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An Efficient Tournament Based Levy Flight Multiverse Optimization for Feature Selection Using Optical Coherence Tomography

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Abstract: Retinal disease is a potentially fatal condition that causes blindness, therefore early prediction of retinal disease is an effective way to minimize the problem of blindness. Optical coherence tomography (OCT) is an efficient technique for scanning precise images of the retina to diagnose the macular holes and to view the age-related macular extension. A tournament based levy multiverse optimization algorithm (T-LMVO) is proposed in this research to identify macular pathologies with efficient feature selection of retinal images. Although the TLMVO was proposed in existing researches, the robustness of the local optimization and the capacity of global optimization is minimum. To improve the robustness of these optimizations, LMVO is enhanced with the tournament based feature selection which has an advantage of handling minimization problems and can continue to update strongly even at the end of iterative phase. Overall, the performance of the proposed accuracy based T-LMVO shows better stability, and robustness. The process of feature selection using T-LMVO resulted in improved performance in the retinal OCT images, which have the accuracy of 98.95%, sensitivity of 99.02%, specificity of 97.61%, MCC of 98.92% and an error rate of 1.05 and noor eye hospital images dataset has accuracy of 98.99%, specificity with 99.38%, matthew's correlation coefficient (MCC) with 96.95%, sensitivity with 97.63%, and the error rate was reduced to 1.01%.

Keywords: Age-related macular detection, Levy flight-based multiverse optimization algorithm, Noor eye hospital data, Optical coherence tomography, Retinal disease prediction, Tournament selection.

1. Introduction

The retina in the human eye helps to acquire visual information, whereas the macular present in the retina is responsible for accurate and sensitive vision quality. Age-related macular detection (AMD), choroidal neo-vascularization (CNV), and diabetic macular edema (DME) are the major macular problems occurring in older persons. AMD and CNV lead to the damage of intra retinal effusion which is not possible to retrieve back and it mainly occurs in diabetic patients [1]. Diagnosis of retinal vasculature and fundus in patients is a complex task for ophthalmologists to perform the diagnosis accurately [2, 3] hence to predict the disease in a patient, edge-based and threshold-based segmentation with various algorithms were used [4].

Diabetes and cataract surgery are the issues to cause the problem of DME retinal disease. OCT is a high-resolution 3D tomography technique for macular retinal diseases. The OCT is a subjective and time taking process in scanning the precise images of the retina in the process of diagnosing the macular. The AMD, retina, and DME were classified using the support vector machine (SVM) which shows efficient classification results [5]. The recognition of macular diseases in earlier stages is important because it leads to blank spots and blur vision. Macular diseases make humans visit the ophthalmologist frequently and need more cost hence identifying the disease at early stages is an efficient way to protect the vision of the eye [6]. The main advantage of OCT is giving efficient results in diagnosis, screening, and necessary treatment for a specific disease by using the automatic prediction systems developed using machine learning algorithms. The results evaluated by using machine learning (ML) and deep learning models in feature extraction were efficient but the classification results need to be improved [7]. The classification and feature extraction takes place by using the OCT-based diagnosis method which is inexpensive and has a high probability. The convolutional neural network (CNN) models are used to automate classification and can be capable to learn various features from large training datasets [8]. The images of retinal OCT were analyzed like retinal classification and segmentation was done efficiently by using the CNN models [9]. The median filter is used to remove the noise during the process of enhancing and preprocessing OCT Images of the retina. The thresholding, and edge detection based on counter, and morphological operations were presented using adaptive histogram equalization (AHE) [10]. To identify the disease more efficiently at earlier stages the 3D volume was used by B-scan which gives efficient results in extracting the features of OCT retinal images and helps ophthalmologists and diagnosis for recognizing various retinal diseases [11]. The diagnosis accuracy is improved by using the information from the fundus and OCT images [12]. An efficient T-LMVO technique is used for the process of feature selection and to reduce the problem of overfitting in the input OCT images. The two datasets are used in retinal OCT and it's preprocessed using normalization techniques [13]. The features are selected using the T-LMVO algorithm. It is simple to settle for local solutions when the fitness function of the algorithm is so close at a later stage. This reduces the selection advantage of the optimal universe. To address these issues, the use of the tournament selection is suggested. The ideal universe can be found by computing the fitness function's reciprocal. This is due to the fact that tournament selection performs better in the minimization problem and can continue to update strongly even at the end of the iterative phase. The enhancement in the TLMVO help to improve the robustness of local optimisation and the capability of global optimisation, leading to a better balance between algorithm exploration and exploitation. The main objectives of the proposed T-LMVO algorithm are presented as follows:

