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DETECTION OF ANEMIA DISEASE USING DPSO ALGORITHM

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ABSTRACT

A novel technique for segmentation of images based on Darwinian particle swarm optimisation (DPSO) algorithm is proposed to detect the anemia disease by using a palm region of the person. Images are captured using a digital microscopic camera, and pre-processing is done. The Darwinian principle is applied to improve the values of fitness function individually to all input images and results in output images. The efficiency of the proposed technique is measured on mean, standard deviation and entropy. The experimental results demonstrate that the DPSO algorithm based analysis is better than PSO algorithm based analysis.

Keywords: darwinian particle swarm optimisation (DPSO) algorithm, segmentation, images.

1. INTRODUCTION

Anemia occurs when there is a reduction of red blood cells circulating in the body. It is the general blood disorder in the world population over 1.62 billion people. The major symptoms are chest pains, headaches and pale skin. The blood requires red blood cells to function. They hold haemoglobin, is a mixture of proteins that includes ion molecules. These molecules transfer oxygen from the lungs to the different parts of the body. There are different types of anemia, and there is no single reason. Overall three major groups of anemia are 1) blood loss, 2) faulty or decreased red blood process and 3) destruction of red blood cells. Some of the existing methods have been discussed below in this research.

Finding an exact count of leukocytes normally called as WBC (white blood cells) in a blood test is vital in measuring and analysing an individual's health especially on a broad range of diseases which includes anemia, infections, leukemia etc. There are two broadly utilised techniques to calculate leukocyte count. First, is through the usage of hematology analyser and the other one is done manually. Now, with the advent of technology leukocyte counting was made better through the usage of digital image processing. In any case, the algorithm of the existing techniques includes an excessive number of steps which make more complex in image processing phase. Thus, we believed counting leukocytes by containing the HSV (Hue, Saturation, and Value) saturation part with blob examination on microscopic blood images which features the eccentricity and area highlights for counting to easier existing techniques which thus produces faster and more exact results [1].

The evaluation of blood cells is more important for the specialist to analyse different diseases such as leukaemia, anaemia etc. Similarly, classification and observation of these cells concede for the estimation and recognising of countless. By calculating white blood cells (WBCs) permits the leukaemia detection (Acute Lymphoblatic leukaemia (ALL) Acute Myloid leukaemia), be cancer which influenced on blood which can be deadly on the off chance that it can be untreated. So the exact counting and classification of blood cells have an essential part. Moreover, the counts particularly differential tallies and shape give essential information to assess leukaemia. In current techniques, the morphological rating of haemocytes is performed physically by specialists and counting of blood cells is done utilising a device called Haemocytometer. However, these methods have several limitations, such as deviant accuracy, a different standard, slow estimation and dependence on the operator ability. For counting hardware arrangements such as the Automated Haematology counter exists, they are extremely costly, unreasonably expensive in each hospital laboratory and also utilise actual blood samples. So there reliably requires a simple, cost-effective and robust technique for analysis, counting and classification of blood cells. The proposed technique gives a complete automatic computerised technique for WBC counting, identification and classification utilising microscopic images [2].

Red blood cell count acts as a fundamental part of identifying the overall health of the patient. Grown red blood cells experience morphological changes when blood issue exists. Automated and manual methods exist in the market to check the number of RBCs (Red Blood cells). Manual counting includes the utilisation of Hemocytometer to count the blood cells. The conventional technique for setting the smear under a microscope and counting the cells manually prompts wrong results, and medical laboratory technicians are put under pressure. Automated counters neglect to distinguish abnormal cells. A computer supported system will accomplish exact results in less time. This research work introduces an image processing methods to split up the red blood cell from different segments of blood. It is objective to determine and produce the blood smear image, with a specific classification of red blood cells into 11 classes. K-Medoids algorithm which is adversity to extraneous noise is utilized to separate the WBCs from the image. The granulometric diagnosis is utilised to split up the red blood cells from white blood cells. Feature extraction is performed to get the significant features that serve for classification. The classification results aid in diagnosing the disease like iron deficiency anemia, hypochromic anemia, hereditary spherocytosis, megaloblastic anemia,

sickle cell anemia and normochromic anemia within few seconds [3].

