CHAPTER 4

Swarm Intelligence and Evolutionary Algorithms for Diabetic Retinopathy Detection

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4.1 INTRODUCTION

In the last few decades, it has been observed that diabetes is rising at an extremely high pace across the world. The number of diabetic patients is increasing exponentially, which is a challenge for the healthcare sector. According to the annual World Health Organization survey, diabetes is on a continuous growth. Diabetes is a disease which is the starting point of various health issues. Macrovascular variations are the major complications that result because of diabetes, e.g. diabetic retinopathy (DR), renal and heart ailments [1].

A latest survey states that diabetes is the fifth dangerous disease type that does not have effective cure and measures [2,3]. DR is a very common problem in diabetes. It is actually the major cause of blindness in the patients. One survey says that more than 75% of the population with DR belong to developing countries, hence the complications cannot be handled due to lack of treatment facilities. Those having DR probably suffer blindness [4] because until the time it can be recognized by an individual the changes in retina reach an extent such that it cannot be curable.

4.1.1 Classification of Diabetic Retinopathy

DR is a micro-angiopathy that shows features of microvascular occlusion and leakage, and it is important to be familiar with the signs of occlusion and leakage in the retina to understand the pathogenesis and signs of DR. DR pathogenesis comprises capillaropathy, haematological changes, microvascular occlusion [1]. So, what happens to blood vessels in the presence of diabetes, high blood sugar causes several things to occur in the blood vessels, there capillaropathy where the blood vessels walls degenerate, haematological changes where deformity of blood cells occurs and thickening of the blood happens and finally microvascular occlusion, causes irregular blood flow and decreased oxygen. Classification of DR are given as follows:

1. Non-proliferative DR(NPDR) (background DR)
2. Maculopathy
3. Pre-proliferative
4. Proliferative

1. Non-proliferative Diabetic Retinopathy

The signs of background or NPDR are microaneurysms, retinal haemorrhages, macular edema and hard exudates. DR stages can be identified on the basis of DR features and severity [5]. NPDR can be further classified into three categories: early NPDR, moderate NPDR, severe NPDR. These stages of NPDR are described as follows:

(a) Early NPDR: It contains microaneurysms with hard exudates and haemorrhage or without them. Almost 50% of the diabetic patients have minimum [6], i.e. mild NPDR symptoms.

(b) Moderate NPDR: In this stage many microaneurysms with hard exudates and haemorrhage are present. A study reveal that 16% patient of non-proliferative DR are probably convert into proliferative DR (PDR) within a year [7].

(c) Severe NPDR: These type of NPDR represents by following characteristics [1]:
   i. In four quadrants multiple haemorrhages and microaneurysms presents.
   ii. Two or more quadrants full of bleeding (venous)
   iii. In minimum one quadrant intraretinal microvascular abnormalities present.

In DR the first stage is NPDR. In NPDR the blood vessels of the retina begin to weaken causing tiny lumps called micro-aneurysms to swell out from the walls of the vessels. In this stage, very mild symptoms may be felt or there may be no symptoms at all. Gradually, the blood vessels start getting blocked and transport less and less blood. Some areas are stared of oxygen and begin to send signals to the retina to create new blood vessels. Hence, it is essential for a diabetic patient to have regular check-ups to ensure early diagnosis and treatment. NPDR will be converted in to PDR within one year, there will be approximately 50% probability of this [7].

2. Maculopathy

Any edema hard exudate or ischemia which involves the fovea is termed diabetic maculopathy, and this is the most common cause of vision impairment in diabetes, especially those with type 2 diabetes as there are few different types of Maculopathy is their focal in one area diffuse spread all around ischemic or clinically significant macular edema[1]. Here we discuss clinically significant macular edema because it is the clinically significant. It is observed in an image of a blurry macula with some dot haemorrhages with hard exudates near, hence a thickened macula is actually easier to detect on OCT.

3. Pre-Proliferative DR (PPDR)

Background DR that shows sign of imminent proliferative disease is called pre-proliferative DR (PPDR). Clinically signs indicate progressive retinal ischemia and the signs include:

i. Cotton wool spots (soft exudates)

ii. Intraretinal microvascular abnormalities (IRMA)

iii. Other changes like venous and retinal arterial changes and dark blot haemorrhages

The risk of actually progressing to PDR depends on the number of lesions seen on the retina, and you can actually have proliferative disease in one eye and pre-proliferative in other [8]. It contains three abnormalities that are intraretinal microvascular abnormalities (IRMA), arterial changes, dark blood haemorrhages.

Intraretinal micro vascular abnormalities (IRMA): They are fine irregular red lines that runs from arteries to the venous. When tiny changes in the vasculature are seen, it is a clear indication that it's actually free of DR and may progress to proliferative venous changes, which are also common in proof relief DR and include symptoms like dilated and tortuous veins. Looping blood vessels bleeding is there where you can see the little bead-like structures where the vessels begin to start to look like little beads and sausage-like segmentation where the vessels look like a string of sausages.