1. The input images are taken from the retinal OCT and Noor eye hospital where the normalization makes the classification of retinal features easier.
2. The feature extraction takes place using GLCM features and local ternary pattern for extracting informative features from the input dataset images.
3. The T-LMVO feature selection technique is presented to minimize the dimensionality concern and select the optimal information from the extracted features.
4. The MSVM classifier is introduced for maximizing the accuracy of the disease classification where the classifier minimizes the false positive rate.

This research paper is organized as follows: the existing works are reviewed in section 2, and the proposed methodology is explained in section 3. Section 4 represents the results evaluated by using the proposed algorithm. The comparative analysis is illustrated in section 5. The conclusion of this paper is given in section 6.

2. Literature review

Hassan [14] presented a cascaded decoupled convolutional network (CDCNet) with two individual modules that work together to evaluate lesion-assisted grading of retinopathy. The proposed CDCNet framework used many scans of multi-vendor over four datasets of state of the art (SOTA) models like U-net, SegNet, fully convolutional network (FCN), and DeepLabv3+ which can able to accept publicly. The proposed CDCNet frameworks gave efficient results of accuracy in retinopathy gradient, dice score, and true negative and true positive rates. The limitations that existed in the proposed CDCNet framework were the framework was limited to grading and classification of the retinal pathologies of age-related macular degeneration (AMD) and macular edema (ME). The CDCNet does not result in efficient predictions hence grading of the retinopathy syndrome need to be improved further. Alqudah [15] presented an automated convolutional neural network (CNN) for the classification of multiple classes based on spectral-domain optical coherence tomography (SD-OCT). The SD-OCT images with four types of retinal diseases like diabetic macular edema (DME), choroidal neovascularization (CNV), drusen, age-related macular degeneration (AMD), and a normal case were used to train and test the CNN model. The SD-OTC does not give efficient detection of retinal disease. Hence CNN based ADAM optimizer is used to improve the accuracy with optimized cost. The proposed CNN methods achieve a high accuracy rate but CNN does not give high performance for the misplaced values in the dataset. Further, the error rate can be reduced by training the system with more retina diseases, which is limitation of the work. Suniji [16] developed an efficient classifier based on a deep neural network for classifying diabetic macular edema (DME), choroidal neo vascularization (CNV), and drusen from the retina images by optical coherence tomography (OCT). The OCT was a tool used for diagnostic patients to identify the presence of disease in retinal layers. The efficiency of training was improved by weight sharing and down sampling techniques which reduces the parameters of training samples. The proposed deep neural networks give efficient results using less number of parameters and the complexity was reduced. Further, an efficient decision-making process can be used in the activation of adversarial and test cases for efficient results.

Motozawa [17] presented a reliable computational deep-learning model for the determination of AMD from OCT images. The classification of AMD illness was done in the presence of the exudative charge and the absence of the segmentation method. The main advantage of using deep learning algorithms in identification was the automatic process within optimized cost and time. The main objective of using AMD in deep learning algorithms was to determine the growth rate or occurrence of disease automatically. But the quality of the image was poor which decreases the performance of the model and various potentially confounding pathologies of retinal were present in the AMD. Further, the deep learning models improved the efficiency of automatic prediction from the OCT images. Santhananthavathi and Indumathi [18] presented an efficient image enhancement technique based on the adjustment of the luminosity for minimizing the illuminance along with the usage of particle swarm optimization (PSO). The PSO shows efficient results in the prediction of retinal diseases and avoiding blindness. The PSO consists of more error rate and less performance of the results hence further efficient hybrid techniques was developed for minimizing the error rate and high predictions. Devarajan [19] presented an ant colony optimization (ACO) technique for optimal feature extraction for efficient classification of image features. The ACO shows efficient results in classification for extracted features but consists of more error rates and less specificity. Further, efficient machine learning classification techniques need to introduce for efficient classification results. Öztürk [20] presented an effective optimization algorithm of artificial bee colony (ABC) for efficient optimization and modification to improve the performance of the model. The threshold of the selection process became optimal using the ABC algorithm but the specificity was less which causes the false prediction of the retinal disease.