Digital image processing is broadly utilised nowadays in biomedical applications. Counting of the red blood cells from the blood smear images can aid in identifying anemia. Since the identification, manual location and counting of red blood cells are a repetitive, error inclined and time consuming there is a rising requirement for automating the whole process. A simulation model for anemia detection utilising RBC counting algorithm is introduced. Both circular Hough Transform and connected component labelling are applied for the counting the number of RBCs, and the results are equated. Watershed transforms to split up overlapping blood cells is also introduced. Error analysis after and before watershed transform and parameters like sensitivity, segmentation accuracy and specificity [4].

The parasite is an organism that presents on or in the different organism from which it acquires its nutrients but takes effect in the process. Human intestine infection is by parasites can be because of food that we drink water or food. The worm infestation symptoms include stomach bloating, digestive disorders and diarrhoea, while many symptoms include asthma, skin rash, anaemia, low immune system, constipation, nervousness, fatigue. In a hospital, the schematic pattern to diagnosing parasites infection in the human body is by manual faecal testing. Trained expert's analysis the faecal specimens, look for parasitic organisms, and the cysts of protozoa and the eggs of helminths. If the dangerous organisms are given, the shapes, sizes, numbers and in some cases the colour of the organisms are analysed to determine the species of parasites, the level of infection and suitable therapeutic modalities. This technique of analysis is inefficient when a huge number of samples are engaged with the analysis since it represents an over workload, and the results depend on the laboratory technologies and the doctors. An automatic system to analyse human intestinal parasites utilising image processing technique has been developed. A new methodology that includes the significant part of image diagnoses such as segmentation, filtering, feature extraction and characterisation will be utilized to classify and detect intestinal parasite. A set of data has been collected from Hospital University Sains Malaysia and has been utilised to examine the system. By result, more than 95% of exactness was acquired for the categorisation of both Parasites TTO and ALO [5].

The investigation of cell morphology is a significant part of the analysis of some disease, for example, sickle cell disease, since red blood cell distortion occurs by these diseases. Because of the lengthened shape of the erythrocyte, ellipse alteration and curved point detection are connected generally to images of peripheral blood samples, together with the identification of cells that are mostly blocked in the clusters produced by the sample preparation method. We propose a technique for the examination of the shape of erythrocytes in peripheral blood smear samples of sickle cell disease, which utilises ellipse changes and a new algorithm for identifying notable points. Moreover, we apply a set of requirements that permits the elimination of important image processing steps developed in the previous investigation. We utilized three kinds of images to approve our technique: artificial images, which were naturally created in a random manner utilising a code; real images from peripheral blood smear sample images that have ordinary and prolonged erythrocytes; and synthetic images produced from real isolated cells. Utilising the proposed technique, the effectiveness of identifying the two kinds of objects in the three image types be over 99.35%, 98.00% and 99.00% respectively. These effectiveness levels were better than the results received with previously developed techniques utilising the same database. This technique can be enlarged to clusters of many cells, and it needs no client inputs [6]

To investigates the capability of image analysis to measure for the presence and degree of pulmonary hypertension secondary to sickle cell disease (SCD). A mixture of fast marching and geodesic active contours level sets were utilized to segment the pulmonary artery from smoothed CT-Angiography images from 16 SCD patients and 16 Matching controls. A fast marching algorithm method is utilized to measure the centreline of the segmented arteries to calculate generally the diameters of the pulmonary trunk and first parts of the pulmonary arteries. Results demonstrate that the pulmonary trunk and arterial parts are fundamentally bigger in diameter in SCD patients as equated to controls (p-values of 0.002 for trunk and 0.0003 for parts). For approval, the results were contrasted with manually calculated values and did not exhibit significant difference (mean p-values 0.71). CT with image processing demonstrates great potential as a surrogate indicator of pulmonary hemodynamics or reaction to therapy, which could be a significant tool for drug detection and noninvasive clinical surveillance [7].