Arterial Changes: These changes in pre proliferative DR include peripheral neuron of the arteries something called silver wiring, where it looks like silver wire that has been inserted into the artery itself and then complete obliteration where it is actually missing and completely blocked.

Dark blood haemorrhages: These are retinal haemorrhages found in the middle retinal layers, and they are exactly as described—dark blood haemorrhages bleeding into the retina.

4. Proliferative Diabetic Retinopathy (PDR)

PDR is an advanced form; DR progressive circulation to the retina is affected due to which new blood vessels begin to grow into the retina and into the gel-like fluid called vitreous that fills the central posterior segment or cavity of the eye. These blood vessels are thin and delicate, and may leak blood into the vitreous causing clouding of vision [1].

The macula is the small region of the retina that is responsible for sharp detailed central vision. When the fluid leaks into the macula, it causes the macula to swell resulting in blurred vision. As the retina gets damaged, scar tissue is formed and pressure builds up in the rear chamber. This could result in damage to the optic nerve at the same time; as scar tissue shrinks it pulls at the retina and a portion of the retina may break loose from the back of the eye, this is called "retinal detachment," which results in gradual loss of vision and ultimately blindness.

The classification of PDR contains neovascularisation, rubeosis, neovascularization at a disc as signs:

(a) Neovascularization (NV): It is stated as a typical emergence of new blood vessels that usually emerges on the internal surfaces of retina [1]. This is caused by angiogenic growth factor increased by hypoxic retinal tissues in an attempt to revascularization of the hypoxic retina, so there is lack of oxygen in these vascular endothelial growth factors and they create new blood vessels and neovascularization. The problem with the new blood vessels is that they are irregular, they are not formed well, they are fragile and then they burst and leak. The sign of neovascularisation is mottled mess of very fine blood vessels.

(b) Rubeosis: It occurs with PDR and rubeosis appears as neovascularization but it is neovascularization at iris and this is definitely not a normal state of affairs.

(c) Neovascularization disc (NVD): The term NVD in a patient file that stands for neovascularization elsewhere and that means neovascularization occurring somewhere in the retina not at the disc.

4.1.2 Swarm Optimization and Evolutionary Algorithms

In swarm optimization, birds, bees, fish and ants, all of these creatures are evolved methods of amplifying their intelligence by syncing together, thinking together in systems, this is why flock in fish school and bees swarm they are together than alone [9]. Actually, there is no discussion about crowd sourcing like humans do by taking votes in polls and surveys, there is a discussion about forming real-time systems with feedback loops, so deeply interconnected that a new intelligence forms and emergent intelligence with its own personality and intellect. There is a discussion about forming a hive mind, biologist call this swarm intelligence and it's a natural step in the evolution of most social species.

A brain is a system of neurons so deeply connected that intelligence forms a swarm, which is a system of brain, swarm is a brain of brains and it can be in any individual. For example, there are group of large number of honey bees and they have a very difficult problem to solve; they need to find a new home to move into that, a new home could be hollow log of a hole in the side of a building or anything. It sounds like a simple problem, but this is connected to life or death decision that could impact the survival of the colony for generations, so to solve this problem the colony sends out hundreds of scout bees which search a 30 square mile area and find dozens of candidate sites. That's the easy part; the hard part is that they need to pick the best possible solution from all the options that they have discovered [10].

Honey bees have a tiny brain which is smaller than a grain of sand and has less than a million neurons; human have 85 billion neurons, so however smart humans think honey bees have the intelligence equal to the human intelligence divide by 85,000. Honey bees are very discriminating house hunters as they need to find a new home that's large enough to store the honey they need for winter, is ventilated well enough to stay cool in the summer, is insulated well enough to stay warm in cold nights, is protected from the rain, is near a good source of clean water, and of course is well located near good sources of pollen: this is a complex multivariable problem and to optimize survival the bees need to pick the best possible solution across all the competing constraints and they do it remarkably.

Biologists have shown that honeybees picked the best possible solution over 80% of the time, however, if a human CEO needs to find the perfect location for a new factory, he or she would face a similarly complex problem and it would be very difficult to pick the optimal solution, and yet honey bees can do it. A honey bee has a brain so tiny that it cannot even conceive the problem, but when they think together in a system they can solve it accurately; they can rival a human brain. How do they do this? They do it by forming a swarm intelligence, a brain of brains that combines the knowledge and wisdom and insight and intuition of the group and converges on optimized decisions [11].

Honeybees do everything by vibrating their bodies; biologists calls this waggle dance because for humans it looks like bees are dancing, but in reality they are generating the signals that represent their support for the various home sites under consideration and by combining these signals the bees engage in a multidirectional tug of war pushing and pulling on the decision until they find that one solution that can be best agreed upon. It is usually the optimal solution and unlike us humans the bees don't entrench, don't fall into gridlock, don't settle for a bad solution that nobody's happy with, instead they find the solution that's best for the group as whole. Swarms are flexible and dynamic reviewing. Why humans amplify our intelligence now if birds, bees and fish can form a brain of brains. Why can't people do it? Swarm turns in to artificial super experts who can make more accurate, predictions, decisions evaluations, and forecasts. This is about the natural swarm. Over the last few years, we have been modelling how swarms like this amplify the intelligence of groups and using those models to create the algorithms and interfaces that enable humans to form similar swarms online [12]. Here swarm optimization and evolutionary algorithms are used to create the models for the detection of DR. This chapter contains the features of DR, models for DR, and approaches for detection of DR.

