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A framework for Modified Firefly Algorithm in Multimodal Biometric Authentication System

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Abstract
Many end users are turning to multimodal biometric systems as a result of the limitations of conventional authentication techniques and unimodal biometric systems for offering a high level of accurate authentication. When high accuracy and security are required, multimodal biometrics are the best choice because to the utilization of numerous identification modalities. It is difficult to identify the best features that contribute to the recognition rate/accuracy and have a high redundancy of features since different features are acquired at the feature level fusion from a variety of physiological or behavioral variables. At the feature selection level, the utilization of meta-heuristic algorithms will reduce the number of redundant features while keeping critical feature sets that are important to biometric performance, accuracy, and efficiency. The study demonstrated a multimodal biometric authentication system that used the features of the face and both irises. In order to avoid being stuck at the local optimum and hasten convergence, the Firefly Algorithm (FFA) was modified by including a chaotic sinusoidal map function and a roulette wheel selection mechanism as deterministic processes. The results of the study demonstrated that in terms of sensitivity, precision, recognition accuracy, and time, the proposed MFFA with multimodal outperformed the MFFA for unimodal, bi-modal, and bi-instance. In addition to being computationally faster, more accurate, and suitable for real-time applications, the modified method, known as MFFA, proved effective in integrating multimodal data sets.

Keyword: Biometric, Firefly Algorithm, Multimodal, Bi-modal, meta-heuristic

1.0 Introduction

Biometrics is the science of assessing personal characteristics such as the iris, face, fingerprints, retina, palm print, hand geometry, voice, or signatures to secure authentication [1]; [2] and is becoming the technology of the future in the field of security [3]. The biometric system identifies people based on their physiological and/or behavioral features. These features are sometimes known as attributes in literature [4]. Fingerprint, face, ear, retina, palm print, iris, hand geometry, inner knuckle print, and so on are physiological traits, whereas voice, gait, keystrokes, and signature are behavioural characteristics. Among the biological traits of identification, the face-based approach such as iris scan, retina, lip and face recognition have been considered to be generally used and acceptable techniques of biometric [5]; [6].

A unimodal biometric system uses only one property to perform a recognition operation, such as a fingerprint, nose, gait, voice, face, iris, or ear [7]. However, [8] observed that existing biometric systems have to deal with a variety of problems with the use of a single trait, such as a fingerprint image with a scar or poor illumination of the subject in face recognition. In real-world scenarios, the majority of biometric technologies are unimodal [9]. The limits of unimodal biometric systems have prompted researchers to focus their efforts on multimodal biometric systems, as the biometric source may become unreliable owing to a variety of factors such as sensor or software failure, noisy data, non-universality, and so on [10]. Combining two or more biometric systems is a promising solution to provide more security according to [11] and, avoiding the falsification of several biometric traits at the same time [12]. A multimodal biometric system recognizes people using data from many biometric sources [13] and created by combining two or more biometric features to create a recognition system. In multimodal biometric systems, information fusion is a crucial step [14]. At different levels, fusion of different modalities can take place[15]. A multimodal biometric must consider a fusion of features to be unique, in which at several phases of a recognition system, biometric features can be fused [16] either at fusion-before-matching, that involves integrating biometric data before matching templates i.e. sensor level and feature level; or fusion-after-matching, which involves integrating data after the matcher/classification step i.e. score level, match level, rank level and decision level [17].

The application of meta-heuristics optimizations approach to feature selection has substantially increased as a result of the exponential rise of real-world problems and the value of having quick access to solutions [18] which have grown to be more common. To choose the best subset of a dataset while maintaining the model's accuracy, meta-heuristic algorithms are therefore particularly effective and efficient [19]. This work concentrates on feature selection issues using meta-heuristic approach based on its strength.

An efficient optimization strategy created by Yang is the firefly algorithm (FA) [20]. The three well-known meta-heuristic methods, particle swarm optimization (PSO), differential evolution (DE) and simulated annealing (SA) have been combined to create the FA according to [21] examined many facets of FFA in their study and came to the conclusion that it is a promising optimization approach when it comes to resolving the most challenging NP-hard numerical optimization issues[22] in both continuous and discrete areas.

FFA suffers from early convergence and inadequate global exploration when dealing with challenging high-dimensional issues, despite the benefit of avoiding the local optimal trap [18]. Due to improvements in the other techniques, hybridizing FFA applications and modifications appear to be advantageous to standard FFA in terms of processing speed and performance. The standard FA may need a lot of time at times to obtain the ideal parameter values. As a result, FA should be modified or hybridized with other techniques to speed up processing [24] and also a good idea to archive high-quality solutions by making the randomness step length decrease with iteration [25]. This serves as the impetus for the current work, which added a chaotic sinusoidal map function and deterministic process to the standard or already existing FA.

This study focuses on improved feature selection method in multimodal biometric systems through handling high features dimensionality and selecting salient features which are the major problems identified in feature level fusion that will continue to be a subject of intensive research due to its potential to improve biometric recognition accuracy according to [20] by introducing meta-heuristic optimization techniques into the feature selection phase of a multimodal biometric system before the classification phase to select the most relevant features from the two biological traits. Finally, to classify a person as authorized or unauthorized, the fused feature vectors were fed into a Support Vector Machine (SVM) classifier.

In this study, the physiological biometrics of the face and iris are used to support the finding of [26] that iris recognition is one of the most accurate biometrics while face recognition is the most natural and acceptable for use in identity verification.

In order to address the issues raised above, particularly high redundancy and irrelevant features, various meta-heuristic optimization techniques, such as Genetic Algorithm (GA), Ant Colony Optimization (ACO), Simulated Annealing (SA), Particle Swarm Optimization (PSO) and Firefly Algorithm (FFA) have been used in the literature as feature selection techniques to choose the best subset of the original features. However, it still has significant limitations. Though, FA has been widely used for dimensionality reduction technique due to its effectiveness, simplicity, and eases of implementation but still suffers from premature convergence, an imbalance between exploitation and exploration, and a significant risk of becoming stuck in a local optimum, especially when applied to high-dimensional optimization problems like fusion [27]. Therefore, in order to further improve the performance of multimodal biometric authentication system, this research introduced a meta-heuristic optimization approach using a modified firefly algorithm for feature level fusion as an efficient feature selection algorithm to select optimal features, reduce redundant features in the feature space and speed up convergence rate for better classification and employed Support Vector Machine (SVM) as the classifier. The study combined the two face-based (iris and face) biometric modalities.

2.0 Review Of Literature

2.1 Firefly Optimization Algorithm

The firefly optimization algorithm is a swarm intelligence or a meta-heuristic algorithm inspired by the flashing behaviour of fireflies and the phenomenon of bioluminescent communication [29]. Firefly Algorithm (FFA) is a reliable and efficient meta-heuristic algorithm capable of solving many real-world problems such as scheduling, optimization problems in dynamic environments, and economic load dispatch problem [30]. This algorithm is influenced by the flashing behaviour of fireflies to attract one another [31]. The firefly attraction process was modeled by the algorithm for solving optimization problems [32]. Brightness and attraction are the two key components of the Firefly algorithm. The brightness of the firefly shows its supremacy in terms of location and determines its movement direction. The travelling distance of the firefly is determined by the degree of attraction [33]. The brightness and degree of attraction are adjusted on a regular basis to meet the optimization goal. In the firefly algorithm sorting of flies is achieved by sorting algorithm. It is constructed based on three rules:

(i) All fireflies are unisex so that one firefly is attracted to all other fireflies.
(ii) The attractiveness of a firefly is proportional to its brightness. For any two fireflies, the dimmer one is attracted by (and thus moves towards) the brighter one. However, if there are no fireflies brighter than a given firefly, the fireflies will move randomly.
(iii) The brightness of a firefly decreases as the distance from it increases. This is because the light is absorbed when it passes through the medium.

Furthermore, because the parameters are constant during all iterations, the search behaviour remains consistent for any condition. As a result, one of the study questions has been to improve the typical firefly algorithm's performance as discovered by [18].

2.2 Classification of Firefly Algorithm

Different researchers have proposed various FA iterations. There is also a multi-objective optimization variant of the firefly algorithm. For the purpose of enhancing performance, FA might introduce chaos. For the sake of performance improvement, hybrid firefly varieties are also created. There are two most efficient ways to classify the firefly algorithm generally:

i. **Parameter Tuning:** Before performing an algorithm, parameter tuning involves determining the optimal values of the utilized parameters and modifying them over the course of iterations.
ii. **Parameter Control:** During the execution process, parameter control modifies the value of the parameter.

The behaviour of the Firefly algorithm depends on both the appropriate parameter value and the characteristics of the method's constituent parts [34]. Therefore, the following factors should be taken into account while classifying FFA:

- What has been changed or modified?

- How are these modifications made?

- What is the extent of the modification?

2.3 Components of Firefly Algorithm (FFA)

The light intensity and the attractiveness of the fireflies are two key components of the firefly algorithm.

i. **Light Absorption:** The brightness of the firefly, which is expressed and quantified using a sort of fitness function, determines how much light is produced by each source.
ii. **Attractiveness**: it is determined by brightness, which depends on light intensity. In the literature, the fitness function was applied as the attractiveness function.

