches at higher speeds than stochastic searches that depend on probabilities (Yang, 2014). Recently chaos is extended to various optimization areas because it can more easily escape from local minima and improve global convergence in comparison with other stochastic optimization algorithms (He *et al.,* 2001). Using chaotic sequences in Firefly Algorithm can be helpful to improve the reliability of the global optimality, and also enhance the quality of the results. The original equation of the firefly algorithm is modified to equation (5) (Strogatz, 2001).

$$x_{\boldsymbol{i}} = x_{\boldsymbol{i}} + \beta_{\boldsymbol{0}} e^{-\boldsymbol{\gamma}(\boldsymbol{t}).\boldsymbol{r}_{ij}^{2}}\left(x_{\boldsymbol{j}} - x_{\boldsymbol{i}}\right) + \alpha(t)\left(rand - \tfrac{\boldsymbol{1}}{\boldsymbol{2}}\right) \quad (5)$$

with

$$\gamma(t) = \mu_1.\gamma(t-1).[1-\gamma(t-1)] \quad (6)$$

2.2 Principal Component Analysis

The Principal Component Analysis (PCA) is often been confused with Exploratory Factor Analysis (EFA), similar statistical procedures are used by both but are not the same (Decoster, 1998). The two procedures will produce different results when applied to the same data. The purpose of PCA is to derive a small number of components that can account for the variations found in a large number of measures. This is called data reduction which is typically performed when a researcher does not want to include all the original data in analysis but still want to work with the information contains in it. The steps involved in determining the PCA are as follows (Raj, 1991):

Compute the mean and standard deviation of the variables

$$\text{mean (X)} = \frac{\text{i}}{\text{n}}\sum_{\text{i}=1}^{\text{n}} \text{x}_\text{i} \quad (7)$$

where X represent mean, n is number of occurrences and x_i is the variables

$$\text{standard deviation } \left(\text{s}_\text{i}^2\right) = \frac{1}{\text{n}-1}\sum_{\text{i}=1}^{\text{n}} (\text{x}_\text{i} - \text{X})^2 \quad (8)$$

where s_i^2 represent standard deviation, n is the number of occurrence,x_i is the variables and X is the mean

i. Normalize the variables to zero mean and unit standard deviation.

$$\mathrm{x}_\mathrm{i}^1 = \frac{\mathrm{x}_\mathrm{i} - \mathrm{X}}{\mathrm{s}_\mathrm{i}} \tag{9}$$

where x_i^1 represent the normalize values, X the mean, x_i the number of occurrences and s_i is the standard deviation.

ii. Compute the correlation among the variables

$$R_{x_i,x_r} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_{si} - X_s)(x_{ri} - X_r)}{s_i s_r} \tag{10}$$

where X_s represent the mean, $s_i s_r$ the standard deviation, X_r the number of observation.

iii. Prepare the correlation matrix
iv. Compute the eigenvalues of the correlation matrix by solving the characteristics equation

$$Det\ (\pi - \pi I) = \ |\lambda I - C| \tag{11}$$

where λ is the eigenvalues, I the identity matrix and C the correlation matrix

v. Compute the eigenvectors of the correlation matrix.

$$C\lambda = \lambda q \tag{12}$$

vi. Obtain principal factors by multiplying the eigenvectors by the normalized vectors in step (ii).
vii. Compute the sum and sum of squares of the principal factors
viii. Plot the values of principal factors.

2.3 Review of Existing Works

Yang (2009) provided a detailed description of the new firefly algorithm FA) for multimodal optimization applications. The proposed firefly algorithm was compared with other metaheuristic algorithms such as particle swarm optimization (PSO). Simulations and results indicated that the proposed firefly algorithm is superior to existing metaheuristic algorithms (Firefly 2). Yang (2010) formulated a new meta-heuristic FA using levy flights move strategy. Numerical studies and results suggested that the proposed levy flight FA was superior to PSO and GA in terms of efficiency and success rate, but mathematically understanding of these algorithms remained a mystery. Also, Gandomi *et al.*(2010) used FA for solving mixed continuous or discrete structural optimization problems taken from welded beam design, pressure vessel design and car side impact design, the optimization results indicated that FA is more efficient than PSO, simulated annealing and GA (firefly 4). Sayadi *et al.*(2010) proposed new discrete FA for minimizing the makespan for the permutation of flow shop scheduling problem(NP-hard Problem). The results showed significant improvement and performed better over existing techniques.