4.1.3 Objectives and Contributions

Diabetes increases day by day in a living being, the mellitus results of diabetes turn into micro-vasculature which causes DR. As the DR increases by time, it causes complete vision loss. For efficient completion of DR practises, it is necessary to identify the variations and morphological changes in micro-aneurysms, optic disk, retinal blood vessels, hard exudates, soft exudates, haemorrhages, etc. These types of identifications are complicated and require computer-aided diagnostic system (CAD) by which the DR may be identified earlier. The aim of this chapter is to discuss and analyse the CAD systems that are designed and implemented for effective identification of DR.

The main objective of the study is to focus on the traditional and latest approaches of CAD systems by which DR can be identified in early stages efficiently. Here the discussion and analysis of number of existing literatures represent DR CAD systems.

The approaches discussed here are evolutionary approaches that contain particle swarm optimization (PSO), genetic algorithm (GA), ant colony optimization (ACO) and bee colony optimization. These evolutionary computing approaches can play an important role for optimizing DR-CAD components like pre-processing, feature extraction, dimensional reduction, feature selection, clustering and classification.

The learning objectives of the chapter are as follows:

(a) Recognize the importance of DR as a public problem.

(b) Discuss DR as a leading cause of blindness in developed countries.

(c) Identify the risk factors for DR.

(d) Describe and distinguish between the stages of DR.

(e) Understand the role of swarm intelligence and evolutionary computing approaches for the prevention of vision loss and early detection of DR.

4.2 FEATURE OF DIABETIC RETINOPATHY

These features represent the deficiency caused by the diabetes disease. It is observed that there are main problems in retinal damage which is to be mentioned below. Table 4.1 represents the characteristics, colour, shape and volume affected by the following abnormalities.

4.2.1 Microaneurysms

This is one of the signs of NPDR; they are localized out pouching of the capillary wall spreading out and in a certain area thickening up and moving in an outward direction so that these microaneurysms can leak plasma into the retina because the blood retinal barrier is

TABLE 4.1 Characterization of various abnormalities based on colour, shape and volume.

Types of Abnormalities	**Characteristics**	**Colour**	**Shape**	**Volume affected**
Microaneurysms	These are tiny aneurysms which causes swelling in the side of blood vessels	Red spot	Small circular	Small
Haemorrhages	These have a flame-like appearance or they can be intra retinal and located in the middle layers of the retina	Bright red	Not defined	Large
Hard exudates	Hard exudates are caused by retinal edema and develop at the junction of normal and swollen retina	Yellow	Circular	Large
Soft exudates	Vessel occlusion as opposed to hard exudates which result from vascular leakage	Yellowish white	Not defined	Large
Neo vascularization	Emergence of new blood vessel on the internal surface of retina.	Red	Not defined	Large
Macular edema	It causes leakage of fluid or solutes around the macula	Not defined	Roundish	Large

broken down or thrombosed and there are some little out-pouching dots of microaneurysms coming out of these tiny little blood vessels. The signs include tiny little red dots initially temporal to the fovea which are the earliest signs of DR, but they are hard to see when you are looking at the fundus and actually more obvious during fundus fluorescein and geography. It is of the eye that had a fundus fluorescein angiogram and their tiny little specks are microaneurysms. The changes in retinal blood vessels formed microaneurysms [8]. It is in round shape and it has dark red spots, temporarily called macula.

4.2.2 Haemorrhages

It's quite easy to get confused with dot haemorrhages which are more easily seen on the retina because they are actually larger and quite similar. The retinal haemorrhages and heritage can appear actually either in the retinal nerve fibre layer and these have a flame-like appearance or they can be intra-retinal and located in the middle layers of the retina and have a red-dot blot appearance, so these dot blot haemorrhages can be a larger version of microaneurysms that they look similar on the retina. The leakage in blood vessels causes haemorrhages [13]. They look like a red spot, having non-uniform margin with varying density.

4.2.3 Hard Exudates

Hard exudates are caused by retinal edema and develop at the junction of normal and swollen retina. They are made up of lipoproteins and lipid-filled macrophages and are waxy yellow in appearance with distinct margins. They are usually arranged in clumps or ring shape around the retina and are often surrounding microaneurysms. When the leakage stops occurring in the retina, these can reabsorb but it can take months or years [13,14].

4.2.4 Soft Exudates

Hard exudates are made up of lipids and they are yellow in colour and often found close to the macula. They have distinct margins and result from blood vessel leakage. Cotton wool spots on the other hand are made up of axonal debris and they are more prominent around the optic nerve, where the nerve fibre lays the cast and are lighter and coloured light yellow or white as opposed to the darker yellow of hard exudates. Cotton wall spots are sort of billowy-like clouds that do not have distinct margins, which result from vessel occlusion as opposed to hard exudates which result from vascular leakage.