2.4 Standard Firefly Algorithm

The FFA is modelled after how fireflies communicate by flashing their lights. The algorithm assumes that all fireflies are unisex, meaning that any firefly can be attracted to any other firefly; a firefly's attraction is proportionate to its brightness, which is determined by the objective function. A brighter firefly will attract it. Furthermore, according to the inverse square law, the brightness diminishes with distance, as seen in Eqn. (1) below.

$$I \prec \frac{1}{r^2}$$ . . . Eqn. (1)

When light passes through a medium with a light absorption coefficient γ, the light intensity at a distance of r from the source can be calculated using Eqn. (2).

$$I = I_0 e^{-\gamma r^2}$$ . . . Eqn. (2)

Where, I_O is the intensity of light at the source. In the same way, the brightness β, can be calculated using Eqn. (3).

$$\beta = \beta_0 e^{-\gamma r^2}$$ . . . Eqn. (3)

In Eqn, (4), there is a generalized brightness function for ω ≥ 1. In fact, one can use any monotonically declining function.

$$\beta = \beta_0 e^{-\gamma r^{\omega}}$$ . . . Eqn. (4)

Each firefly will follow fireflies with higher light intensity after the intensity or brightness of the solutions is assigned. The brightest firefly will conduct a local search by traveling around in its immediate vicinity at random. If firefly *j* is brighter than firefly *i* then firefly *i* will migrate towards firefly *j* using the updating method for two fireflies in Eqn. (5).

$$x_i := x_i + \underbrace{\beta_0 e^{-\gamma r_{ij}^2}}_{=\beta} (x_j - x_i) + \alpha(\varepsilon() - 0.5)$$ . . . Eqn. (5)

Where,

β0 is the attractiveness of *xj* at *r* = 0,

γ is an algorithm parameter which determines the degree in which the updating process depends on the distance between the two fireflies

α is an algorithm parameter for the step length of the random movement and

ε( ) is a random vector from uniform distribution with values between 0 and 1.

For the brightest firefly, x_b, the second expression in Eq. (6) will be omitted, as given in Eq. (6).

$$x_b := x_b + \alpha(\varepsilon() - 0.5)$$ . . . Eqn. (6)

In FA, the form of attractiveness function of a firefly is depicted by the following:

$$\beta(r) = \beta_0 \exp\,(-\gamma r^2) \qquad (7)$$

where,

r = The distance between any two fireflies

β_0 = The initial attractiveness at r = 0

γ = An absorption coefficient which controls the decrease of the light intensity.

The distance that exist in-between any two fireflies i and j, at a particular position xi and xj, can be defined respectively as a Cartesian or Euclidean distance as show below:

$$r_{ij} = ||x_i - x_i|| = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2} \quad (8)$$

where,

d is the dimensionality of the given problem.

The pattern of movement of a particular firefly i that is attracted by another firefly j that is brighter can be represented by the following equation:

$$x_i = x_i + \beta_0 \exp(-\gamma r_{ij}^2) * (x_j - x_i) + \alpha * (rand - \tfrac{1}{2}) \quad (9)$$

$$x_i = x_i + \alpha * (rand - \tfrac{1}{2}) \quad (10)$$

Advantages of Firefly Algorithm

(i) It is not complicated which makes it easy to understand and implement.
(ii) It can be used in different application for different discipline.
(iii) It is highly effective and efficient.
(iv) It accepts modification to boost its performance and makes it suitable for a problem at hand.

Disadvantages of Firefly Algorithm

(i) It is prone to premature convergence
(ii) It can easily get trapped in local optimum for multimodal biometrics
(iii) Its update depend on current performance
(iv) No memory of previous best solution and performance

2.5 Modification of Firefly Algorithm

The firefly algorithm, like any other meta-heuristic algorithm, is vulnerable to parameter values. It has been discovered that altering the parameters based on the state of the search is effective. As a result, modifying the settings is a straight-forward way to improve the performance of the firefly algorithm according to [35]. There are three (3) classes of modification for Firefly algorithm namely: Parametric Modification, Modification to Formulas and Modifications on the Search Space.

Class 1: Parametric Modification - The parameters of the algorithm are changed in this category but, the same updating techniques or formulas are used.

$$\alpha = \frac{itr(\alpha_{mean})}{MaxGen} + \alpha_{std}$$

Class 2: Modifications on the Search Space - It may be easier to transit to another 'easy-to-search' space, as well as changes in the probability distribution while generating random numbers, if the same updating technique is used.

$$\gamma_n = \exp(-\delta * \gamma_o{}^2) + \mu$$

Where, γ_o is the existing firefly parameter;

γ_n is the chaotic gauss mapping firefly parameter,

where $\delta = 4.9 \text{ and } \mu = 0 - 0.58$ is considered as chaotic map parameters.

Class 3: Modification to Formulas - It covers changes such as adding mutation operators, changing part or all of the updating formulas, and so on.

2.6 Theoretical Framework

The theoretical framework of this study shows the relationships that exist among different types of fusion in multimodal biometrics system. Biometric fusion is a mechanism which can combine the outcome from all the biometric modalities. The primary motivation behind this fusion is to make the biometric systems more secure. However, matching-score level fusion and decision level fusion are more popular in the literature and there is not much research on feature level fusion. Currently, feature level fusion is more effective than other alternative levels of fusion because it provides greater information on the biometric input information than the coordinating score or the classification output of a classifier but, are more prone to irrelevant data and high dimension vector space. In order to address this issue, the feature level fusion is subsequently provided with a meta-heuristic optimization approach as a feature selection technique for eliminating redundant features and selecting the best features to improve the classification performance. Figure 2.22 below shows the theoretical framework.

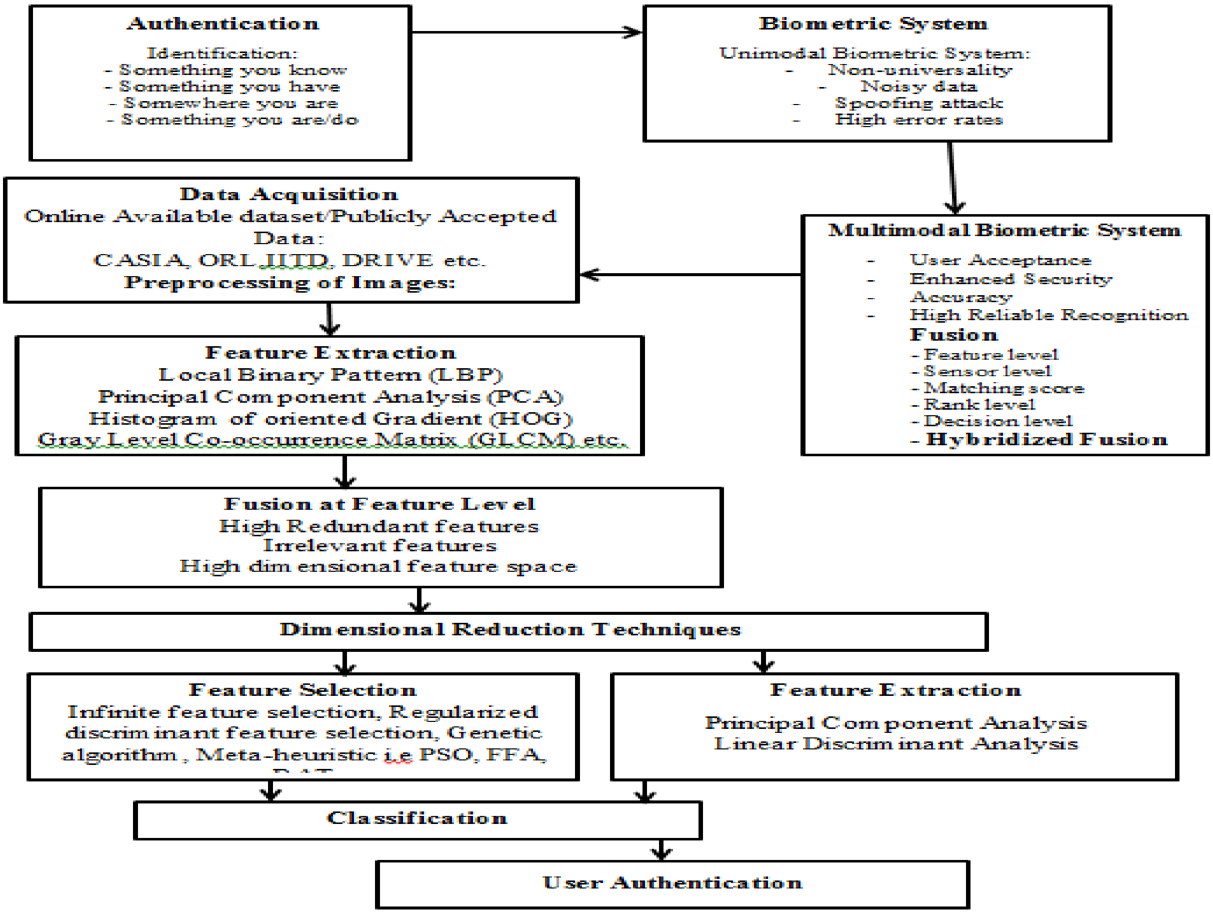

Figure 2.23: Theoretical Framework (Researcher's design)

2.7 Review of Related Works

Numerous studies on optimization techniques have been conducted utilizing various meta-heuristic algorithms in domains like engineering design, mathematics, computing, economics, and route planning. Time and resources are limited in the real world. The objectives of the optimization algorithms are to maximize these resources that are already available. There are several promising meta-heuristic algorithms. One of the most current meta-heuristic algorithms, the firefly algorithm (FFA) has been employed in numerous applications and has undergone different modifications and hybridization for better performance of the system.

Recently, [38] proposed a return-cost-based binary FA, a powerful feature selection technique based on the Firefly algorithm (FA) (RcBBFA). By using binary variables, the suggested method expands on the FFA concept. The new algorithm, which is particularly successful in handling the feature selection (FS) problems, used three novel strategies: return-cost attractiveness, Pareto dominance-based selection, and binary movement with adaptive leap. To gauge a firefly's attractiveness compared to other fireflies, a return-cost indicator is first defined. The most appealing option is then offered for each firefly using a Pareto dominance-based technique. In order to update a firefly's position, a binary movement operator based on return-cost appeal and adaptive leap is created. The suggested strategy was demonstrated to be a highly competitive option for resolving feature selection issues by experimental findings on a number of open datasets.