The proposed method is to analyse three kinds of abnormal Red Blood cells (RBCs) referred to as Poikilocytes in Iron deficient blood smears. Characterisation and calculating the number of Poiklocyte cells is conceived as a significant step for the automatic identification of Iron Deficiency Anemia (IDA) disease. Schistocyte, Elliptocyte and Dacrocyte cells are three important poikilocyte cells that are common in IDA. The proposed cell recognition methods have processing, feature extraction, segmentation and classification steps. Classification is processed by utilising three quality classifiers including Support Vector Machine (SVM), Neural Network (NNET), and K-Nearest Neighbor (KNN) classifiers. Finally, to identify the proper class a maximum voting theory of all the three classifiers are utilised. In maximum voting theory, the class that gets the maximum number of votes is selected as the final forecast class of a sample cell. The accuracy of the developed technique is %100, %97 and %99 for detecting Schistocyte cells, Elliptocyte cells and Dacrocyte cells, respectively [8].

Establishing an exact count and characterization of leukocytes normally called as WBC (white blood cells) is vital in the evaluation and analysis of illness of a person, which includes difficulties on the immune system that

prompts different kinds of diseases including anemia, infections, leukemia, AIDS (Acquired Immune Deficiency Syndrome), cancer etc. The two generally utilized techniques to count WBC is with the utilisation of manual counting and haematology analyser. Currently, at modernisation stage there have been various researches in the field of image processing joined with different segmentation and characterisation methods to have the capacity to initiate changes for WBC characterisation and counting. However, the exactness of these existing techniques could even improve. So, we proposed a new technique that could segment different kinds of WBCs: neutrophils, basophils, eosinophils, lymphocytes and monocytes from a microscopic blood image utilising HSV (Hue, Saturation, Value) saturation element with blob diagnosis for segmentation and incorporate CNN (Convolutional Neural Network) for calculating which in turn produces more accurate results [9].

A pathological blood test is the most significant key issues in the medical field important to disease analysis. So, a new design is introduced and develops an independent application for the usage of both the management and acquisition of patient blood pathological data and create automated anemia analysis report utilising computer vision approach. The proposed system can send to any pathological research to help pathologist by contributing help of computer report generation and automated anemia analysis. Data mining approach and boosted the image processing algorithm have been utilized to diagnosis patient medical data. The pathological data diagnosis module can produce the blood test result to distinguish anemia type in blood. The image diagnosis module can distinguish the abnormal erythrocytes in the smear images utilising shape-based classification. 38 shape features are removed from every erythrocyte. Also, the administered decision tree classifier C4.5 is utilised to classify image tests with a specificity of 90.6% and sensitivity of 98.1%. The developed system will save patient medical data like microscopic smear images, clinical data and blood test data. Weka, Image J, Java Swing, Java cryptography extension and so on libraries have been utilized to create various applications module of the proposed method [10].

Embedded system has become prominent as a significant engineering technology in different biomedical applications. It is utilised as both non-invasive and invasive sensors for sensing, transportation, processing, visualisation and archiving mostly utilising a computer device. It instantly helps humankind in paramedical and medical applications that consider monitoring, clinical analysis and patient management. Non-accessibility of genetic architecture defuses the design and manufacturing of this kind of autonomous embedded system and also a highly expensive task. Here, proposed one type of embedded system for application of a habits genetic disease, sickle cell anemia (SCA) by merging engineering and technologies utilising ARM7 microcontroller [11].

One's life can save from drop of blood. Some diseases are anemia is more feared, particularly in pregnant women and children. The diseases require a regular blood test for diagnosis, but it requires denoting equipment with a trained technician. The rural settings are many facilities not available. Non-availability poses are difficult health hazards. The methods are simpler and effective to diagnose these diseases. The colour of blood can indicate the severity of these devices. Finally, our approaches suggest the noninvasive diagnosis of anemia [12].

World Health Organization considers anemia, a health condition noticed by the deficiency of red blood cells or haemoglobin in the bloodstream, as dragging a quarter of the total world population. Hence, the responsibility of anemia detection is an automated, quick and reliable. The preliminary analysis of anemia is visuals of the physician by analysing the colour of the prior conjunctiva of the eye and confirmed with an invasive blood test. The present paper designed a mechanism for the automated detection of anemia through non-invasive visual method. The current process needs the detection of anemia by examining the anterior conjunctival pallor of the eye. The conjunctival colour operates by quantifying from digital photographs with smartphone camera of the appropriate solution under enough lighting conditions of an Android application [13].