In general, CWS occurs because of the occlusion of arteriole [15]. The reduced blood flow to the retina results into ischemia of the retinal nerve fibre layer (RNFL) that eventually influences the axoplasmic flow and thus accumulates axoplasmic debris across the retinal ganglion cell axons. Such accumulation can be visualized like fluffy white lesions in the RNFL, which is commonly known as CWS [15,16].

4.2.5 Neo-Vascularization

This is caused by angiogenic growth factor increased by hypoxic retinal tissues in an attempt to revascularization of the hypoxic retina, so what happens is that there is lack of oxygen in these. Vascular endothelial growth factors kick in and they create new blood vessels and neovascularization. The problem with the new blood vessels is that they are irregular, not formed well, are fragile, and then they burst and leak[17].

4.2.6 Macular Edema

This is caused by extensive capillary leakage or leakage from microaneurysms and dilated capillaries, so what happens is fluid accumulates in the inner retinal layers and if the fluid accumulates under the fovea it can eventually develop a sea storied appearance and is called "sisterhood macular edema." You can observe the retinal thickening and the cyst with space in the OCT scans generally, in which surely the bottom part shows a fundus fluorescein angiogram of a patient with macular edema, it will typical a flower-like pattern where the cysts fill up with fluorescein and have this little roundish appearance. Actually it is a swollen part of the eye retina, it occurs due to problems of anomalous retinal capillaries [18,19].

4.3 DETECTION OF DIABETIC RETINOPATHY BY APPLYING SWARM INTELLIGENCE AND EVOLUTIONARY ALGORITHMS

There are many mathematical models and a number of different analytical approaches has been proposed and developed for DR. The traditional approaches are found limited so there will be consideration of complex features, many computational complexities and many solutions presence, etc. For DR and related problems, there will be some approaches of evolutionary computing, which are based on the concepts of natural phenomenon and human centric which drives an affinity, effectiveness and an idea for treatment, attention across the society and industry. There will be some efforts on exploring its efficiency towards DR, so there will be description of different types of Evolutionary Computing algorithms for DR.

An evolutionary computing (EC) approaches are based on natural phenomenon and it is observed that EC are most effective procedure to build a model because these are primarily evolved from the concept of natural bird's quality. There are number of approaches and models built for DR detection and diagnoses that are based on EC algorithms. There will be consideration of complex feature, different solutions, computational problem and traditional approaches are found confined, so to handle these different problems recently EC and swarm intelligence approaches are used [9]. Here a discussion of different efforts taken by EC approaches towards DR. In this given context we explore the EC algorithms for DR processes.

4.3.1 Genetic Algorithm

The GA is a method for solving both constrained and unconstrained optimization problems that is based on natural selection, the process that drives biological evolution. GA is a powerful tool for solving large-scale design optimization problems [9]. The research interests in GAs lie in both its theory and applications. GA is a type of meta-heuristic search and optimization algorithm inspired by Darwin's principle of natural selection. The central idea of natural selection is survival of the fittest. Through the process of natural selection, organisms adapt to optimize their chances for survival in a given environment.

The general procedures of a GA include:

1. Create a population of random individuals
2. Evaluate each individual's fitness
3. Select individuals to be parents
4. Produce children

5. Evaluate children
6. Repeat 3 to 5 until a solution with satisfied fitness is found or some predetermined number of generations is met.

To yield better solutions higher fitness value signifies higher probability of a chromosome to take participate in the next generation. Offsprings are built using GA based on estimated fitness value, mutation probability (P_m) and crossover probability (P_c). Implementing the population generation continues till the criteria is reached and optimal solution is obtained. Considering robustness of GA, it has been used in an array of applications, including DR, where it is primarily suggested for feature selection and as the enhancement model for classifiers. The following sections discuss the key literatures exploiting GA for DR model development. The methods and salient feature used by the authors for research are shown in Table 4.2.

a) Feature in fundus

Osareh et al. [20] suggests a computational intelligence techniques-based model which takes images of retinopathy as input and identifies

TABLE 4.2 Performance measures of GA based models

Author	Method	Salient feature
Osareh et al. [20]	Neural network, GA	Gabor filters, retinal exudates
Rashid et al. [21]	Fuzzy C-means, GA	Fuzzy histogram equalization
Naluguru et al. [22]	Neural network, GA	Bacterial foraging algorithm
Karegowda et al. [23]	GA- correlation based feature selection, BPNN	Feature selection, Decision tree
Ganesan et al. [24]	GA, SVM	Trace transformation
Nirosha et al. [25]	GA, Adaptive Neuro Fuzzy Inference system	Low-cost CAD model
Santos et al. [26]	GA, SVM	Optical coherence tomography (OCT)
Quellec et al. [27]	GA, Powell's direction set descent.	Local lesion template matching, optimal wavelets transform.
Akram et al. [28]	GA, SVM	GMM, eeightestimation
Lee et al. [29]	GA	Fundus auto-fluorescence (FAF), age-related macular degeneration (AMD)
Hung et al. [30]	RIS system, TRDD system, GA	Tractional retinal detachment

exudates pathologies automatically. The segmentation of images is done by fuzzy C-means clustering. These segmentations contain pre-processing steps, i.e. contrast enhancement and colour normalization. To classify the segmented region, they need to set some feature initially, such as strength, size, colour etc. The GA is used to learn the given features to rank them and to identify the subset and to identify the subset which gives the accurate classification results.