The attraction of fireflies (FA) meta-heuristic-based optimization technique was used by [39] to propose a solution to the balancing curriculum problem. In order to evaluate the effectiveness of the proposed solution, a series of tests and actual situations were run. The study aimed to provide a system that would streamline the process of establishing a curricular network in higher education institutions. The experimental results demonstrated that the new method finds the known optimum in the majority of the tested cases and converges rather quickly.

In another study, two types of improved firefly algorithms, the inertia weight based firefly algorithm and the chaos based firefly algorithm, were compared in [40] research. Each algorithm's principle is examined. The three algorithms' optimization performances were simulated and compared to five common two-dimensional or multi-dimensional benchmark functions. The results reveal that CSFA has the best accuracy and stability, and that it can effectively balance global and local search capabilities while overcoming the flaws of the classic firefly algorithm.

[40] used evolutionary optimization approaches to construct microstrip antennas with different goals. Particle Swarm Optimization, Genetic Algorithms, and the Firefly Algorithm were among the biologically inspired algorithms included in the new software, Antenna Optimizer, which combined the electromagnetic design environment of CST Microwave Studio with the technical computing and programming environment of MATLAB. For this uni-planar antenna design method, FA performed better than PSO and GA; the study then proposed modified FA to create optimal parameters that match the given design requirements.

Recently, [41] presented a novel immune multi-population firefly algorithm (IMPFA) to solve multimodal function optimization problems. The suggested approach combines a multi-population clonal selection technique with a genetic algorithm (NUMCSA). The MPFA based on multi-population learning mechanism is used to search globally in the feasible region, followed by the NUMCSA to search locally to improve the accuracy of the sub-optimal solutions found with MPFA. The IMPFA is particularly effective and boosts the precision of solutions, according to simulation data. When tackling high-dimensional and complicated optimization problems, a higher iterative count of recurrent search is necessary, this takes longer time and leaves potential for algorithm adjustment to strike a balance between exploration and exploitation.

Also, the ability of the firefly algorithm to achieve the best results for optimization problems (maximization or minimization) in a bottling company that manufactures a variety of different kinds of soft drinks with various flavours was introduced by [42]. The problem is developed as a linear programming model. The model is run through Lindo software, and the output from both techniques is compared in order to gauge the firefly algorithm's effectiveness. The business can determine whether products can still be manufactured based on the availability of raw resources by using the firefly algorithm. It is also expanded to compare each algorithm's result and select the best one. This study can be expanded to create a model based on other inventory-related aspects.

[43] applied the distributed computing concept to an optimized version of the Firefly Algorithm (FA) and proposed a parallel version of the Firefly algorithm to an MLTP problem with natural images to analyse the real speed of a serial firefly algorithm adapted for MLOTP purposes and determine if distributing it is a viable option and then to analyse the performance of the distributed algorithm. There was no discernible difference in results between the serial and parallel versions. Furthermore, employing a collection of computer nodes, the time might be greatly decreased.

Several researches in the literature employed the Firefly Algorithm for feature selection. [21] proposed a variation on the Firefly Algorithm (FA) for the selection of discriminative features in regression and classification models to aid in the support of decision-making processes utilizing data-based learning techniques. The FA variant uses Simulated Annealing (SA)-enhanced local and global promising solutions, chaotic-accelerated attractiveness parameters, and diversion mechanisms of weak solutions to avoid falling into the local optimum trap and to address the issue of premature convergence in the original FA algorithm. The statistical test results showed that the proposed FA variant is successful at improving classification and regression models to aid decision-making processes.

Another research [44] proposed the use of Genetic Algorithm (GA) and Firefly algorithm (FFA) for estimating the amplitudes of the Cancellation subcarriers (CCs) that were inserted on either side of the used Non Contiguous orthogonal frequency division multiplexing NCOFDM signal to cancel the side lobes. The suggested methods produce greater side lobe reduction than current strategies in the literature, and the FFA's overall performance is superior, according to simulation data.

In [45] an improved maximum power point tracking (MPPT) algorithm for photovoltaic (PV) systems in partial shadowing conditions (PSCs) was presented. It is based on the fusion firefly algorithm (FFA) and uses a novel simplified propagation process (SPP). The proposed FFA was capable of accurately tracking the global maximum power points (GMPPs) by combining the neighbourhood attraction firefly algorithm (NaFA) and simplified firefly algorithm (SFA). Furthermore, the suggested SPP approach decreases sampling events by removing duplicate propagations, speeding up tracking and minimizing energy loss and oscillations during the sample process. A hardware assessment device was used to mimic the planned FFA's performance and the speed enhancement brought forth by the SPP procedure. The suggested FFA algorithm provides good accuracy and efficiency with quick tracking speed.

The study by [37] focused on the functions of diabetes prediction, where an issue with data imbalance makes it difficult to forecast the correctness of diabetes data. The Proposed Tailored Firefly Algorithm and Map Reduce are utilized to increase the efficacy and precision of prediction. A variety of categorization techniques are applied with the goal of enhancing the performance of the new enhanced Firefly by comparing it to several benchmark algorithms. The suggested EFA approach is utilized to enhance the accuracy of the diabetic data set, together with fuzzy sets and map reduce. The new approach speeds up prediction, increased accuracy, and decreased time.

In recent study, meta-heuristic algorithm was introduced by [46] to tackle and reduce the demand side management problem and provide the optimum outcome. Particle Swarm Optimization, Firefly Algorithm and Salp Swarm Algorithm were the three evolutionary algorithms that were employed. This study's main goal is to enhance the use of renewable resources for electricity generation while reducing overall load demand, operating costs, and utility costs across three separate sectors; residential, commercial, and industrial. In all the three instances, it is discovered that the load after load shifting curve is more closely related to the project's objective curve, proving that the firefly algorithm was successful in achieving the project's goals by lowering costs and reducing peak demand. In comparison to PSO and SSA, the Firefly algorithm is discovered to have the best cost and better accuracy.

2.8 Application of Firefly Modification

[47] proposed a modified version of the firefly algorithm based on the existing firefly algorithm and enhanced particle swarm optimization. The increased velocity notion of particle swarm optimization is used in the suggested modified method to improve the conventional algorithm's searching performance. Through simulations, the firefly algorithm and the modified firefly algorithm are compared for a few common benchmark functions. The proposed improved algorithm converges more quickly and produced the best answer while improving the performance of the original Firefly algorithm.

In order to enhance the original Firefly algorithm, [41] hybridized the Firefly algorithm by adding mating behaviour and the GA crossover operator (FA). The suggested method is shown to perform noticeably better than canonical FA and a variety of other comparison techniques. The technique will still find a local minimum for some functions.

Another modified Firefly Algorithm-based feature selection method was proposed by [48]. The classic Firefly Algorithm is modified by the use of the K-Nearest Neighbourhood (K-NN) classifier and an additional feature selection stage. The proposed approach is tested on four different datasets containing diverse forms of attacks. The proposed modified Firefly Algorithm successfully reduced the dimension of data by picking features based on the accuracy rates of the K-NN approach. The proposed modified FFA lowers the dimension, which results in a more than 50% reduction in memory usage. The outcomes demonstrate a method that conserves both time and memory. Though, the distance formula for large dimensional data had a problem.

In another study, [49] proposed an improved firefly algorithm (IFA) by combining two specialized operations: sigmoid-based attractiveness to increase the likelihood of finding a viable solution and, the local refinement capacity to strengthen the use of a dynamical step parameter tuning technique. These two customized activities are anticipated to complement one another and achieve a good balance between global exploration and local exploitation. Twelve well-known benchmark functions were used as the basis for six algorithms' numerical trials and statistical analyses. IFA is a strong and competitive algorithm that surpasses the majority of other FA variations, as shown by the numerical results and statistical comparisons.

An updated firefly technique was proposed in [50]. In this study, fireflies are modelled by simulating their position by altering the cell chi-square value after each movement and their intensity by computing a set of different fitness functions as a weight for each characteristic. K-Nearest Neighbour and Discriminant Analysis were used as classifiers to assess the suggested firefly strategy for selecting features. The research suggested either developing a firefly algorithm based on parallel processing to process all fireflies simultaneously, thereby speeding up processing, or developing a comprehensive model using firefly approaches, in which both feature selection and classification procedures are based on fireflies.

In order to boost diversity, a craziness operator is added to the existing firefly algorithm in [51] paper to create the crazy firefly algorithm. The updated method makes use of the crazy factor to broaden the scope of the normal algorithm's search behaviour. The feasibility and effectiveness of the proposed algorithm were confirmed by testing the benchmark functions. Results show that when the proposed method is used with a certain set of control settings, it performs better than the traditional approach. The suggested modification algorithm improves the standard firefly algorithm's performance convergence even more quickly to the best solution while requiring less time to produce it.

3.0 Methodology

Due to the drawbacks of a single biometric solution, researchers are becoming interested in multimodal biometric user recognition system which combines information from multiple biometric traits of an individual at several levels. In feature level fusion, features from several biometric modalities are fused to create a total feature vector with a large dimension feature space, redundant and irrelevant data increasing computing cost and impairing the performances of the classifiers. This can be addressed by using feature selection to obtain a subset of optimal features. By lowering the dimensionality of datasets, we can reduce the computing time, memory usage and classification error an increase the system accuracy.