Fan [21] presented a scheme for detecting the severity level of diabetic retinopathy (DR) using the MobileNetV3 network depending on multi-scale features of the image of the retinal fundus. The classification performance was improved using the proposed MobileNetV3 network. The proposed MobileNetV3 network was having fewer parameters, and faster speed, and the process of extracting the features was efficient and very robust in identifying various changes in the image. The disadvantage of using the MobileNetV3 network was inexplicable for extracting the weight, GAP, and operations for divisions having unrelated features which reduce the accuracy of the model. Further, the network was developed with lightweight architecture and the operation of fusion for retrieving the intermediate features. Das [22] developed an efficient data classifier based on a semi-supervised generative adversarial network (GAN) for automatic diagnosis using a limited amount of data. The difficulty of processing the retinal image consists of annotation with the high cost and large data acquisition was reduced by using the proposed GAN network. The generalization was improved by GAN in case of limited data conditions and efficient pre-scanning and the automated diagnosis was done using efficient classification results for retinal disease. The main drawback of using the GAN network was, it has a huge amount of labeled data during training. Further, the classification performance needs to be improved more and the automatic diagnosis process for retinal diseases. Fang [23] presented a fusion of iteration convolution neural network (IFCNN) method classification of OCT retinal image automatically. The various convolutional layers were used for extracting the information about features from various scales in CNN. The strategy of iterative fusion was adopted using the proposed CNN, where the features in the current CNN are combined iteratively and to result in the classification with more accurate results of OCT images of various features of convolutional layers. The classification of OCT images was improved using the strategy of iterative fusion. Further, the OCT images of various pathologies were developed for more efficiency of the proposed iterative fusion CNN model.

Pawan Kumar Upadhyay [24] developed a deep learning based automatic retinal disease classification method known as coherent convolutional neural network. It was developed by using pre-trained VGG-16 to perform the salient activities by increasing the number of optimized layers. The output of the system is validated with the retinal images of OCT dataset and achieved better classification results due to the coherent nature of the neurons. However, due to high error rate the

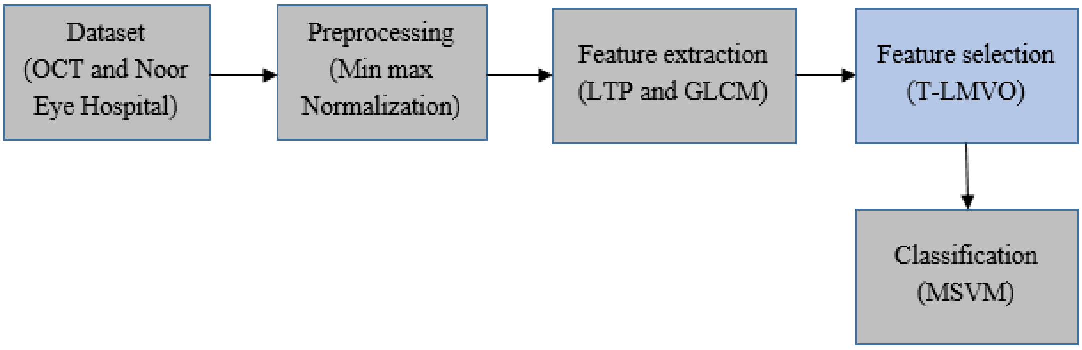

Figure. 1 Flow chart of the proposed feature selection optimization algorithm

suggested approach has achieved robust results. Amin Alqudah [25] suggested a hybrid intelligence system for classifying retinal diseases with the help of automated deep features based on advanced OCT network architecture. The classification was carried out on eight ML classifiers on SD-OCT dataset and achieved better classification results. However, the time required to extract feature is more which is a drawback of this work. Alex Liew [26] developed an automatic quantification and classification system retina diseases using OCT images. The extraction of macular disease features was also performed. The better classification results have been obtained with the used of multi-size kernels ξcho-weighted median patterns (MSK ξ MP). However, constructing 3D OCT images and obtaining results which determines the spread of the disease, would have obtained greater results with the developed framework.