Rashid *et al.* [21] proposed an efficient screening model for exudates detection in fundus images which are compatible to real-time applications. In this automated model, fuzzy C-means techniques are used in collaboration with morphological techniques, to improve the robustness of blood vessel and optic disc detection. There are different set of initial features considered to discriminate exudates regions from other segmented regions such as compactness of the region, region size, length of the perimeter of the region, region edge strength, mean value inside the region, mean value outside the region, standard deviation of mean values inside and outside the region and region mean filter responses.

b) Segmentation of Retinal Lesions

EC techniques for segmentation are presented by Naluguru et al. [22]. It is a type of feature extraction technique which contains blood vessel segmentation in automatic DR. They are using GA with SVM and Bacterial Foraging Algorithm (BFA) to extract the blood vessels, texture, optic disc and entropies from the retina. It involves in segmentation after that it will extract the features from the images based on bifurcation points, texture, entropy then moves to statistical feature extraction. After statistical feature extraction, authors use GA and BFO with neural network to classify the images into three categories, normal, NPDR and PDR, and then find the best classifier for retinal lesion and grade them into gentle moderate and extreme.

c) Feature extraction of exudates

Karegowda et al. [23] developed a CAD system or automated system that can effectively classify the retinopathy images and improve the diabetic screening program. They have used a BPNN (Back Propagation Neural Network) model to classify the images and detect exudates. That model further improved by using two methods that are DT (Decision tree) and GA-CFS (GA correlation-based feature selection).

Ganesan et al. [24] formed an efficient model for feature extraction of exudates. First, they have taken retinal images dataset, then perform pre-processing, and then visualize a model based on Trace Transform function. This model will do the feature ranking and selection and then classify them by using SVM and PNN (probabilistic neural network) and optimize that with GA.

d) Segmentation of exudates

A very effective CAD model has been developed by Nirosha et al. [25] in which author has used GA and ANFIS (Adaptive Neuro Fuzzy Inference System) together to classify and detectabnormalities of DR. Santos et al. [26] focused on OCT (optical coherence tomography) data for effective classification using SVM classifier. The classification is totally based on OCT data. In the proposed approach, different materials and methods are used like data gathering and OCT data model based on logarithmic of linear spaces. Perform discrimination between eyes of healthy peoples and diabetic patients, at last measures parameter choice through GA heuristic search. After parameter choice validation of the selected data model for SVM, discrimination is performed.

e) Microaneurysms detection

Quellec et al. [27] proposed an automatic detection model to test microaneurysms in retina images. For microaneurysms model validation, a multimodal photographic image database is used to find the mean and standard deviation of the pixel. The proposed approach represents template matching in the wavelet domainthese wavelet domains consider template matching, adaptation in the wavelet domain and moving windows approach. Overall learning procedure will be follow as the images of the learning dataset then form a wavelet transform using wavelet filter, these wavelets transformed the images and compute the distance of the model.. It will follow by grid search with a particular threshold and calculate the efficiency. This proposed model learning procedure contains model parameter selection, subset learning and wavelet learning. It will efficiently detect microaneurysms. Akram et al. [28] in this author proposed a hybrid model for classification using support vector machine and GMM classify region as micro aneurysms or non-microaneurysms. To improve the accuracy author applied GA with weight estimation for classification that increases the accuracy. This approach includes pre-processing which can extract feasible Region of interest.

f) Segmentation of blood vessel

Lee et al. [29] present a segmentation method to preserve interest of features. Author has used fundus auto-fluorescence (FAF) images, which is used to show segmentation then GA plays an important role, in this GA prone to inter and intra observer variability. Here classification and segmentation is done by using GA quantification and this automatic quantification for determining AMD diagnosis and disease progression. They are identifying hypo-fluorescent GA regions from retinal vessel structures. Hung et al. [30] proposed a system of segmentation to detect blood vessels from retinal images, dark spots, bright spots, etc. Author proposed a tractional retinal detachment diagnosis system based on retinal images that can provide impressive results in segmentation of bright spots and dark spots. The system they have made is RIS (retinopathy image segmentation) that correctly segments all the regions. In this to identify the most appropriate results of the parameters resides in RIS system; author has used genetic-based parameter detector—retinopathy image segmentation method (GBPD-RIS). Another system they have developed is called TRDD (tractional retinal detachment disease), which is based on diabetic patient's retinal images. The TRDD contains three steps: first analysis of GLCM (Gray-level Co-occurrence matrix), BFM and GBPD-TRDD system. The co-occurrence texture statistics contain different features like contrast, dissimilarity, correlation, inverse difference moment. The methods and salient feature used by the authors for research are shown in table 4.2.