Farahani, Abshouri and Meybodi (2011) proposed Gaussian FA for solving optimization problems. FA used Gaussian distribution to move all fireflies to global best in each iteration. The algorithm was tested on five standard functions. Experimental results show better performance and more accuracy than standard FA (Farahani *et al.,* 2011). Leandro, Diego and Viviana (2011) introduced a modified FA approach combined with chaotic sequences (FAC) applied to reliability-redundancy optimization. Mixed integer programming in reliability-redundancy design of an overspeed protection system for a gas turbine was evaluated. FAC outperformed previously best known solutions available (Leandro and Diego, 2011). Also, Palit (2011) proposed a binary FA for cryptanalysis in order to determine the plain text from the cipher text using Merkle-Hellman Knapsack cipher algorithm. The results showed that proposed algorithm was more efficient than GA.

Yang (2011) provided an overview of convergence and efficiency studies of meta-heuristics and framework for analyzing meta-heuristic in terms of convergence and efficiency. Three well known heuristics were also analyzed namely; SA, PSO and GA. The results showed that newly developed provided a balanced trade-off between local exploitation and global exploration. Luthra *et al.*(2011) proposed hybridized FA for cryptanalysis of the mono-alphabetic substitution cipher with operators of mutation and crossover. The results showed that the algorithm worked better for large input cipher text length while with short input gave unconvincing results. Also, Khadwilard *et al.*(2011) developed FA for solving the job shop scheduling problem (JSSP). A computational experiment was conducted using five benchmark datasets of JSSP instance. The FA found the best known solution but get trapped into local optima.

Chandrasekaran (2012) proposed binary coded FA for solving network and reliability constrained unit commitment (UC) problem without satisfying the network security constraints. The effectiveness of the proposed algorithm was demonstrated on 10 unit of IEEE-RTS system. The results of the proposed algorithm were promising compared to other techniques. Subotic *et al.*(2012) developed parallelized FA for constrained optimization problems tested on standard benchmark functions. The result of the speed and quality was placed by the author. The parallelized FA obtained better results over much less execution time. The result was valid only when more than one population was taken into account. Abdullah *et al.*(2012) proposed a hybrid evolutionary firefly algorithm (HEFA) that combined the classical firefly with the evolutionary operations of the differential evolution method in order to improve searching accuracy and information sharing among the fireflies .The experimental results showed that thr accuracy and speed performance of HEFA had significantly outperformed the results produced by the GA, PSO and evolutionary programming.

Farahani (2012) proposed three classes of algorithms for improving the performance of the classical firefly algorithm. Learning automata were used for adapting the absorption and randomization parameters in the first class. The second class hybridized the genetic algorithm with FA to balance exploration and exploitation. Random walk based on Gaussian distribution to move the fireflies over the search space was used in the last class. The experimental results on five benchmark functions showed that the proposed algorithms were highly competitive with classical FA and PSO. Abedinia *et al.*(2012) developed multi-objective FA for an environmental/ economic power dispatch (EED) problem. The proposed algorithm run on the IEEE 30 and 118-bus systems. The results demonstrated feasibility for solving multi-objective EED problem when compared with other known multi-objective algorithms.