Mesut Togˇac¸ar [27] developed an AI based hybrid approach for detecting retinal diseases by extracting class based activations with nine transfer learning models. A slime mold algorithm (SMA) was used to select the features and classified using softmax classifier. This approach has achieved better classification results with the use of SMA on UCSD, OCT, and duke dataset. However, this approach is not validated clinically in the experimental analysis. Sapna S. Mishra [28] suggested a fully automated attention based deep CNN for classifying macular disease. A fine tune deep CNN model was initialized with the attention mechanism to extract the discriminative features in macular OCT images. This approach has achieved better classification results without the need to perform any pre-processing steps. However, the effectiveness of this approach is less in detecting several complicated macular diseases. Esraa Hassan [29] developed an enhanced optical coherence tomography based on the modified ResNet50, and random forest to classify the retinal OCT using OCT dataset with four categories: CNV, DME, drusen, and normal. This approach has achieved better classification results with the random forest. However, the analysis of choroidal features is not performed which is important for understanding systematic pathologies. Zongqing Ma [30] suggested a hybrid convent transformer network (HCTNet) for classifying images of retinal OCT. A low level features extraction module was designed to build two parallel branches for feature extraction. The obtained classification results are better with the use of weighted based feature fusion module. However, the time consumed for training the network is more.

The limitations observed from the existing researches are poor image grading, high error rate, low specificity, low detection accuracy, high training time. To overcome these limitations a tournament based selection with LMVO is proposed in this research which will result in accurate prediction, better specificity, and low error rate.

3. Methodology

The proposed optimization algorithm of T-LMVO was used for an efficient feature selection process of the retinal diseases from the input OCT Images. The flow chart of the proposed feature selection process is presented in Fig. 1.

3.1 Dataset

The input images of the retinal diseases are taken from OCT images and noor eye hospital datasets. The macular problems including age-related macular detection (AMD), choroidal neo-vascularization (CNV), and diabetic macular edema (DME) are presented in the sample input images dataset. Noor eye hospital dataset consists of 148 SD-OCT volumes (48 AMD, 50 DME, and 50 Normal) [24]. An efficient technique of normalization was applied to enhance the images and where the normalization makes the classification of retinal features easier. The feature extraction takes place using GLCM features and local ternary pattern for extracting informative features from the input dataset images. The T-LMVO feature selection technique is presented to minimize

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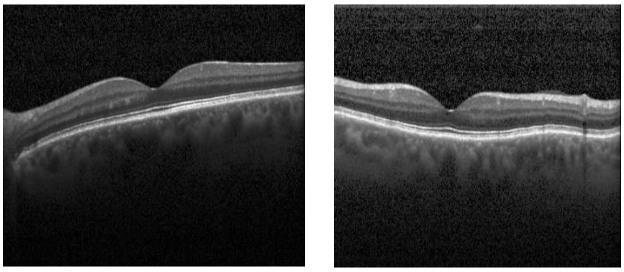
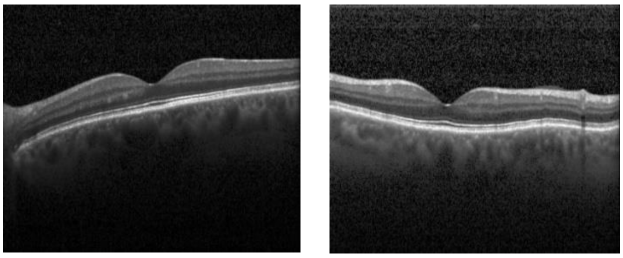


(a) (b)

Figure. 2 Sample input images of retinal disease



(a) (b)

Figure. 3 Preprocessed images

the dimensionality concern and select the optimal information of features that are extracted. The MSVM classifier is introduced to improve the accuracy of the disease classification where the classifier reduces the false positive rate and minimizes the false prediction of the disease which is represented in Fig. 2.

The sample input retinal images of retinal OCT images and the images of noor eye hospital are represented in (a) and (b) figures.