4.3.2 Particle Swarm Optimization

A particle is a small localized object to which several physical or chemical properties such as volume or mass can be ascribed. Swarm is a collection of something that move somewhere in large numbers, e.g. flock, crowd, flood, etc. Optimization is the action of making the best or most effective use of a situation or resource [31], e.g. minimizing the total travel time from one city to other. PSO is a population-based stochastic technique inspired by social behaviour of bird flocking or fish schooling. The scenario of PSO is that, a group of birds are randomly searching food in an area [32]. There is only one piece of food in the area being searched. All the birds do not know where food resides, but they know how far the food presents. So, using the best strategy to find food, the effective one is to follow the bird which is nearest to the food. In PSO, each single solution is a "bird" in the search space called "particle". All of particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles [33]. In this study, the PSO is used for detection of DR. The methods and salient feature used by the authors for research are shown in Table 4.3.

a) Retinal images feature extraction

Anitha et al. [34] compare the performance of GA and PSO and prove that both the techniques yield optimal solutions with different strategies and computational efforts. IT is used for feature selection in retinal images. They classify the retinal images in to four classes named central retinal vein occlusion (CRVO), choroid neo-vascularisation membrane (CNVO), NPDR, and central serious retinopathy. There is a methodology of the automated retinal classification in which retinal images database is used for experiment. Feature extraction of retinal images can be done by GA and PSO then classified using SOFM based classification. The selected features in PSO are area, perimeter, skewness, and correlation and inverse difference moments and in GA the features selected are area, perimeter, kurtosis, correlation and contrast. Balakrishnan et al. [35] proposed a hybrid model for classification and feature

TABLE 4.3 Performance measures of PSO based models

Author	Method	Salient feature
Anitha et al. [34]	SOFM Neural Network, PSO, GA	Central retinal vein occlusion (CRVO), choroidal neo-vascularization membrane (CNVO)
Balakrishnan et al. [35]	PSO, SVM, differential evolution (DE) algorithms	Histogram of orient gradient (HOG), complete local binary pattern (CLBP)
Ravivarma et al. [36]	PSO, SVM, FCM	Hyperbolic median filter
Sreejini et al. [37]	Retina vessels, PSO	Optic disc, Fovea, multiscale matched filter
Sreejini et al. [38]	PSO, ETDRS	Mathematical morphology
Devasia et al. [39]	PSO, DRION database	Histogram, localized optic disc

extraction from retinal images. Channel extraction and median filter areused for pre-processing of retinal images. After pre-processing of images, authors used histogram of oriented gradient (HOG) with complete local binary pattern (CLBP) to perform feature selection. In this model, PSO is used to optimize the results.

b) Exudates segmentation

An efficient system is designed and implemented for detection of exudates in colour fundus images using image processing techniques. Ravivarma et al. [36] present a novel approach to achieve efficient identification of exudates in low-quality retinal images. Hyperbolic median filter is used for pre-processing then segmentation is done by using fuzzy C-means clustering algorithm. The features like colour, size, and texture extract from segmentation of images. After segmentation the features are optimized through PSO and then classified by SVM. Sreejini et al. [37] implement a multiscale matched filter for retina vessel segmentation using PSO algorithm. The performance of multiscale matched filter is much better then single scale matched filter. This approach removes the noise suppression feature of multiscale filter. For finding optimal filter parameters of the multiscale Gaussian matched filter author used PSO.

c) Segmentation of blood vessels

Sreejini et al. [38] developed a model which is unsupervised in nature and can classify the severity of diabetic macular edema in colour fundus images. The early detection of macula for the treatment of DR is necessary and to achieve this author use PSO. Hassan et al. proposed an approach for enhancing segmentation and extract the vasculature on retinal fundus images using PSO.

d) Optic disc segmentation

A histogram-based approach is developed by Devasia et al. [39] in collaboration with PSO to identify optical disc. Optical disc detection is a major problem in DR image datasets. By this approach author get higher positive correlation which possess by localized optic disc centres.

4.3.3 Ant Colony Optimization

Ants have inspired a number of methods and techniques among which the most studied and the most successful is the general-purpose optimization technique known as ACO. ACO takes inspiration from the foraging behaviour of some ant species [40]. These ants deposit pheromone on the ground in order to mark some favourable path that should be followed by other members of the colony. The pheromone is a chemical substance released into the environment by an animal, especially a mammal or an insect, affecting the behaviour or physiology of others of its species. Ants navigate from nest to food source, ants are blind. Shortest path is discovered via pheromone trails. Each ant moves randomly and pheromone is deposited on the path. More pheromone on path increases probability of path being followed [36]. The methods and salient feature used by the authors for research are shown in Table 4.4.