Main components of the blood and control haemoglobin are the Erythrocytes. The main Erythrocytes function is to transport oxygen from the lungs to tissues and carbon-di-oxide from tissues to lungs. The Erythrocytes sizes changes then they form Poikilocyte cells. The anaemia characterised by poikilocytes such as Elliptocyte, Schistocyte, Dacrocyte, and Degmacyte. The Iron creation of haemoglobin become smaller in size, change their shape and paler in normal colour. The present paper produces the RBC and poikilocyte cells assigned as Artificial Neural Network, but it's based on the features. At the point, blood disorders are distinguished by the visual review of digital images by treating alteration in the colour, size and statistical analysis of digital images. The steps have been enforced to the blood smear microscopic images to identify the cells are preprocessing, segmentation, morphological operations, feature extraction and classification. The cells separation of overlapped has done automatically, efficiently and accurately. The Matlab environment acquired for entire work [14].

Red Blood Cell (RBC) count area of major problems in the clinical laboratory is to develop an exact result for every test. The number of red blood cell is significant to find as well as to follow the treatment of various diseases like anaemia, leukaemia etc. The vital information of Red blood cell count establishes that help diagnosis many of the patient's sickness. The RBC counting of the old conventional method is under microscope establishes unreliable and incorrect results depend on clinical laboratory technician skill. The conventional method sets a lot of strain on the technician. Some other method for RBC counting uses the automatic hematology analyser; this machine is more expensive. The hospital's clinical laboratory applies such an expensive machine to count the blood cell in the laboratory. The present paper establishes an efficient and cost-effective

computer vision system for automatic red blood cell count using image-based analysis [15].

2. INFERENCES FROM LITERATURE SURVEY

In the existing method, the anemia disease is derived by using a PSO method. A large number of iterations is utilized then differential evolution gives good outputs for multilevel segmentation in the PSO algorithm. Therefore a new method was required that can present faster output without adjusting the quality; a DPSO method is introduced and discussed below.

3. METHODOLOGY

Image segmentation is a method to divide the original image into different regions or classes, where the pixels in the same region will have certain common features. For certain applications, such as image segmentation or image recognition, the entire image cannot be worked, as it does not gain computational complexity, but it also needs more memory. Thus, colour image segmentation is used. Colour image segmentation is the method of educing from the image domain one or more joined regions filling uniformity standard which is established by features derived in the spectral element. These elements are defined by the colour space model. The segmentation method could be increased by some additional knowledge of the object in the image. A M*N*3 array of colour pixels in RGB colour image, where all colour pixel is a tierce representing red, green and blue elements of an RGB image at the particular spatial location. The main goal of the segmentation method is to simplify the image more significant and easier to examine. Image segmentation technique includes histogram-based methods, optimisation techniques, thresholding methods, clustering techniques, etc., are considered, but Darwinian PSO technique is utilized.

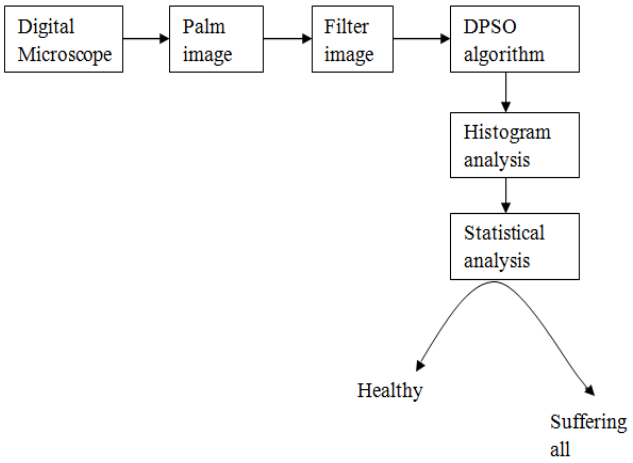


Figure-1. Block diagram of the proposed technique.