Coelho *et al*. (2013) proposed a combination of FA with chaotic maps to improve the convergence of the classical firefly algorithm. The proposed firefly algorithms used chaotic maps by tuning the randomized parameter α and light absorption coefficient γ. Reliability-redundancy optimization were used as benchmark to test the efficiency of this method. Simulation results revealed that proposed algorithm outperformed the previously best –known solutions available (Coelho, Bernert and Mariani, 2013). Gandomi *et al*.(2013) introduced chaos into FA to increase global search mobility for robust global optimization. The author analyzed the influence of using 12 different chaotic maps on the optimization of benchmark function. The results showed that chaotic FA outperformed classical FA.
Olabiyisi, Aladesae, Oyeyinka and Oladipo (2013) evaluated the efficiency of searching algorithms using factor analysis by principal component. The search time, distance dependence and number of comparison were used as decision variables to evaluate their efficiencies. The result showed that number of comparisons is the most critical factor affecting the searching techniques and binary search is the most efficient search technique. The search algorithms considered have limited applicable areas.

Nadhirah (2014) did a comprehensive review on the modification and hybridization of the firefly algorithm (Firefly5). Amarita *et al.(*2014) proposed an improvement on the original firefly algorithm. The proposed algorithm takes into account not only the firefly's reaction to light but also the following contributing factors: firefly's gene exchange, its pheromone, and the impact the wind has on pheromone dispersion. The proposed algorithm was tested against the traditional firefly algorithm and the original genetic algorithm with six standard benchmark functions and found that proposed algorithm is not only more effective but also faster than the other two algorithms.

Osama, Mohamed and Ibrahim (2014) presented an improved firefly algorithm with chaos (IFCH) for solving definite integral. The IFCH satisfies the question of parallel calculating numerical integration in engineering and those segmentation points are adaptive. Several numerical simulation results show that the algorithm offers an efficient way to calculate the numerical value of definite integrals, and has a high convergence rate, high accuracy and robustness. Krishna and 1qbal (2015) implemented bat algorithm (BA) and FA using chaotic sequence and levy flight. These two algorithms were applied to optimize parameters of parameterized high boost filter, entropy, number of edges pixel. The experimental results showed that BA with chaotic levy outperformed FA via chaotic levy.

Raed *et al.(*2017) implemented FA to find best decision hyper-plane in the feature space. The proposed classifier used cross-validation of 10- fold portioning for training and testing phases used for classification. Five pattern recognition binary benchmark problems were used to demonstrate the effectiveness of the proposed classifier. The experimental results indicated that FA classifier shows better results over the other algorithms in the experiment performed (Binary Journal). Gabriel *et al.*(2018) introduced the distributed computing concept to an optimized version of the firefly algorithm. The proposed distributed version show remarkable superiority over the regular existing algorithm.
However, various authors have demonstrated the performance of the different modified firefly algorithms in solving different optimization problems such as continuous, constraint, multi-objective and engineering applications. However, the level of contribution at which each factor affecting the performance of modified firefly algorithm is still open for discussion and not fully investigated. Therefore, this research will evaluate the performance of these factors affecting the efficiency of different modified firefly algorithms using principal component analysis.

3. METHODOLOGY

3.1 The Approach

The four selected variant of modified firefly algorithms will be implemented using MATLAB 2014 version. Binary, Gaussian, parallel and chaos modified fireflies algorithms were applied using different population size on the Wisconsin Breast Cancer (WBC) database. The underlying factors that influence the performance of the modified firefly algorithms were determined. The critical factors that were considered are light intensity, distance dependence sand randomization term.