a) Segmentation of blood vessel

Bajčeta et al. [41] developed a model for segmentation of blood vessels in which they have applied ACO in fundus images and ACO perform feature extraction. Hooshyar et al. [42] proposed a mathematical model in which they have used Eigen values of hessian matrix and Gabor filter bank to extract the features from retinal images. An approach for classification is developed by using fuzzy c-means and ACO. Asad et al. [43] proposed an approach and ensure an improvement of the ant clustering-based segmentation. The first approach is developed with the help of new heuristic function of the ACO algorithm. The second approach is based on global update mechanism of ACO. They have compared the proposed system

TABLE 4.4 Performance measures of ACO based models

Author	**Method**	**Salient feature**
Bajčeta et al. [41]	ACO	Blood vessel segmentation
Hooshyar et al. [42]	ACO, Fuzzy clustering	Eigen value of hessian matrix, Gabon filter.
Asad et al. [43]	ACO	Heuristic function
Asad et al. [44]	Enhanced ACO	Feature pol technique
Pereira et al. [45]	Unsupervised model, Image processing, ACO	Multiagent system, exudates
Karthikeyan et al. [46]	FP growth model, ACO	Association rule mining
Kavitha et al. [47]	ACO	OTSU method, optic disc, macula
Arnay et al. [48]	ACO, OPTIC CUP segmentation model	Heuristic function, intensity gradient, vessel's curvature

with various traditional systems of blood vessel segmentation. Proposed approach followed by phases like pre-processing phase in which extraction of green channel of retinal image is perform then the linear transformation of its intensity to cover the whole intensity range [0, 255], then removal of the central light reflex from it. Next phase will be ACS-based segmentation and at last applying median filter of size 3*3 to remove all remaining isolated pixels. Asad et al. [44] proposed an improved model against previous one. In this proposed work, author try to achieve early detection by automatic segmentation of retinal blood vessels in retinal images that is also called a two-class problem. They proposed two improvements in previous approaches, first including features to the feature pool which was further used for classification, in second improvement they combined probability theory based heuristic function with ACO and remove the old Euclidean distance method used in previous.

b) Segmentation of exudates

For early detection of exudates, Pereira et al. [45] proposed an unsupervised method with ACO for exudates segmentation. They have taken green plane images given to median filter background estimation then normalize them and place a double threshold and perform candidate selection. Analyse the exudates with ACO algorithm, then ACO presents edges enhancement. Karthikeyan et al. [46] proposed a new algorithm-based approach in which they used association rule mining in collaboration with enhanced FP growth algorithm which is similar to ACO. The algorithm used in this approach is also called as CACO, i.e. Continuous Ant colony Optimization algorithm for segmentation of exudates.

c) Segmentation of optic disc

Kavitha et al. [47] classify optic disc and macula in normal and abnormal classes. They have used ACO-based method for macula and optic disc detection. The radius of optic disc and distance between the centres of optic disc is used as a feature in this approach. The approach is followed by input of the images for pre-processing. Pre-processed images are given for optic disc detection by ACO and further Macula is detection done by Otsu method, and then features are extracted and analysed.

d) Segmentation of optic cup

Arnay et al. [48] proposed a model for retinal fundus images based on ACO and perform optic cup segmentation. They combine the curvature of the vessels with intensity gradient of the optic disc area and will construct the solutions. The agent's capabilities are limited. Agents are capable to find accurate cup segmentation. For testing they have used RIM-ONE dataset.

4.3.4 Cuckoo Search

The Cuckoo search is inspired by the brood parasitism of cuckoo birds. Cuckoo lays their eggs in the nest of other host birds. If a host bird finds that the eggs are not their own, it either throws these alien eggs away or simply abandon its nest to build a new nest elsewhere [49]. Cuckoo search algorithm is a met heuristics optimization algorithm, which is classified into three considerations:

1. Every cuckoo lays approximately one egg at a time and the eggs are exactly set in a nest.
2. The nest having better quality eggs are carried onto the next round.
3. The number of nests is fixed and the quality of nest is static and is not alterable.

The cuckoo search is used in DR models for exudates detection. Srishti et al. [50] design a computational approach based on cuckoo search algorithm for exudates detection using multi-level thresholding; it has been fine-tuned for edge detection. The proposed method starts with initialization of cuckoo with an upper threshold value and lower threshold then selecting a best threshold value via Levy's flight. The threshold value must be less than 0.25. If the value less than maximum than keep threshold values with maximum gradient values otherwise reject. If the maximum iteration obtained then end the process otherwise find best values, keep best threshold values and initialize cuckoo again.

Glaucoma is a main problem for vision loss, which cause increase in fluid pressure in the eye and may damage the optic nerve. So, Raja et al. [51] developed an optimal hyper analytic wavelet transform for glaucoma detection. It is found that by using hybrid GSO- Cuckoo search algorithm they have got an optimal coefficient for transformation process. In this proposed work they give fundus mages as input then pre-process them by using RGB to GRAY scale conversion histogram equalizer. For optimal transformation, author used hyper analytic wavelet transform and GSO-Cuckoo search and give the statistical features to classification modules i.e. ANN and SVM. The methods and salient feature used by the authors for research are shown in Table 4.5.