3.1 Darwinian particle swarm optimization algorithm (DPSO)

The PSO algorithms is that of getting cornered in a local optimum, such that it may work good in one problem but it may go wrong with another problem. To avoid this problem, a better model developed by Tillett is Darwinian Particle Swarm Optimization (DPSO), in which various swarms of test results may survive at any time. Each swarm separately functions just like a normal PSO algorithm with terms regulating the collection of swarms that are projected to natural selection. A computational technique that is processing a issues by iteratively trying to enhance a candidate solution as to a given quantity of quality. The DPSO algorithm comprises of a swarm of particles flying with the help of search space. Each particle's motion is determined by its local best-known position (pbest) and is even guided towards the best-known position in the search space (gbest), which are refreshed as better positions are found by different particles. The DPSO algorithm is continued until the conclusion is obtained or the alter in velocity get close to zero. The algorithm discontinues when the current position of each particle is equal to the end of the swarm (N-dimensional space). The DPSO algorithm can be performed as follows:

1. Initialise $i_{max}, w_1, \emptyset_1, \emptyset_2, n$ (population size), $x_{i,min}\ and\ x_{i,max}$.
2. Determine off initial velocities and position of the variables as

$x_{i,k} = x_{i,min} + (x_{i,max} - x_{i,min})\mu_i$
$where\ k = 1,2, \dots n, v_{i,k} = 0$

3. Compute $p_{i,k} = f(x_{i,k}). k = 1,2, \dots n$
4. Calculate

$pbest_{i,k} = p_{i,k} and gbest_i = \min imum(pbest_{i,k})$

5. The location of $gbest$ and $pbest_k$is represented as g_{ix} andp_{xik}.
6. Change velocity utilizing $v_{i+1,k} = w_1 v_{i,k} + \emptyset_1(p_{xik} - x_{i,k})\mu_i + \emptyset_2(g_{xik} - x_{i,k})\mu_i$
7. Modify position $x_{i+1,k} = x_{i,k} + v_{i+1,k}$
8. Modify fitness $x_{i+k} = f(x_{i+1,k})$
9. If $p_{i+1,k} < pbest_{i,k}$ and so $pbest_{i+1,k} = p_{i+1,k}$
10. Change $gbest_{i+1} = \min imum(pbest_{i+1,k})$
11. If i<i max, and so step-up i and go to step 5, otherwise stop.

Table-1. Iinitial parameters of the DPSO.

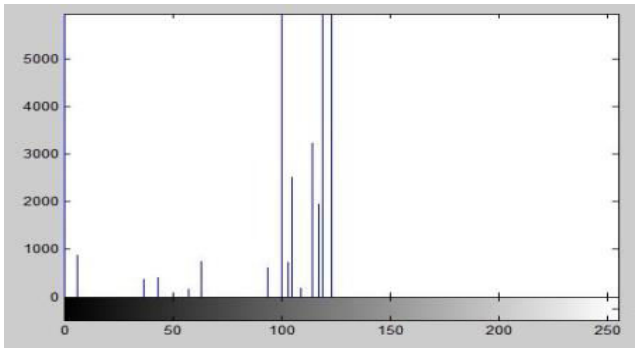
Serial number	parameters	DPSO
1	Num of Iterations	150
2	Population	30
3	ρ_1	0.8
4	ρ_2	0.8
5	V_{max}	1.5
6	V_{min}	-1.5
7	X_{max}	255
8	X_{min}	0
9	W	1.2
10	Min population	10
11	Max population	50
12	Num of swarms	4
13	Min swarms	2
14	Max swarms	6
15	Stagnancy	10
16	Fractional coefficient	----

After the cancellation of the particle, rather than being set to zero, the counter is reset to a value approach the threshold number, as indicated by where Nkill is the number of particles erased from the swarm over a period in which there was no change in fitness. To generate a new swarm, a swarm must not have any particle ever erased, and the most extreme number of swarms must not be surpassed. Still, the new swarm is just made with a probability of p = f/NS, with f a random number in [0, 1] and, NS the number of swarms. This factor maintains a strategic distance from the formation of more swarms when there are a large number of swarms in presence. The parent swarm is unaffected, and half of the parent's particles are chosen randomly for the kid swarm and half of the particles of a random part of the swarm gathering are also chosen. On the off chance that the swarm starting population number isn't acquired, the remaining particles are randomly instated and joined to the new swarm. A particle is brought forth at whatever point a swarm accomplishes another global best and the greatest characterised population of a swarm have not been attained. Like the PSO, some parameters are required to be changed to perform the algorithm effectively are initial swarm population, minimum and maximum swarm population, starting some swarms, minimum and maximum number of swarms and stagnancy threshold.