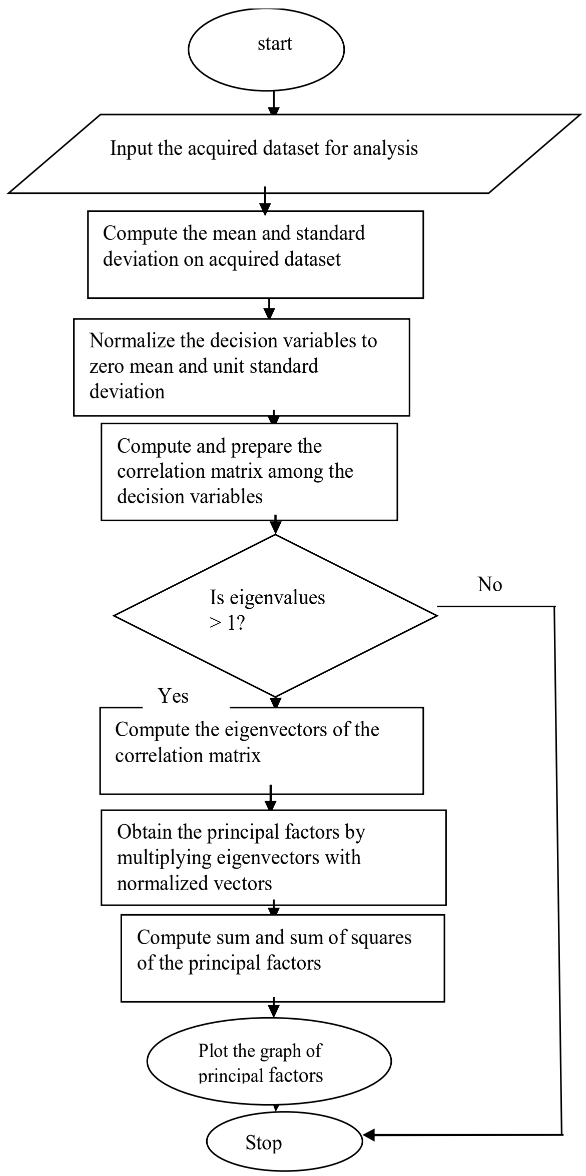

Figure 1: Flowchart of PCA as Factor Analysis Technique

These three factors are interdependence and critical to the efficiency of the modified firefly algorithms. Also, the level at which each of these factors contributed to the performance of the firefly algorithms differs as well. The parameters used for this study were set as number of fireflies *n*, attractiveness β_0, light absorption coefficient γ and randomization α. The amount of fireflies to perform this evaluation was 100 individuals (population size) and max generation was set at 1000.

For each of the modified firefly algorithm, data were obtained based on the factors considered which are light intensity, distance dependence and randomization term adopting the mathematical models (equations) as stated in section 1.2.1. The results of each of the binary, Gaussian, parallel and chaotic firefly algorithms were obtained for the light intensity, distance dependence and randomization term. The factor analysis by principal component was performed by adopting the mathematical model (equations) in section 1.2.2; on the results obtained for further statistical analysis to establish the level of contribution of each factor towards the performance of the different aforementioned modified firefly algorithms to validate the most critical factor. The flow chart to explain the generation and validation of eigenvalue of the extracted (most critical) factor; is presented in Figure 1.

4. RESULTS AND DISCUSSION

Descriptive statistics show the mean and standard deviation of the rating of the impact of the light intensity, distance dependence and randomization term on the efficiency of firefly algorithms by the experimental results. For instance, mean and standard deviation for binary firefly on light intensity, distance dependence and randomization term are (65.9443, 7.0053), (1815.7143, 1465.6270) and (88.3557, 24.0639) respectively. The mean and standard deviation of Gaussian on rating of light intensity, distance dependence and randomization term are (55.2171, 5.3987), (1544.2857, 1285.4553) and (68.4357, 20.7530) respectively.

Table 1a: Descriptive Statistics of Binary Firefly

	Mean	Std.Deviation	N
Light intensity	66.9443	7.0053	7
Distance dependence	1815.7143	1465.6270	7
Randomization term	88.3557	24.0639	7

Table 1b: Descriptive Statistics of Gaussian Firefly

	Mean	Std.Deviation	N
Light intensity	55.2171	5.3987	7
Distance dependence	1544.2857	1285.4553	7
Randomization term	68.4357	20.7530	7

Table 1c: Descriptive Statistics of Parallel firefly

	Mean	Std.Deviation	N
Light intensity	47.4757	8.3932	7
Distance dependence	1279.2857	1111.4950	7
Randomization term	68.3014	19.5001	7

Table 1d: Descriptive Statistics of Chaotic firefly

	Mean	Std.Deviation	N
Light intensity	41.3443	10.1021	7
Distance dependence	1072.8571	931.2127	7
Randomization term	60.4314	18.4726	7

In Parallel search, mean and standard deviation on rating of light intensity, distance dependence and randomization term are (47.4757, 8.3932),(1279.2857, 1111.4950) and (68.3014, 19.5001) respectively. In Chaotic, mean and standard deviation on rating of light intensity, distance dependence and randomization term are (41.3443, 10.1021),(1072.8571, 931.2127) and (60.4314, 18.4726) respectively. Table 1a-d shows the descriptive statistics of the Binary, Gaussian, Parallel and Chaotic firefly algorithms.