Meta-heuristic optimization techniques are appropriate for the selection of features because feature subset representation is direct and the evaluation is easily accomplished. Here, a promising meta-heuristic approach Firefly Algorithm (FFA) because of its simplicity and efficiency is being used as a feature selection technique for feature level fusion in multimodal biometric recognition system. The selection of features is a general problem common to large datasets. Fewer researchers utilize swarm intelligence algorithms for feature selection than those that use statistical techniques. As a result of its capacity to choose the most suitable features used for classification, the application of swarm intelligence algorithms has become a motivator for researchers to address dimensionality issues. The Firefly Algorithm (FFA) is regarded as a meta-heuristic algorithm that was inspired by the behavior of the flashing lights of actual fireflies. It is one of the most recent proposed swarm intelligence (SI) algorithms. With its enhanced search capabilities, it can solve multimodal optimization problems and allow fireflies with low light intensities to travel toward nearby fireflies with higher light levels. To improve the feature selection process and potentially reach the best classification accuracy possible.

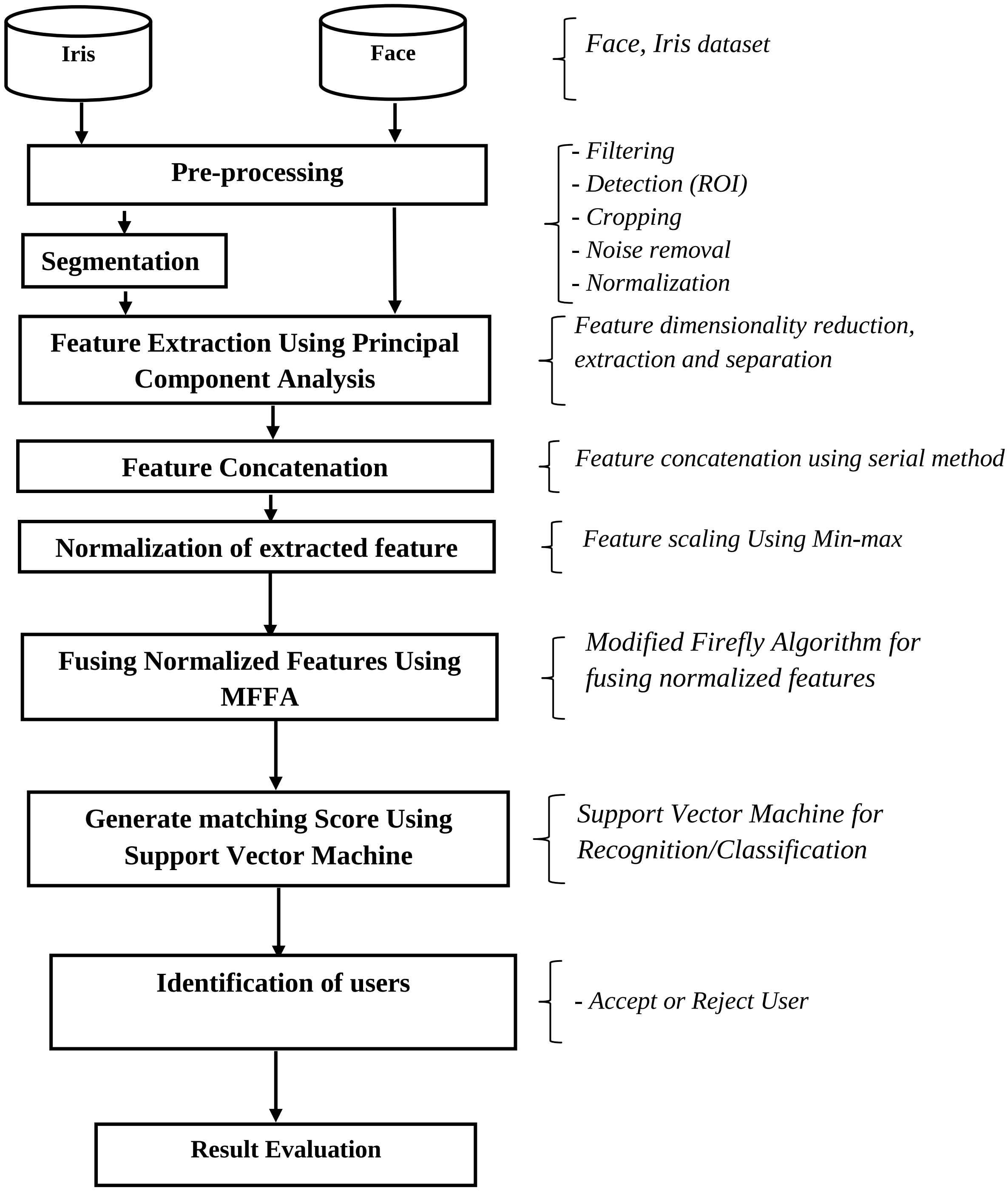

Figure 3.1: MFFA Conceptual Design (Researcher's Design)

3.1 Meta-heuristic Approach for Feature Level Fusion for Multimodal Biometric Authentication System

The approach that was employed in the proposed study to achieve the objectives of this work is discussed here. Data collection, feature extraction, feature selection, and classification are the four processes that make up the proposed multimodal biometric authentication system.

i. Image Acquisition

Face and iris images acquisition refers to the capture of both face and iris images simultaneously using an iris camera. A CMITECH IRIS Camera device was used to accomplish this. The subjects involved some interested Ladoke Akintola University of Technology, Ogbomoso (LAUTECH) students' and staff within the campus. The study took into consideration 840 subjects with three different expressions each for the two biometric traits. The total datasets captured was 7560; 70 percent of the dataset were used for training and 30 percent for testing.

ii. Image Preprocessing

Face and iris images were preprocessed to extract only the parts of the image that contain useful information. Preprocessing techniques were performed differently on face images and iris images in their datasets. The preprocessing phase of facial images involved were image cropping, image resizing and image enhancement using Histogram Equalization. The preprocessing phases of iris images involved were iris localization/segmentation and iris normalization.

iii. Feature Extraction

Through the process of feature extraction, enormous amounts of redundant data are minimized and reduced computational complexity of the system is made possible. Using Principal Component Analysis, the feature values from the preprocessed data are extracted for this study's feature extraction.

iv. **Feature Concatenation**

This is the feature concatenation at the feature extraction level that aids in the consideration of those features that have the greatest impact on verification accuracy. This function maximizes the performance of the biometrics system by picking features extracted in the previous steps. In the study, the extracted features of both face and iris were combined to have a single feature vector using serial rule method. The feature extracted string size for face is 70 x 70, 60 x 60 for left iris and 60 x 60 for right iris. After the application of serial method to the initial string size; the concatenated string size is 170 x 170.

V. **Feature Normalization**

Features extracted from the face and irises are high dimensional, due to the variation in distribution and range. The high dimensional issue is overcome by normalizing the features. The features extracted by the PCA from each biometric trait were heterogeneous. The normalization of the face and iris features was achieved by using Min-max method. The Min-Max technique was used to retain distribution and map the features into a common range. Normalization maps the raw biometric features to the interval [0, 1] and retains the original distribution of the features. The normalization of the features of the biometric traits by the min-max rule is given in Equation 3.1,

$$x' = \frac{x - min(x)}{max(x) - min(x)} \tag{3.1}$$

Where,

x is the original value,

$x'$is the normalized value,

$max(x)$ is the maximum weight and,

$min(x)$ is the minimum weight.

v. Feature Level Fusion

In the feature-level fusion process, features that are extracted from the raw data are fused with one another to produce a single feature set that is sent to the subsequent classification stage. After the extracted features from face and both irises images have been normalized, we move to the feature level fusion phase to combine the extracted feature vectors. The two main stages of feature level fusion are feature fusion and feature selection:

a. Feature Fusion

A single vector that boosts the feature vector's discriminating strength has been generated by fusing the normalized features of the face and both iris images. The most important/optimal features are chosen from a vast range of features using certain significant feature selection strategies.

b. Feature Selection

The feature selection technique was developed to choose the most important features from a dataset, increase prediction accuracy, and eliminate redundant and unimportant features for a better understanding of the dataset.

vi. **Feature selection Using Modified Firefly Algorithm**

To enhance performance and reduce extracted feature dimensions for better classification in this study, the best features were selected using a feature selection technique, modified firefly algorithm (MFFA).

a. The Existing Firefly Algorithm (FFA)

FFA is a type of meta-heuristic algorithm that draws inspiration from the nighttime illumination behavior of fireflies. The primary function of a firefly flash is to act as a signaling mechanism to draw in additional fireflies. The following are the three guiding concepts behind firefly movement.

1) Fireflies are all genderless. Any firefly can draw the attention of another firefly.

2) There is an inverse relationship between firefly distance and attractiveness. With more gaps between fireflies, attractiveness will diminish. It will move randomly throughout the search area if there are no fireflies that are brighter than it.

3) The objective function that needs to be optimized determines how bright a firefly will be.

The attractiveness of the FFA can be calculated by using the equation (1)

$$\beta(r) = \beta_0 \exp\left(-\gamma r^2\right) \qquad (1)\ [50]$$

where, r = Distance between any two fireflies, β_0 = Initial attractiveness at r = 0

γ = Fixed light absorption coefficient which controls the decrease of the light intensity

As presented in the equation (2) below, the distance between any two firefly, i and j, at a given position, xi and xj, can be characterized as either a Cartesian distance or a Euclidean distance.

$$r_{ij} = \left\|x_i - x_i\right\| = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2} \qquad (2)\ [50]$$

where, d is the dimensionality of the given problem.

The attractiveness formula that indicates new position of less bright firefly to move to the brighter one is calculated using equation (3)

$$x_i = x_i + \beta_0 \exp\left(-\gamma r_{ij}^2\right) * \left(x_j - x_i\right) + \alpha * \left(rand - \tfrac{1}{2}\right) \qquad (3)\quad [50]$$

where,

x_i = the first term is the present position of a firefly,

$\beta_0 \exp\left(-\gamma r_{ij}^2\right) * \left(x_j - x_i\right)$ = movement of firefly towards the most attractive of the fireflies by the intensity of light.