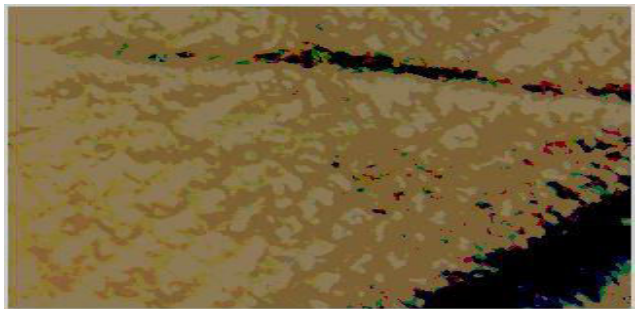
4. RESULTS AND DISCUSSIONS

The functioning of the proposed system is compared utilising different statistical parameters such as mean, standard deviation and entropy of the input image and output image as tabulated in Rable-2. The high value of entropy indicates the presence of anemia disease to that patient. The entropy values in the range above 3.0000 will be considered as a severe stage of anemia disease, and the values in the range of above 2.6000 to below 3.0000 will be considered as a moderate stage of anemia disease. The entropy value in the range above 2.5000 to below 2.6000 will be considered as the starting stage of anemia diseases. The entropy value below 2.5000 will be considered as anemia disease nil to the patients. The patient's samples output is mentioned in the Figures 2-6 with the different entropy value. The value demonstrates that the DPSO technique is more efficient and is applied to the input image to get the better statistical analysis to the output image.

2. (a)

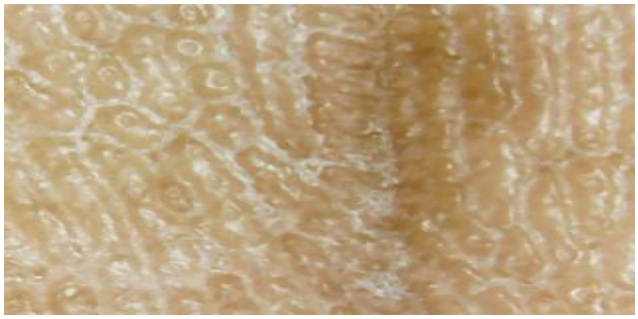


2. (b)

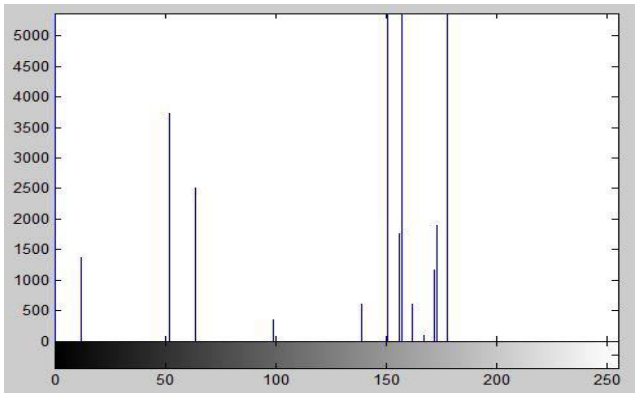


2. (c)

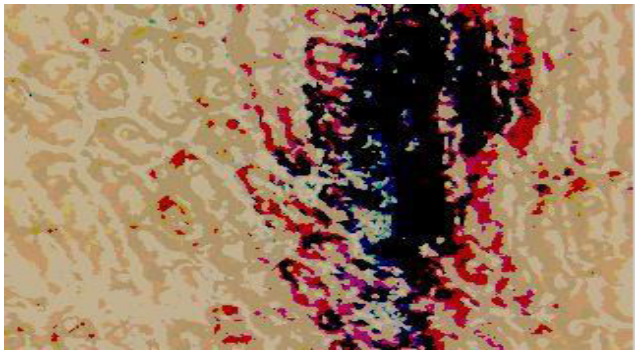
Figure-2. (a) Original input image, (b) Histogram analysis of DPSO image, (c) DPSO image for a patient P1 with entropy value is 2.5439.