Extraction method determined the number of factors to be extracted using Principal components. The extraction of the initial factors is based on eigenvalues greater than 1. Communalities show the proportion of variance of a variable explained by the common factors as indicated in Table 2a-d. For Binary firefly, the communality in light intensity is 0.757, this implies that 75.7% can be explained by the extracted factors while the remaining 24.3 are extraneous. Distance dependence is 0.837, this implies that 83.7% can be explained by the extracted factor, the remaining 16.3 are extraneous. The randomization term is 0.962, this implies that 96.2 % can be explained by the extracted factor, the remaining 3.8 are extraneous. For Gaussian, the communality of light intensity is 0.254, this implies that 25.4% of variance in light intensity can be explained by the extracted factors while the remaining 74.6% are extraneous.

Distance dependence is 0.841, this implies that 84.1% of distance dependence can be explained by the extracted factors while the remaining 15.9 are extraneous. The randomization term is 0.939, this implies that 93.9% can be explained by the extracted factors while the remaining 6.1% are extraneous. For Parallel, the communality in light intensity is 0.975, this implies that 97.5% can be explained by extracted factors, the remaining 2.5 are extraneous. Distance dependence is 0.941, this implies that 94.1% can be explained by extracted factors, the remaining 5.9 are extraneous and the randomization term is 0.925, this implies that 92.5% can be explained by extracted factors, the remaining 7.5 are extraneous. For Chaotic firefly, the communality in light intensity is 0.967; this implies that 96.7% can be explained by extracted factors, the remaining 3.7 are extraneous. Distance dependence is 0.940; this implies that 94% can be explained by extracted factors, the remaining 6 are extraneous.

The randomization term is 0.927; this implies that 92.7% can be explained by extracted factors, the remaining 7.3 are extraneous. The tables show that all values are close to 1 which indicated that model explained variation of the factors.

Table 2a: Communalities of Binary Firefly

	Initial	Extraction
Light intensity	1.000	.757
Distance dependence	1.000	.837
Randomization term	1.000	.962

Table 2b: Communalities of Gaussian Firefly

	Initial	Extraction
Light intensity	1.000	.254
Distance dependence	1.000	.841
Randomization term	1.000	.939

Table 2c: Communalities of Parallel Firefly

	Initial	Extraction
Light intensity	1.000	.975
Distance dependence	1.000	.941
Randomization term	1.000	.925

Table 2d: Communalities of Chaotic Firefly

	Initial	Extraction
Light intensity	1.000	.967
Distance dependence	1.000	.940
Randomization term	1.000	.927

The total variance explained determined the number of components to be extracted. Component with eigenvalues greater than 1 would be extracted as presented in Table 3a-d and eigenvalues form the basis for estimating the level of contribution of each factor on the efficiency of the four techniques. For binary firefly, only component one (1) which was light intensity, was extracted with eigenvalues of 2.556 and percentage of variance of 85.211%, while components 2 (Distance dependence) and 3 (Randomization term) were discarded as result of their eigenvalues less than 1.

For Gaussian firefly, components 1 was extracted with eigenvalue of 2.034 and percentage of variance of 67.800% while components 2 and 3 were discarded as result of their eigenvalue less than 1. For Parallel firefly, component 1 was extracted with eigenvalue of 2.566 and percentage of variance of 86.201% discarding components 2 and 3. For Chaotic firefly, component 1 was extracted with eigenvalues of 2.605 and percentage of variance of 88.201% respectively while components 2 and 3 were discarded.