$\alpha * \left(rand - \frac{1}{2}\right)$ = random movement of a firefly when it lacks the brighter ones

α = a parameter for randomization.

$$x_i = x_i + \alpha\left(rand - \frac{1}{2}\right) \qquad [48]$$

xi represents the current value of each feature,

(xi) is the probability of xi taking 1

If $P(x_i)$> rand Select the feature Else Do not select the feature

where, $P(x_i) = \frac{1}{1+e^{x_i}}$

[48]

b. Derivation of Modified Firefly Algorithm (MFFA) as a feature selection technique.

Modification was made to the existing Firefly Algorithm at the movement of the brightest fireflies and at the attractive phase of the fireflies, to allow a balance of exploitation and exploration which gives room for selecting well-balanced and relevant features that is expected to reduce the false positive rate (FPR), computational time and increase the accuracy of the system. The modified firefly algorithm (MFFA) was developed from the existing firefly algorithm by introducing roulette wheel selection as a deterministic process instead of a random process and a chaotic sinusoidal map function in order to resolve the problem of premature convergence. The algorithm is shown in Figure 3.8. Figure 3.9 described the flowchart for modified Firefly Algorithm. We derived the firefly modification by introducing a deterministic process into the existing FFA instead of random process and integrating a chaotic theory into the attraction phase of FFA using a sinusoidal map function.

Modified Firefly Algorithm (MFFA)

In the existing Firefly, the procedure starts from an initial population of randomly generated individuals. The quality of each individual is calculated using equation 3.2 and the best solution among them is selected. In FFA, the form of attractiveness function of a firefly is depicted by the following:

$$\beta(r) = \beta_0 \exp\left(-\gamma r^2\right) \tag{3.2}$$

where,

r = The distance between any two fireflies

β_0 = The initial attractiveness at r = 0

γ = An absorption coefficient which controls the decrease of the light intensity

The distance that exist in-between any two fireflies i and j, at a particular position xi and xj, can be defined respectively as a Cartesian or Euclidean distance as shown below:

$$r_{ij} = \left||x_i - x_i|\right| = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2} \tag{3.3}$$

where,

d is the dimensionality of the given problem.

The pattern of movement of a particular firefly *i* that is attracted by another firefly *j* which is brighter can be represented by the following equation:

$$x_i = x_i + \beta_0 \exp\left(-\gamma r_{ij}^2\right) * \left(x_j - x_i\right) + \alpha * \left(rand - \tfrac{1}{2}\right) \tag{3.4}$$

$$x_i = x_i + \alpha * \left(rand - \tfrac{1}{2}\right) \tag{3.5}$$

In equation 3.4, the term x_i which is the first term is the present position of a firefly;

The term $\beta_0 \exp\left(-\gamma r_{ij}^2\right) * \left(x_j - x_i\right)$ which is the second term is meant for movement of firefly towards the most attractive of the fireflies by the intensity of light and;

The third term $\alpha * \left(rand - \frac{1}{2}\right)$ is meant to cater for the random movement of a firefly (random part), when it lacks the brighter ones. The α coefficient is a parameter for randomization, its value depends on the problem that is to be solved, while 'rand' is consistently distributed in the space (0, 1) as it is a random number generator. In equation 3.5, the movement of the best candidate is done randomly.

The modified Firefly Algorithm was formulated using Equation 3.6 to model the pattern of movement of firefly as a deterministic process instead of a random process in the existing firefly. The pattern of movement of a particular firefly *i* that is attracted by another firefly *j* that is brighter was modified by roulette wheel selection ($\boldsymbol{p_i}$) as expressed in Equation 3.3.

$$\boldsymbol{p_i = rand} \leq \frac{f(x_i^t)}{\sum_{i=1}^{N} f(x_i^t)} \tag{3.6}$$

Where, $\boldsymbol{f(x_i^t)}$ is the objective function value of the firefly. Given the modified pattern of movement of firefly as in Equation 3.5

$$x_i = x_i + \beta_0 \exp\left(-\gamma r_{ij}^2\right) * \left(x_j - x_i\right) + \alpha * \left(\boldsymbol{p_i} - \tfrac{1}{2}\right) \tag{3.7}$$

$$x_i = x_i + \alpha * (\boldsymbol{p}_i - \tfrac{1}{2}) \quad (3.8)$$

In equation 3.7, the term x_i which is the first term is the present position of a firefly, the term $\beta_0 \exp(-\gamma r_{ij}^2) * (x_j - x_i)$ which is the second term is meant for movement of firefly towards the most attractive of the firefly by the intensity of light and the third term is meant to cater for the random movement of a firefly (random part), when it lacks the brighter ones. The α coefficient there is a parameter for randomization, its value depends on the problem that is to be solved, while '$\boldsymbol{p}_i$' is consistently distributed using roulette wheel selection. In equation 3.8, the movement of the best candidate is done randomly.

The challenges of imbalance between exploration and exploitation experienced in the existing firefly algorithm were resolved in this study by modifying the attractiveness of the firefly with the application of chaotic theory using a sinusoidal chaotic map function. This describes the chaotic absorption coefficient (CA) which controls the decrease of the light intensity, but not limiting these fireflies to search space boundaries but count on the nature of the chaotic system that generates random and unpredictable outputs from preceding conditions. The new attractiveness of the firefly was expressed in Equation 3.9, Equation 3.10 and Equation 3.11.

$$CA_{old} = \frac{mod(abs(\beta(r), \beta_0)}{\beta_0} \quad (3.9)$$

$$CA_{new} = \alpha * CA_{old}{}^2 \sin(\pi CA_{old}) \quad (3.10)$$

$$c\beta(r) = CA_{new} \times sign(\beta_0 \exp(-\gamma r^2)) \quad (3.11)$$

Where,

β_0 is the initial attractiveness at r = 0,

r is the distance between any two fireflies,

γ is an absorption coefficient which controls the decrease of the light intensity,

$\beta(r)$ is the existing light intensity update;

CA_{new} is the chaotic sinusoidal mapping, where $\alpha = 2.3$ as chaotic map parameter.

CA_{old} is calculated to transform the $\beta(r)$.

$c\beta(r)$ is the modified updated light intensity of the firefly. The modified firefly algorithm (MFFA) is thus established in this section.

Objective/Fitness Function of fused features selected by Modified Firefly Algorithm

In this work, the broad formulation of the problem of selected fused features was given:

$$\min_{best, F_f^d} \emptyset(y(F_f^d))$$

Subject to: C1: $0 \le (normfeature, fit1, best, F^d) \le 1 \quad F^d \in F_n$

C2: $fit1 = \begin{cases} 1 & if\ fit1 \le \overline{fit1} \\ 0 & otherwise\ fit1 > \overline{fit1} \end{cases}$

$fit1 = \emptyset$ = accuracy - (k / F_f^d)

Where, *k* is a penalty term that discourages the use of too many features and

F_f^d is the total number of features in the dataset.

The desired trade-off between accuracy and simplicity can influence the penalty term.

Where,

$normfeature \in R^n$ are the vectors of the normalized feature $f_{normfeature}$ state variables, respectively.

$\overline{fit}$ is the mean square error for fit.

The entire state vector is denoted as $y = [normfeature]$,

Where, $normfeature$ is the set of the feature vector of $f_{normfeature}$.

The problem was defined on the feature's horizon $F_n = [F_n^d\ F_f^d]$.

Where, F_e consists of the original feature of F_o^d of y and final feature F_f^d selected from the normalized feature.
The decision variables for optimization include the local and global best position feature-dependent control variables $best \in R^n$ as well as potentially the final feature F_f^d. Finding the ideal set of decision variables to minimize the fitness function$\emptyset$, that is, $\emptyset(y(F_f^d))$ is the aim of the optimization.
The search space for the optimum is limited by constraints that specify the proper fitness error and feature parameter requirements to be met during feature selection at the feature selection stage.

In this study, fitness constraint and feature constraint were treated as C1 and C2, respectively. C1 made sure that the feature values fall between 0 and 1.
C2 validated that the fitness value for the features to be chosen was marked as 1 and the irrelevant features was labelled 0.

3.2 String Sizes for Face and Iris

String sizes for the face and iris biometric traits are displayed in the table 3.1 below:

Table 3.1: String Sizes for the Face and Iris biometrics

S/N	TECHNIQUES	FACE	LEFT IRIS	RIGHT IRIS
1	Original Size	720 x 960	640 x 480	640 x 480
2	Pre-processing Size	100 x 100	100 x 100	100 x 100
3	Feature Extraction	50 x 50	60 x 60	60 x 60
4	Concatenated features	170 x 170		
5	Feature Selection	20 x 20	24 x 24	24 x 24