3 (a)



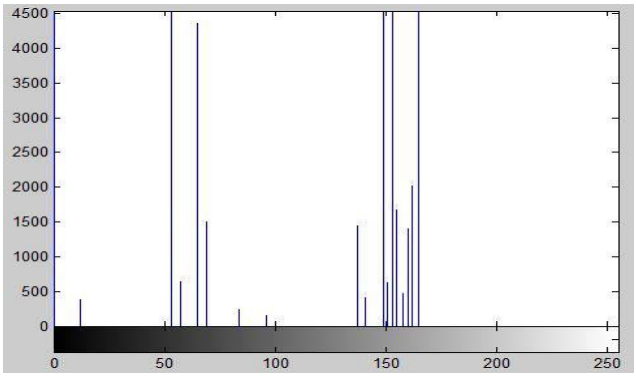
3 (b)



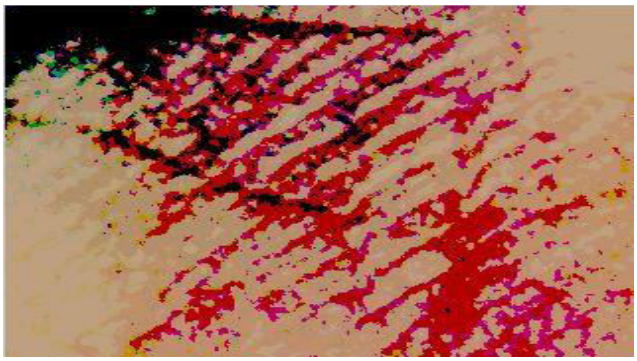
3(c)

Figure-3. (a) Original input image, (b) Histogram analysis of DPSO image, (c) DPSO image for a patient P6 with entropy value is 2.7415.

4(a)



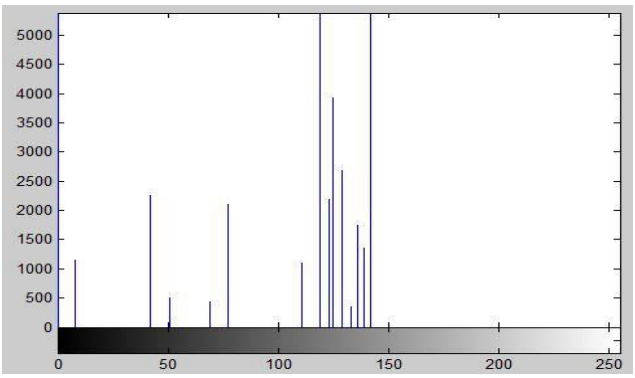
4(b)



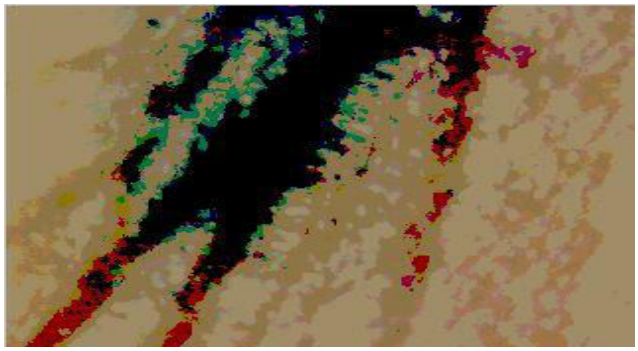
4(c)

Figure-4. (a) Original input image, (b) Histogram analysis of DPSO image, (c) DPSO image for a patient P13with entropy value is 3.1779.