4.3.5 Bee Colony Optimization

It is a powerful algorithm of artificial intelligence; it is a swarm-based meta-heuristic optimization algorithm inspired by the life cycle of honey bees. There are different honey bee algorithms that have been developed based on the style of building hives, searching under, collecting food, etc. This study will explore the concept of honey bee algorithm. Before explaining the honey bee algorithm it is necessary to understand the lifestyle of honey bees. They look for food in nature by exploring the neighbourhood fields of their hives and collect and accumulate nectar for the future use. To collect food the bees constantly search the region looking for new rubber patches. Once the bee finds food sources, it returns to hive and informs their mates about location, quality and quantity of the available food source [10]. They begin from everything through waggle dance that is move with short quick moment form side to side or ups and downs. In this waggle dance, every movement has different meaning, that is dancing area on hive, number of rounds on

TABLE 4.5 Performance measures of Cuckoo search and bee colony-based models

Author	**Method**	**Salient feature**
Srishti et al. [50]	Cuckoo search, PSO, Artificial bee colony	Stationary wavelet transforms
Raja et al. [51]	Cuckoo search, SVM	GSO-Cuckoo, CGD-BPN, Hyper analytic transform
Emary et al. [52]	Bee colony optimization, FCM	ABC-PS multi-objective vessel localization
Hassanien et al. [53]	Artificial bee colony, FCM, Swarm optimization	Compactness fitness function, Bee swarm optimization
Maaneesh and Chaya [54]	Artificial bee colony, FCM	Perform segmentation by assigning each pixel to the cluster
Kavya et al. [55]	Artificial bee colony, FCM, SVM	Fundus camera, vessel segmentation

left side and right side and jumping ups and downs based on these signs will advertise the food location and they encourage the remaining of their colony to follow [11]. After the dance some recruited members follow the scout bee to find the food source to collect more food.This cycle is repeated continuously while the bees are at their hive with accumulated nectar and they explore new areas with a potential food source. In their lifestyle, there are two phases: first is discovering food source and second is collecting food from food sources [12]. This bee colony algorithm is used to make a CAD system for earlier detection of DR. The methods and salient feature used by the authors for research are shown in Table 4.5.

It is important to find accurate segmentation of retinal blood vessels using CAD systems. Emary et al. [52] proposed an automated model for retinal blood vessel segmentation. The model is based on artificial bee colony optimization in collaboration with fuzzy C-means algorithm. Here artificial bee colony algorithm is used to find the cluster center of Fuzzy C-means objective function. This approach is tested on the freely available Drive and stare database. There will be three steps for segmentation of retinal blood vessels: first, to pre-process the data using Band selection and Brightness correction. Second, retinal blood vessel images are given for segmentation then find cluster with ABC using Fuzzy C-means fitness function. Third is post processing which is done by ranking the order filtering, gap filling, non-thin connected component removal methods. Hassanien et al. [53] enlighten us with an approach containing ABC and FCM algorithm in which they focus on the pattern search optimization to enhance the segmentation resulting in a feature called shape description. A fitness function called thinness ratio is used for pattern search optimization. In this they compare to algorithm BSO- and ABC-based approaches in terms of sensitivity, specificity and accuracy.

Maaneesh and Chaya [54] also used ABC and FCM algorithm for their proposed approach. After pre-processing initialize the data and randomly putting bees into target images and generate membership matrix and evaluate function gives to recruit bees for the best site and poor bees for the remaining site select the fittest bee from each site by probably off solution. If iteration equals to MNC, then obtain the optimal centroids and do segmentation by assigning each pixel to the cluster for which the membership value is higher, otherwise replace the solution with a new randomly produced solution by scout bee and construct new population of scout bee. Kavya et al. [55] proposed a system to classify the images through level of damage in blood vessels using support vector machine. Author has used ABC algorithm to improve the accuracy of the system and FCM to assign the values of membership to the pixels.

4.4 CONCLUSION

It is observed that in previous decades diabetes has given rise to number of health issues witnessed universally and increasing day by day. The most common issue caused by diabetes is DR. DR majorly affects human retina and leads to complete vision loss. Few key features of DR are MA, HE, HEM, SE or CWS, and NVD. Traditionally, doctor's manually check the patients and take decisions for the society. It is very complicated to identify DR with complex features. In this context, to fight with the current problem of DR, industries move towards CAD. CAD system enables optimal diagnosis decisions and early DR detection. The automatic DR detection model takes DR images as input to perform various experiments on different models made by different algorithm. Swarm intelligence and EC algorithms play a vital role in dealing with earlier identification of DR. GA, PSO algorithm, ant colony algorithm, bee colony algorithm and cuckoo search algorithms of evolutionary computing and swarm optimization are used to make automatic CAD system for earlier detection of DR. In this chapter, number of CAD system and approaches developed for DR have been studied and assessed on the basis of strength and weakness of the approach. The automatic DR models follow pre-processing, feature extraction, segmentation and classification. Here methods and salient features uses for feature extraction and classification are explored on a large scale.

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