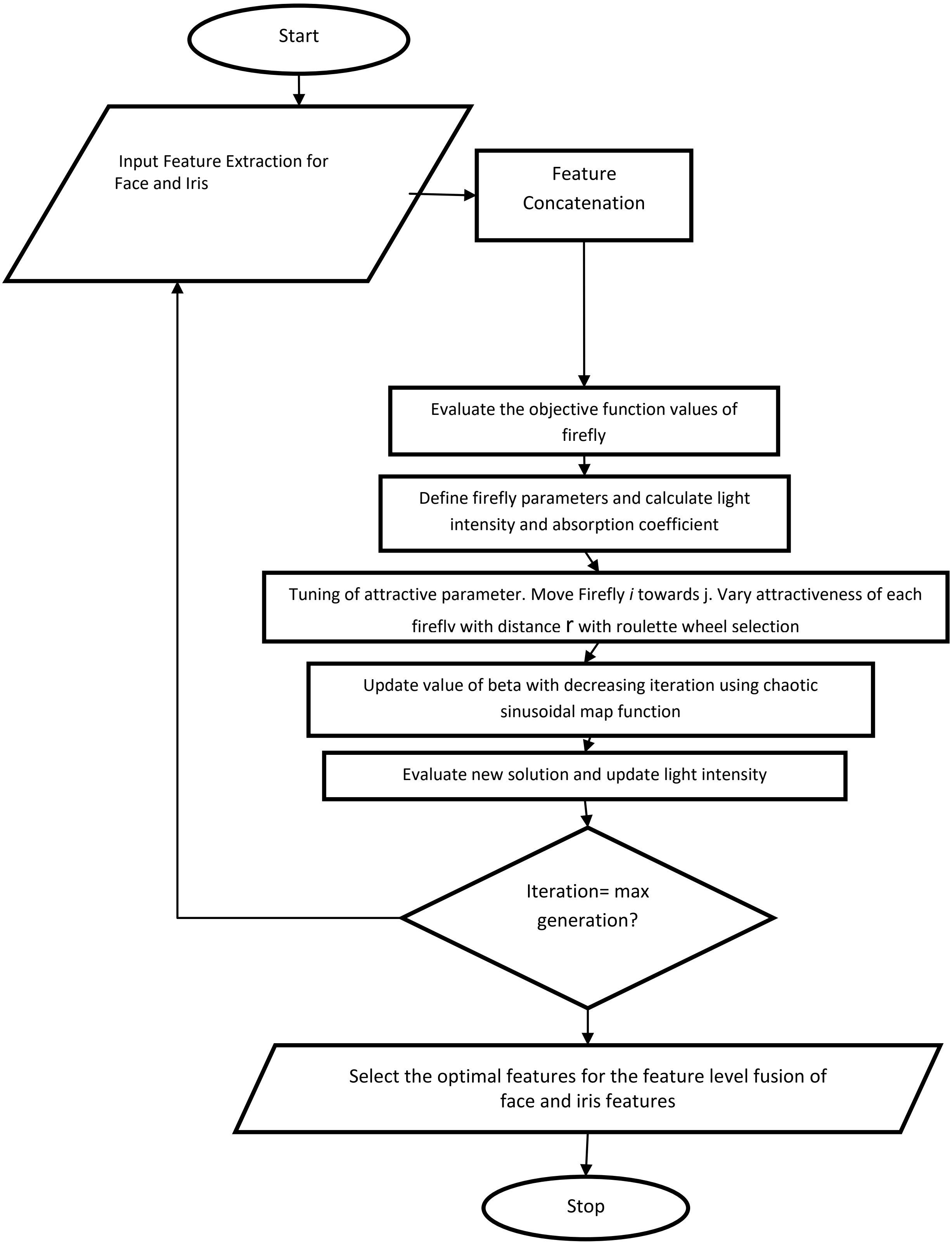

Figure 3.2: Flowchart for the Modified Firefly Algorithm (MFFA) (Researcher's Design)

2b. Development of a feature selection technique for multimodal system

3.3 Classification Using Support Vector Machine (SVM)

The fireflies (features) created in the preceding phase are presented to a classifier during the classification phase. Support Vector Machine (SVM), one of many machine learning approaches that can be employed as classifiers, was used in this study. The features selected by MFFA technique as derived in the objective 2a above were classified using Support Vector Machine (SVM) which is a statistical learning theory-based controlled classification technique. To differentiate between classes, SVM creates a hyper plane in multidimensional space. SVM iteratively develops the best hyper plane which is then utilized to reduce the classification error. SVM's main goal is to create a maximum marginal hyper plane (MMH) that splits the dataset into classes as evenly as possible. The following procedures are used by SVM to find the maximum marginal hyper plane:

a. Create hyper planes that effectively separate the classes.
b. Choose the hyper plane with the greatest separation from the nearest data points.

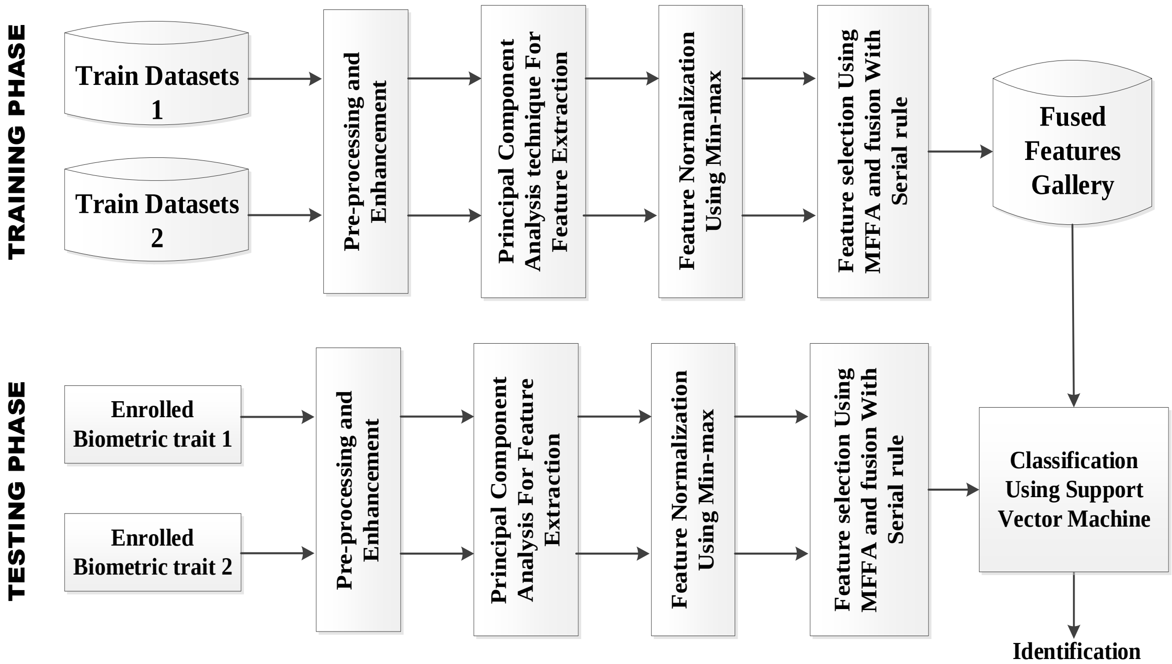

Figure 3.3: Multimodal Biometric Authentication System (Researcher's Design)

3.4 Ethical Consideration

This research was carried out under the supervision of the Babcock University Health Research Ethics Committee (BUHREC) following standard rules and guidelines. Every effort to avoid any form of ethical conflict was made.

4.0 Data Analysis, Results And Discussion Of Findings

This session presents the MFFA model for feature selection in multimodal biometric recognition system, implementation of the model, and the evaluation of the developed MFFA. The model is represented in Figure 4.1

4.1 The Meta-heuristic MFFA Model for Feature Selection Technique in Multimodal Biometric Authentication System

The MFFA model shows the meta-heuristic optimization approach for feature level fusion in multimodal biometric recognition system adopting Modified Firefly Algorithm (MFFA) as the feature selection technique for the face and iris biometric traits.

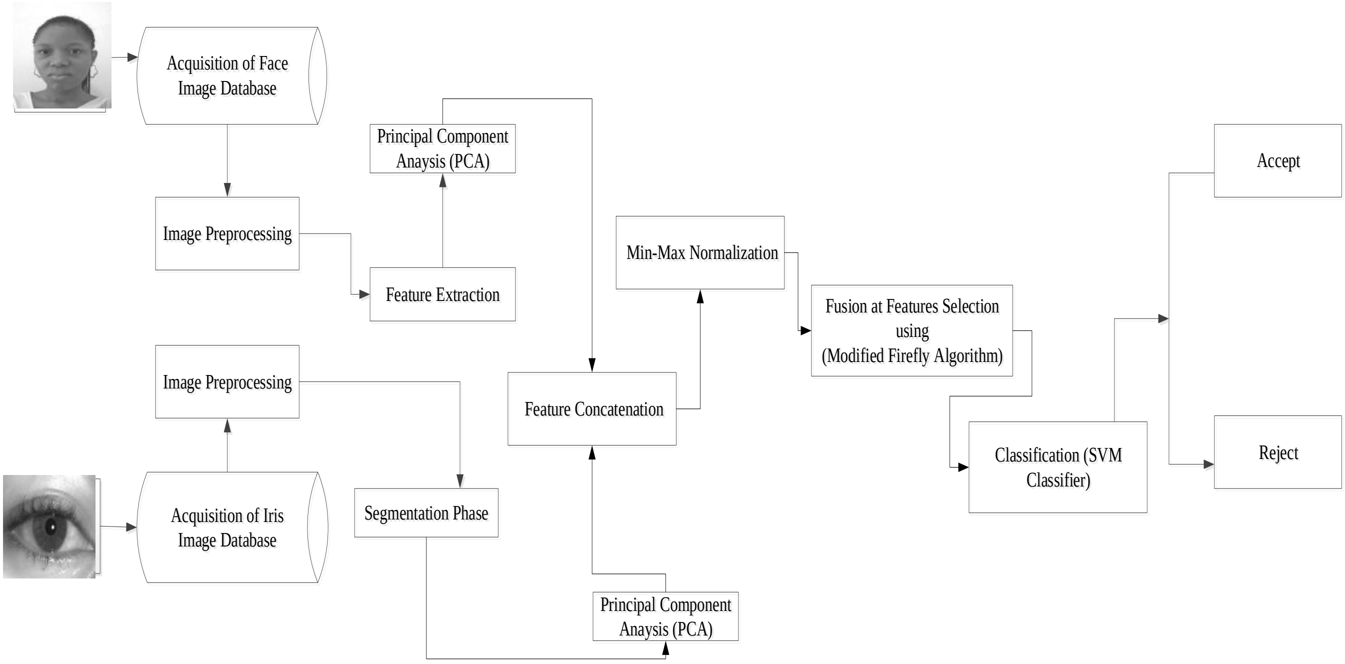

Figure 4.1: Model for Modified Firefly Algorithm for Feature Selection Techniques (Researcher's Model)