Table 3a: Total Variance Explained of Binary Firefly

		Initial Eigenvalues		Extractions Sum of Squared Loadings		
Components	Total	% of var.	Cum. %	Total	% of Var.	Cum.%
1	2.556	85.211	85.211	2.556	85.211	85.211
2	.390	13.005	98.211			
3	.054	1.784	100.000			

Table 3b: Total Variance Explained of Gaussian Firefly

		Initial Eigenvalues		Extractions Sum of Squared Loadings		
Components	Total	% of var.	Cum. %	Total	% of Var.	Cum.%
1	2.034	67.806	67.806	2.034	67.806	67.806
2	.878	29.252	97.059			
3	.088	2.941	100.000			

Table 3c: Total Variance Explained of Parallel Firefly

		Initial Eigenvalues		Extractions Sum of Squared Loadings		
Components	Total	% of var.	Cum. %	Total	% of Var.	Cum.%
1	2.566	86.201	58.855	2.566	86.201	58.855
2	.276	11.796	94.711			
3	.159	2.003	100.000			

Table 3d: Total Variance Explained of Chaotic Firefly

		Initial Eigenvalues		Extractions Sum of Squared Loadings		
Components	Total	% of var.	Cum. %	Total	% of Var.	Cum.%
1	2.605	88.201	27.252	1.844	88.201	27.252
2	.235	11.241	69.806			
3	.160	0.558	100.000			

5. CONCLUSION

The results obtained from the study showed that light intensity was the main factor affecting the efficiency of the modified firefly algorithm based on the influence. Light intensity time contributed 85.21, 67.80, 86.20 and 88.20 % percentage of variance for Binary, Gaussian, Parallel and Chaotic firefly algorithm respectively. The distance dependence contributed 13.01, 29.25, 11.80 and 11.24 % percentage of variance for Binary, Gaussian, Parallel and Chaotic firefly algorithm respectively. Also, randomization term also contributed 1.78, 2.94, 2.00 and 0.56% percentage of variance for Binary, Gaussian, Parallel and Chaotic firefly algorithm respectively. Percentage of variance forms the basis for prioritizing each factor based on their influence on the performance of the firefly algorithm.

Therefore, Light intensity is the most critical factor with the highest number of 88.20 % percentage of variance. Chaotic firefly algorithm is the most efficient algorithm with the light intensity of 88.20% followed by Parallel, Binary and Gaussian is the least efficient firefly algorithm. The research prioritized light intensity as the main factor affecting the efficiency of modified firefly algorithms.

REFERENCES

Abedinia, O., Amjady, N., and Naderi, M. (2012):" Multiobjective Environmental or Economic Dispatch using Firefly Techniques*, 11th International Conference on Environment and Electrical Engineering*, IEEE, 461-466.

Coelho, D.L., Bernert, D.I., and Mariani, V.C.(2013) :" A Chaotic Firefly Algorithm applied to Reliability-Redundancy Optimization, *IEEE Congress on Evolutionary Computation, IEEE*, Vol. 18, 89-98.

Decoster, J. (1998): Overview of Factor Analysis, Department of Psychology, University of Alabama, Gordon Palmer Hall Tuscaloosa.

Farahani, Sh. M, Abshouri, A. A, Nasiri, B. and Meybodi, M. R. (2011):"A Gaussian Firefly Algorithm"*,International Journal of Machine Learning and Computing*, Vol.1(5).

Farahani, Sh. M, Abshouri, A. A, Nasiri, B. and Meybodi, M. R. (2012):" Some Hybrid Model to Improve Firefly Algorithm Performance, *International Journal of Artificial Intelligence*, Vol.8(12), 97-117.

Gandomi, A., Yang, X.S., Talatahari, S. and Alavi, A.: "Metaheuristic in Modelling and Optimization, Metaheuristics Application in Structures and Infrastructures, Elsevier, 1-24, 2013, Waltham.

He, D., He, C., Jiang, L.G., Zhu, H.W., and Hu, G.-R. (2001): "Chaotic Characteristics of One-Dimensional Iterative Map with Infinite Collapses," Circuits and Systems I: Fundamental Theory and Applications, IEEE Transactions, Vol. 48, 900-906.