Dataset link: https://hrabbani.site123.me/available-datasets/dataset-for-oct-classification-50-normal-48-amd-50-dme

3.2 Preprocessing

The input OCT retinal images and noor eye hospital images are preprocessed using the normalization technique to reduce the noise content and to extract the relevant features which help in predicting the level of the disease. The diseases like diabetes, cardiovascular, and stroke were evaluated from the images of the retinal fundus. The retinal fundus images have less illumination, blur, and low contrast because of complex imaging. The repeating entries and noisy elements were removed in preprocessing by the normalization process and the morphological process was used for correcting the illumination between various images. The contrast between the two regions in the variance image was evaluated using the normalization preprocessing.

The preprocessing was done on the input images of normal, AMD, and DME where the noisy and unwanted part of the image was removed using the normalization technique. The preprocessing of an image takes place by including the steps of cleaning the data, reducing the dimensions, extracting the features, and transforming the data by using the normalization technique. The input OCT images were improved using the normalization technique which helps in the further process to achieve efficient results. The n-dimensional greyscale image was transformed using the normalization technique consisting of the range of (Min, Max) of intensity values into a new image with the values of intensity in the range (new Min, new Max) which ranges between (0,1). The formula for calculating min_ max limits was represented in the Eq. (1).

Min-max formula

$$v^{|} = \frac{v-\min(A)}{\max(A)-\min(A)}\left(new_{\max(A)} - new_{\min(A)}\right) + new\_\min(A) \quad (1)$$

The minimum value in a dataset-A is presented as Min(A) and the maximum value was presented as Max(A) with initial value v and the updated value is $v^{|}$ .. The range of boundary values of min and max ranges between new_Min(A) and new_Max(A) respectively. The normalization preprocessing images of the retinal OCT dataset-1 and noor eye hospital dataset-2 are given in Fig. 3.

The preprocess retinal disease images of the Retinal OCT and noor eye hospital are represented in Fig. 3.

3.3 Feature extraction

3.3.1. GLCM algorithm

The most informative features from the input OCT images like color and texture are evaluated using the GLCM algorithm which makes the input images more effective and informative. The GLCM helps to extract the features from the input OCT images and the features are further moved on the selection and classification process to result in the output values. The GLCM and local ternary patterns were used in the process of extracting the features. The statistical GLCM method is used to measure the spatial relationship between the pixels of the image. By evaluating the spatial relationship and pixel pairings with certain values that exist in an image was identified and creating GLCM, where G is the image's grey level. The ratio of the two pixels with the matrix element $\frac{P(i,j)}{\Delta_x \Delta_y}$, where ($\Delta$x, Δy) is the pixel's separation distance. The statistical probability values of second order for the changes taking place in grey levels at a particular angle and specific distance of displacement were evaluated as the matrix element of $\frac{P(i,j)}{d,\theta}$ in GLCM. The first and second-order features are extracted using GLCM with various intensities including the contrast, correlation, homogeneity, energy, entropy, sum average, variance, sum variance, sum entropy, difference variance, difference entropy, information measure of correlation-1, and information correlation-2.

Correlation

The measurement of the occurrence of the joint probability of the particular pixel values results in a Correlation feature in the GLCM. The summation of the overall existence of pixel value i, which is present together in the pixel value j in the input image and results in the pixel element $p(i,j)$ in GLCM. The size of the GLCM was presented based on the number of grey levels existing in the image. An efficient correlated image results value of 1 for positive and -1 for negative correlation and the measuring formula was represented in Eq. (2).

$$Correlation = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{\{i \times j\} \times P(i,j) - \{\mu_i \times \mu_j\}}{\sigma_i \ \sigma_j} \quad (2)$$

Where the intensity (grey level) of the pixel i with the spatial relationship with the pixel value j and results in the element $p(i,j)$, μ_i, μ_j are the mean values and the σ_i, σ_j indicates the variance values which are formulated in Eqs. (3) and (4).