4.2. Image Pre-processing

1. FACE IMAGES

Samples of the original face images before preprocessing were shown below:

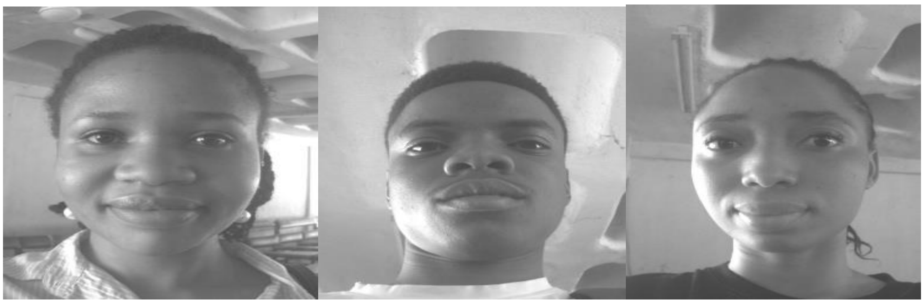

Figure 4.2: Original Captured Face Images

i. **Image Cropping**
Face images cropping were done by making use of an image cropping toolbox of MATLAB called "imcrop" and the samples of the cropped face images were shown below:

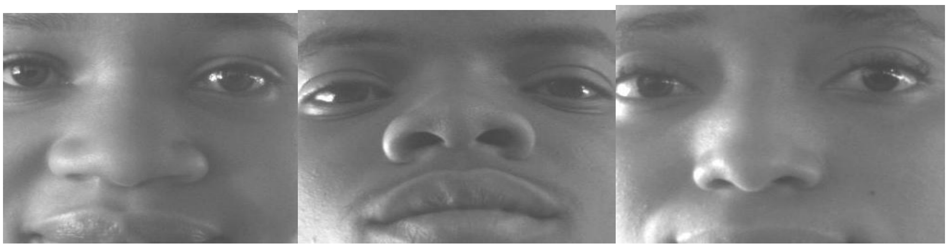

Figure 4.3: Cropped Face Images

ii. **Image Resizing**

Face images were resized through a resizing tool in MATLAB called "imresize".

iii. **Contrast Enhancement of Face Images**

Conrast enhancement of face images were done by using Histogram Equalization. It is also one of the preprocessed toolbox of MATLAB called “histeq”. The enhanced face images are shown below:

Figure 4.4: Contrast Enhanced Face Images

2. **IRIS IMAGES**

Preprocessing of both left and right irises images acquired was carried out separately.

i. **LEFT AND RIGHT IRIS IMAGES**

Samples of the original left iris images before preprocessing were shown below:

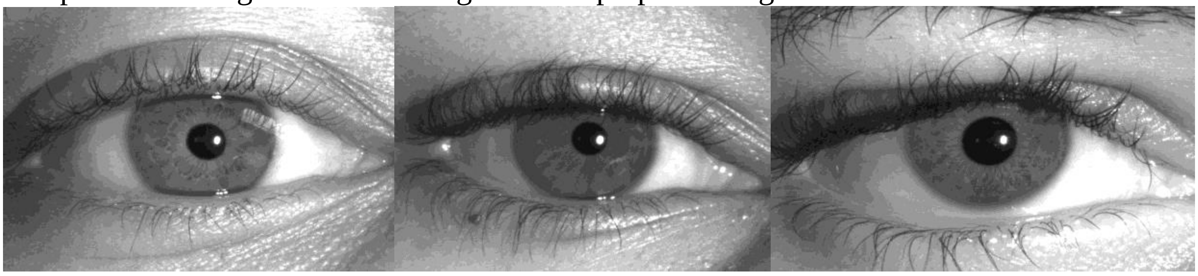

Figure 4.5: Original Captured Left Iris Images

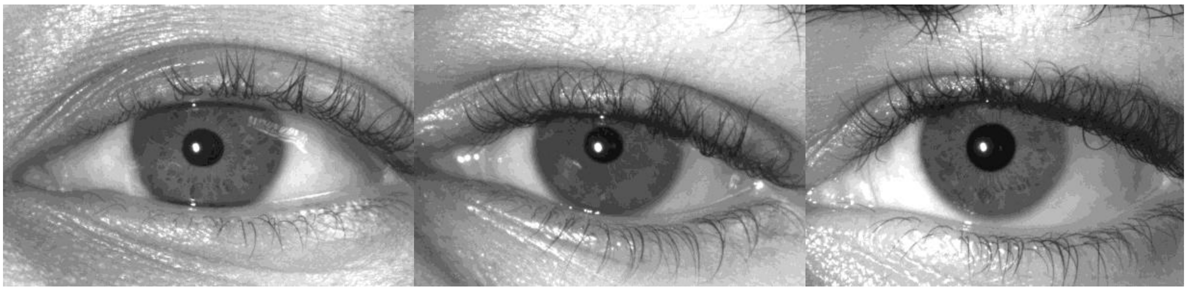

Figure 4.6: Original Captured Right Iris Image

ii. **Localization of Left Iris Images**

The left and right iris images gone through the preprocessing called localization separately. We localize such that the regions of the iris were rescaled. The extraction of the intensity values into the normalized polar representation through interpolation techniques were done. Examples of the localized left and right irises were shown in figures 4.7 and 4.8 below:

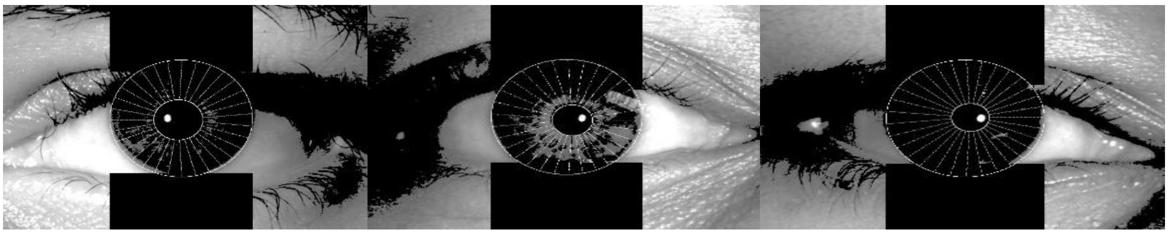

Figure 4.7: Localized Left Iris Image

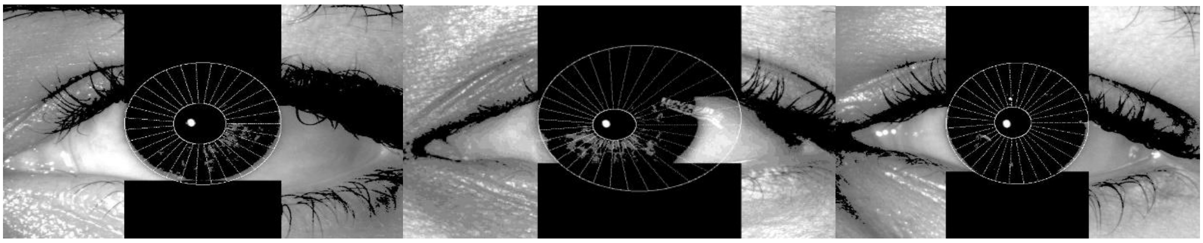

Figure 4.8: Localized Right Iris Image

iii. **Iris Segmentation**

For the segmentation, Hough Transform technique was employed to capture the regions of the iris and the pupils.

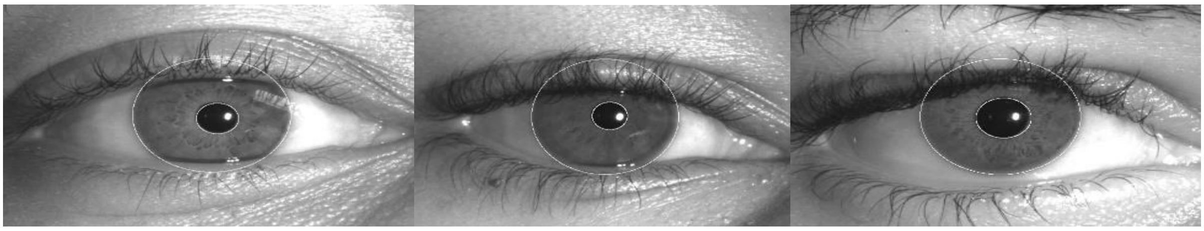

Figure 4.9: Segmented Left Iris Image

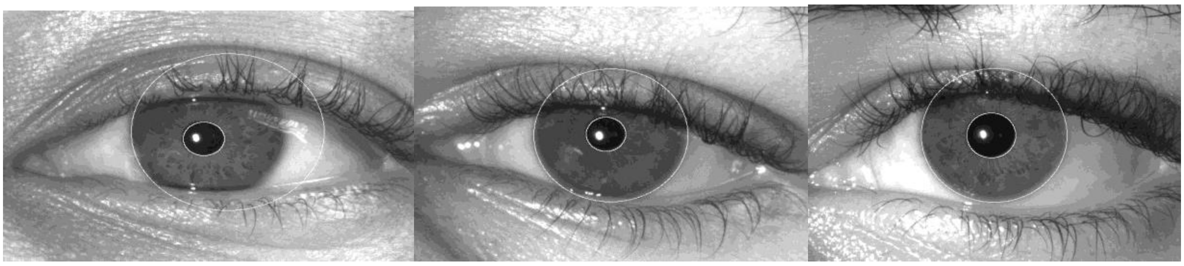

Figure 4.10: Segmented Right Iris Image

iv. **Normalization**

After the segmentation process, the segmented iris images were converted from the circular shape to rectangular shape using Daugman's Rubber Sheet Method by un-wrapping the circular region into the rectangular blocks of constant dimensions. For the purpose of appropriately extracting features, the segmented images were reduced to a regularized size.