5 (a)



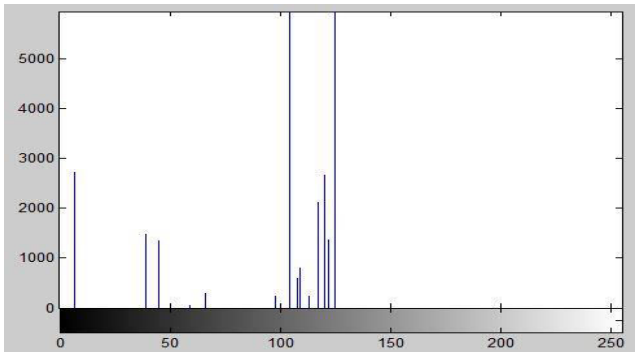
5 (b)



5(c)

Figure-5. (a) Original input image, (b) Histogram analysis of DPSO image, (c) DPSO image for a patient P16 with entropy value is 2.8302.

6(a)



6(b)

6(c)

Figure-6. (a) Original input image, (b) Histogram analysis of DPSO image, (c) DPSO image for a patient P21 with entropy value is 2.5066.

Table-2. The values determined using the DPSO algorithm to identify the disease.

Image	Input image			Output image		
Patient number	Mean value	Standard deviation value	Entropy value	Mean Value	Standard deviation value	Entropy value
P1	117.9337	15.4563	5.6391	99.5236	33.7820	2.5439
P2	136.7268	13.2645	5.4503	97.9455	56.4390	2.8750
P3	130.1201	20.8028	6.0892	103.0734	45.6671	2.6616
P4	147.5691	14.9434	5.6398	95.4940	66.8690	2.9524
P5	146.7314	15.0495	5.6391	96.8835	65.6632	2.9597
P6	166.2690	20.7084	6.1325	126.0443	64.4816	2.7415
P7	173.3156	19.2181	5.9962	132.2777	66.1869	2.8105
P8	140.6774	19.2680	5.9584	110.6922	51.8006	2.7366
P9	166.2690	20.7084	6.1325	126.7467	63.9157	2.7533
P10	166.7951	21.0780	6.1550	126.3740	65.4061	2.7347
P11	170.2874	19.9757	6.0748	128.4647	66.0668	2.8574
P12	172.2835	18.9303	5.9715	130.4018	66.7826	2.8472
P13	155.7754	11.6547	5.2671	115.3454	55.9997	3.1779
P14	124.3411	26.4555	6.4687	91.2027	51.0860	2.5351
P15	149.2719	15.4665	5.5306	120.8652	53.1385	2.7283
P16	133.7183	18.7898	5.9162	101.5814	52.6167	2.8302
P17	122.2910	15.0192	5.5911	93.9918	47.7026	2.7444
P18	151.7098	25.9094	6.4181	115.1214	59.7065	2.5737
P19	152.5078	26.4254	6.4485	113.1808	63.0497	2.5535
P20	141.2770	23.6608	6.2960	105.1926	57.8320	2.5623
P21	115.7491	16.5237	5.7546	85.5785	47.6192	2.5066
P22	158.7798	13.2169	5.4828	120.1570	59.6852	2.8016
P23	136.1617	20.0893	6.0236	103.6980	54.4042	2.4727
P24	162.5809	12.0193	5.3431	117.8235	66.1186	2.8621
P25	121.3516	15.2172	5.6393	91.0105	48.4101	2.6017
P26	141.7598	29.0015	6.0747	116.0022	48.2386	2.1903
P27	144.5932	11.7671	5.2726	104.9418	59.4889	2.8175
P28	112.5734	29.7923	6.5241	85.1284	42.2954	2.5423
P29	138.1798	20.9294	6.1003	96.2471	60.8102	2.6321
P30	124.5700	20.7346	6.1247	88.7562	53.3935	2.6053

5. CONCLUSIONS

PSO algorithm holds the original data of the image even segmentation is processed. PSO based segmented images give better divergence estimation, with a great number of evaluated depth levels. The subjective quality of images acquired utilising DPSO method is superior to PSO using MATLAB program. As future work, the FODPSO will be assessed in the detection of anemia disease and further compared with the comprehensive methods.

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