Iztok, F., Iztok(Jr), F., Yang, X.S., and Janez, B. (2013) :" A Comprehensive Review of Firefly Algorithms", Swarm and Evolutionary Computation, Elsevier Journal, 34-46.

Krishna, G.D., Iqbal, Q., and Sanjoy, D., :" A Chaotic Levy flight Approach in Bat and Firefly Algorithm for Gray level Image Enhancement*", International Journal of Image, Graphics and Signal Processing,* 2015.

Leandro, D.C., Diego, L.B., and Viviana, C.M., :" A Chaotic Firefly Algorithm Applied to Reliability-Redundancy Optimization", University of Parana, 2011, Brazil.

Mingjun, J., and Huanwen, T. , "Application of Chaos in Simulated Annealing," Chaos, Solitons & Fractals, Vol. 21, 933-941, 2004.

Nadhirah Ali, Mohd Azlishah Othman, Mohd Nor Husain and Mohamad Harris Misran:"A Review of Firefly Algorithm", *ARPN Journal of Engineering and Applied Sciences*, Faculty of Electronics and Computer Engineering, Universiti Teknikal Malaysia Melaka (UTeM), Melaka, Vol.9(10), 2014, Malaysia.

Olabiyisi S.O., Aladesae T.S., Oyeyinka F.I., and Oladipo Oluwasegun (2013): Evaluation of Critical Factors Affecting the Efficiency of Searching Techniques", *International Journal of Advanced Research in Computer Science and Software Engineering*, vol.3(7), pp.34-40.

Olusi T., Balogun M.O., Adepoju M.T., Sotonwa K.A., Adetunji B., Olabiyisiisi O & Omidiora O. (2025). "Overcoming Computational Challenges of K-Nearest Neighbors: A Memory-Efficient Approach using Gray Level Co-Occurrence Matrix and Firefly Optimization Technique". *Department of Computer Science, I. I. C. T. Kwara State Polytechnic, Ilorin, Nigeria. Department of Electrical and Computer Engineering Kwara State University, Malete, Kwara State Nigeria. Department of Computer Engineering, Ladoke Akintola University of Technology, Oyo State, Nigeria. Department of Computer Science, Lagos State University, Lagos, Nigeria. Department of Computer Science Ladoke Akintola University of Technology, Ogbomoso, Oyo State, Nigeria. *olusititilayo@gmail.com; tmadepoju@lautech.edu.ng; monsurat.balogun@kwasu.edu.ng; kehinde.sotonwa@lasu.ng. Nigeria Research Journal of Engineering and Environmental Sciences. Journal homepage: www.rjees.com*

Palit, S., Sinha, S., Molla, M., Khanra, A., and Kule,M.,:" A Cryptanalytic attack on the Knapsack Crytosystem using Binary Fireflies Algorithm", 2nd International Conference on Computer and Communication Technology, IEEE,428-432, 2011.

Raed, Z.A., Ameera, S.J., Iyad,A.D., and Yazan, A.J. :" A Binary Classifier Based on Firefly Algorithm", *Jordanian Journal of Computers and Information Technology* (JJCIT), Vol.3(3), 2017.

Strogatz, S. H. , :" Nonlinear Dynamics and Chaos", Perseus Publishing, Massachussetts, 2000. Swarm Optimization", 2008.

Yang, X. S. : "Firefly Algorithm Stochastic Test Functions and Design Optimization". *International Journal of Bio-Inspired Computation*, Vol.2 (2), 78-84, 2010.

Yang, X. S.,:"Firefly algorithms for multimodal optimization", in Stochastic Algorithms Foundations and Applications, Stochastic Algorithms: Foundations and Applications (SAGA '09), Vol. 5792 of Lecture Notes in Computing Sciences, 169-178, Springer, 2009.

Yang X. and Karamanoglu M.:"Swarm Intelligence and Bio-Inspired Computation. Swarm Intelligence and Bio-Inspired Computation, 3-23, 2013.