Figure 4.11: Rubber Sheet Left Iris Representation

Figure 4.12: Rubber Sheet Right Iris Representation

4.3 Results Based on Performance Metrics for Unimodal, Bimodal, Bi-instance and Multimodal Biometrics

The results for unimodal, bimodal, bi-instance and multimodal biometrics are presented based on some performance metrics: false positive rate, sensitivity, specificity, recognition accuracy and computational time at the thresholds of 0.2, 0.34, 0.5 and 0.75.

4.3.1 Results of Unimodal Biometric system

The outcome displayed in Tables 4.1 MFFA provides evidence of how effective the strategies based on single biometric features were. Among the unimodal biometric traits are the face, the right and left irises. Each dataset used for testing contains 756 images. The effectiveness of the algorithms was evaluated at the threshold values of 0.2, 0.34, 0.5 and 0.75 as displayed in Tables 4.1.

Table 4.1: Results of the Modified Firefly Algorithm for Unimodal Biometric System

MFFA UNIMODAL (FACE, LEFT IRIS AND RIGHT IRIS)												
	Face	**Liris**	**Riris**	**Face**	**LIris**	**Riris**	**Face**	**LIris**	**Riris**	**Face**	**LIris**	**Riris**
TP	529	531	543	528	530	542	527	529	541	526	528	540
FN	38	36	24	39	37	25	40	38	26	41	39	27
FP	46	44	32	43	41	29	40	38	26	38	36	24
TN	143	145	157	146	148	160	149	151	163	151	153	165
FPR (%)	24.34	23.28	16.93	22.75	21.69	15.34	21.16	20.11	13.76	20.11	19.05	12.70
SEN (%)	93.30	93.65	95.77	93.12	93.47	95.59	92.95	93.30	95.41	92.77	93.12	95.24
SPEC (%)	75.66	76.72	83.07	77.25	78.31	84.66	78.84	79.89	86.24	79.89	80.95	87.30
PREC (%)	92.00	92.35	94.43	92.47	92.82	94.92	92.95	93.30	95.41	93.26	93.62	95.74
ACC (%)	88.89	89.42	92.59	89.15	89.68	92.86	89.42	89.95	93.12	89.55	90.08	93.25
TIME	67.63	83.79	115.45	65.36	81.47	114.77	64.51	82.54	113.88	66.54	85.03	111.51
THRES (%)	**0.2**			**0.34**			**0.5**			**0.75**		

4.3.2 Results of Bimodal Biometric System

The face and iris biometrics were used to build bimodal biometric schemes; the Face-Left Iris (FACE-LIRIS) and the Face-Right Iris (FACE-RIRIS). The results displayed in Tables 4.2 and 4.3 demonstrate how effective the bimodal biometric feature-based techniques are. The effectiveness of the approaches included in this study was evaluated at the threshold values of 0.34.

Table 4.2: Result of MFFA using Face-Left Iris

	MFFA (FACE AND LEFT IRIS)			
TP	541	540	539	538
FN	26	27	28	29
FP	34	31	28	26
TN	155	158	161	163
FPR (%)	17.99	16.40	14.81	13.76

SEN (%)	95.41	95.24	95.06	94.89
SPEC (%)	82.01	83.60	85.19	86.24
PREC (%)	94.08	94.57	95.06	95.39
ACC (%)	92.06	92.33	92.59	92.72
TIME (%)	91.94	90.82	91.64	91.51
THRES (%)	0.2	0.34	0.5	0.75

Table 4.3: Results of the MFFA using Face-Right Iris

	MFFA (FACE AND RIGHT IRIS)			
TP	542	541	540	539
FN	25	26	27	28
FP	33	30	27	25
TN	156	159	162	164
FPR (%)	17.46	15.87	14.29	13.23
SEN (%)	95.59	95.41	95.23	95.06
SPEC (%)	82.54	84.13	85.71	86.77
PREC (%)	94.26	94.75	95.24	95.57
ACC (%)	92.33	92.59	92.85	92.99
TIME (%)	97.69	98.50	98.94	97.98
THRES (%)	0.2	0.34	0.5	0.75

Results for sensitivity, precision, accuracy and computational time for the MFFA technique using the bimodal Face-Left Iris biometric are shown in Table 4.2 and Table 4.3. At the threshold value of 0.2, 0.34, 0.5 and 0.75 for the face-left iris biometrics. The results showed that the MFFA bimodal performed better than the MFFA unimodal in terms of timing, sensitivity, precision, and recognition accuracy. The Face-Left Iris bimodal biometric has indicated that the MFFA bimodal is more accurate and computationally less expensive. According to the results, the MFFA bimodal performed better than the MFFA unimodal in terms of sensitivity, precision, recognition accuracy, and time. Concluding from the computational time for the Face-Right Iris bimodal biometric, the results demonstrated that the MFFA bimodal approach is more accurate and computationally less expensive. However, the addition of Iris biometrics appears to offer greater performance with a significant increase in computational time. When MFFA bimodal was applied, the computation time appeared to be shortened. It was shown that the MFFA bimodal beat the MFFA unimodal modal biometrics, delivering greater performance with less sensitivity, precision, computing time, and recognition accuracy. In this work, the bimodal biometric outperformed the unimodal biometric in terms of sensitivity, precision, and recognition accuracy. However, because the training and testing sets included more features, the bimodal biometric required more computing time.

4.3.3 Results of Bi-instance Biometrics System

The results of the unimodal biometric test showed that a certain person's left and right irises are different from one another. In order to analyze the bi-instance biometrics based on the left and right iris, an approach was adopted in this study. Table 4.4 showed the results for the left and right iris bi-instance biometrics obtained using the MFFA approaches in terms of sensitivity, precision, accuracy and computational time.

Table 4.4: Results of the Evaluation performance of MFFA using Left Iris-Right Iris

	MFFA (LIRIS_RIRIS)			
TP	543	542	541	540
FN	24	25	26	27
FP	32	29	26	24

TN	157	160	163	165
FPR (%)	16.93	15.34	13.76	12.70
SEN (%)	95.77	95.59	95.41	95.24
SPEC (%)	83.06	84.88	86.24	87.30
PREC (%)	94.43	94.92	95.41	95.74
ACC (%)	92.59	92.86	93.12	93.25
TIME (%)	115.44	114.77	113.88	111.41
THRES (%)	0.2	0.34	0.5	0.75

According to the results, the MFFA bi-instance performed better than the MFFA in unimodal and bimodal in terms of sensitivity, precision, recognition accuracy and time. The fact that the left and right iris bi-instance biometrics computational time was faster suggests that the MFFA bi-instance is accurate and computationally less expensive. The results demonstrate that in terms of sensitivity, precision, recognition accuracy and time, the MFFA bi-instance surpassed the MFFA unimodal. The left and right iris bi-instance biometrics computational time which is faster demonstrated that it is more precise and computationally less expensive.

4.3.4 Results of Multimodal Biometrics System

The results of the performance metrics for the multimodal biometrics (face, left iris and right iris) for the developed MFFA based on the four thresholds values of 0.2, 0.34, 0.5 and 0.75 are displayed in table 4.5 below.

Table 4.5: Result Evaluation performance of MFFA using Face, Left Iris and Right Iris (Multimodal)

METRICS	**MFFA (FA_LIRIS_RIRIS)**			
TP	559	558	557	556
FN	8	9	10	11
FP	16	13	10	8
TN	173	176	179	181
FPR (%)	8.46	6.88	5.29	4.23
SEN (%)	98.59	98.41	98.24	98.06
SPEC (%)	91.53	93.12	94.71	95.77
PREC (%)	97.22	97.72	98.24	98.58
ACC (%)	96.83	97.09	97.35	97.49
TIME (%)	130.78	131.92	130.36	130.53
THRES (%)	**0.2**	**0.34**	**0.5**	**0.75**

The results showed that the multimodal biometric system (face, left iris and right iris) gave better and more distinguishable results than the unimodal, bimodal, and bi-instance biometric systems utilizing the same threshold values. The MFFA method is hence more precise and computationally faster.

5.0 Conclusion And Recommendations

5.1 Conclusion

For a multimodal biometric authentication system, a modified firefly algorithm (MFFA)-based meta-heuristic approach for feature selection was created in order to reduce the dimensionality of feature vectors and choose the most important and balanced features from black people's faces and both iris samples taken locally. A chaotic sinusoidal map function and the roulette wheel approach were included into the current FFA by the newly developed technique, called MFFA. In order to improve the classification performance of the system and prevent being caught at the local optima, it selected the most pertinent characteristics and reduced the high dimensional feature vectors space. These features make the MFFA a useful feature selection method for biometr identification systems. Results from our experiments showed that the developed technique was effective in fusing multimodal feature sets. Additionally, the MFFA technique is highly efficient computationally and appropriate for real-time applications.

5.3 Recommendations

This study is highly advised for use in institutions like schools, businesses, governmental bodies, and forensics that need multimodal biometric authentication systems that are dependable, effective, and quick to process in order to authenticate a person. It can also be used due to its contactless capabilities, and to a certain extent, the biometric qualities unaffected by old age or disease can be used by the INEC to lower the false acceptance rate where many people were denied civic rights. It can also be used in JAMB for student registration and identification, as the currently used fingerprint biometric technology is antiquated and unsecure. Further research would look into the potential of combining iris and face with other heterogeneous biometric traits such as palm prints ear and fingerprints. Additionally, by utilizing the developed MFFA using hybridized meta-heuristic optimization approach for feature selection.

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