Mean

The relationship of the pixels for measuring the texture of the features results in the statistical GLCM method, where the mean value was calculated by the Eq. (3) for the intensity pixel value of i, with the relation of the pixel j in the pixel element of $p(i,j)$.

$$\mu_i = \sum_{i,j=0}^{N-1} i(P_{i,j}) \quad \mu_j = \sum_{i,j=0}^{N-1} j(P_{i,j}) \quad (3)$$

Variance

The degree of the mean value elaboration in a dataset represents the variance of the data where all the deviations from the mean take place without depending on the direction of the data. The variance is measured by using the Eq. (4).

$$\sigma_i^2 = \sum_{i,j=0}^{N-1} P_{i,j}(i-\mu_i)^2 \qquad \sigma_j^2 = \sum_{i,j=0}^{N-1} P_{i,j}(j-\mu_j)^2 \quad (4)$$

Where i is the value of the pixel in the dataset, μ represents the mean value of the dataset, and the total number of values is represented by N.

Energy

In GLCM, the sum of squared elements is provided as energy or angular second moment or uniformity where it ranges from [0 1], and for a constant image the energy has resulted as 1. The texture disorders like the random presence of pixels can identify and textural uniformity is measured. The image with a large number of small entries will result less homogeneity of the image in the GLCM. The measurement of the energy was done using the Eq. (5).

$$Energy = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P_{i,j}^2 \quad (5)$$

Where g indicates the grey level of the image and the value of i, j in the pixel element $p(i,j)$.

Homogeneity

The closeness of the distribution of the elements in GLCM to the diagonal of GLCM was measured. The homogeneity of the image for larger values where the inverse moment of statistics takes place and in the case of the same images it results in the maximum values. The rate of homogeneity was measured in Eq. (6) which is inversely proportional to the contrast in case of energy is constant.

$$Homogeneity = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{P(i,j)}{(1+(i-j)^2} \quad (6)$$

Contrast

The difference occurs between the various image features in the greyscale of the images which are resulted in the contrast of the image. The difference between the lower and the upper values of pixels was measured and the various moment of GLCM and spatial image frequency was measured. The contrast of the images was calculated using Eq. (7).

$$Contrast = \sum_{i,j=0}^{N-1} P_{ij} \ (i-j)^2 \quad (7)$$

Entropy

The number of pixels or bits used to encode the data of the image and the complexity of the image was measured. The entropy is inversely proportional to the energy in case of high entropy with complex textures was calculated as the entropy which was represented in the Eq. (8).

$$\text{Entropy} = \sum_{i,j=0}^{N-1} P_{i,j}(-In \ P_{i,j}) \quad (8)$$

3.3.2. Local ternary pattern (LTP)

The discriminative power of LTP was used to analyze the texture of the image along with the local binary pattern (LBP) which reduces the illumination and noise of the image. The green (G), red (R), and blue (B) colors consist of various radius which was obtained using the LTP. The classifiers of the random forest, KNN, and DE are the existing feature sets, and the proposed feature set classifier is MSVM which was used for the classification of the features of input OCT images. The GLCM and LTP were presented for extracting the features and the features extracted from the retinal OCT images resulted in a length of feature 560 and the Noor, eye hospital images resulted in a length of feature 560.

The LTP has encoded the codes with the values of {-1,0,1} and the ternary pattern of every pixel is separated into two binary patterns and results in the less than, equal, and greater than relations between the binary patterns. The LTP gives efficient results in the case of discriminative modelling of features on textures as compared to binary patterns. The multi-scale sampling where the classification texture algorithm was efficient and the dimensions were reduced using the LTP. The measurement of the LTP was done using Eq. (9).

$$s^{|}(g_{c,}g_{p,}\delta) = \begin{Bmatrix} +1, g_p - g_c > \delta \\ 0, |g_p - g_c| \le \delta \\ -1,\ g_p - g_{c<-\delta} \end{Bmatrix} \tag{9}$$

Where the empirical thresholding was represented using δ, the grey scale intensity of the central pixel was represented as g_c, and g_p presents the p-th term sampling point of estimated intensity.

3.4 Feature selection

The process of selecting relevant features from the extracted features to improve classification accuracy is known as feature selection. An optimization algorithm will significantly improve the accuracy. Since the optimization is a total randomization process, the exploration and exploitation need to be balanced to acquire best features. To achieve this, a tournament based feature selection is used for multiverse optimization (MVO). The MVO has the ability to select optimal features. A levy flight distribution is used with the MVO, to control the parameters and for faster convergence.

The use of T-LMVO for choosing relevant features from the retinal images has major advantages such as uniform distribution, and balance between exploration and exploitation. These features will be optimised using T-LMVO which involves choosing a best individual from the overall population based on the objectives or fitness function. The advantage of using tournament selection in retinal images, especially in optimization algorithms is that, it helps the algorithm to make sure that variety of solutions are given the opportunity to compete in order to possibly be chosen. This will result in a population of solutions that is more varied and evenly distributed.

The T-LMVO results in high robustness and improved performance using the tolerance selection compared to MVO. The update for the location was done by adding the mutation factor during the process of screening in the proposed T-LMVO. The global and local optimization was improved by reaching a better balance between the algorithms of exploitation and exploration. The convergence speed is improved using the T-LMVO optimization algorithm and convergence of the optimal solution. Eq. (10) describes the mathematical model of the T-LMVO.

$$Levy\ (\lambda) = 0.01 \times \frac{\mu \times \sigma}{|v|^{\frac{1}{\beta}}} \tag{10}$$

Where the v and μ obey the normal distribution which is represented in Eqs. (11) and (12) represents the standard deviation measurement.

$$\lambda = \beta + 1$$

and

$$\mu \sim N(0, \sigma^2),\ \ v \sim N(0, \sigma_v^2) \tag{11}$$

$$\sigma = [\frac{r(1+\beta) \times sin\left(\frac{\pi\beta}{2}\right)}{r\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}}]^{\frac{1}{\beta}} \tag{12}$$

where $\sigma_{v=1}$ and the β is the parameter for controlling which will vary based on the density function.

The step length is calculated as:

$$s = \frac{\mu}{|v|^{\frac{1}{\beta}}} \tag{13}$$

The initial and the final points of every step were measured in Eq. (13) which results in the step length. The selected feature consists of a length of 213 pixels per inch (PPI) for retinal OCT images and 256 PPI for Noor eye hospital images. The related features are summarized into single content for efficient results and fitness function. The optimal solutions were resulted using the fitness function which is measured in terms of accuracy using Eq. (14).

$$y = 100 \times \left(X(1)^2 - X(2)\right)^2 + \left(1 - X(1)\right)^2 \quad (14)$$

Where, X is the row vector and y is the augment.

From the extracted features of 250 from OCT and noor eye dataset, 213 and 216 features are selected respectively and given as input to MSVM classifier.

3.5 Classification

The classification took place using the multi-class support vector machine (MSVM) where the images were classified into various labels of 1 and 0 or as negative and positive. The machine learning MSVM process was presented which can able to learn the data without depending on any alternate external technical approaches. The MSVM is used to classify the data under various approaches to improve the performance of the model. The classification using the MSVM reaches the high margin around the hyper plane. The MSVM machine learning technique evaluated efficient results in training features and testing the trained features. The features of the retinal OCT images were trained to identify the disease and the process of testing is done to verify the efficiency and correctness of the trained images.

The classification process was done using the MSVM method where the patterns are recognized and analyzed the data in statistics. The classification model of MSVM was designed using the samples of the training set and resulted in the new samples from the testing dataset and separated into two types. The sample data points resulted in a space where there is a clear gap between every category. The MSVM classifier creates a hyperplane in the space of the dataset to separate the nearest and the largest training data points in a class. Less error of generalization and higher margin exists in the SVM classifier. The input data was transformed into a higher dimension using the function of the kernel to reduce the issue of the nonlinear classification which was calculated using Eq. (15).

$$K(x_i, x_j) = exp\ (-\gamma \|x_i - x_j\|)\ ,\gamma > 0 \quad (15)$$

Where the k is the number of classes and the classes of i^{th} and j^{th} terms of the training dataset.

4 Results and discussions

The T-LMVO optimization algorithm for feature selection presents effective results by validating on the MATLAB R2020b software environment with the Windows 10 operating system, 16 GB random access memory, and Intel i7 processor. The performance of the proposed T-LMVO model has measured the performance metrics of accuracy, specificity, sensitivity, MCC, and error-rate. The single value metric of the efficient MCC ranges between 0 and 1, where 0 indicates without agreement and 1 indicates the agreement between the predicted and the actual value. The mathematical equations of the performance parameters resulted in Eqs. (16), (17), (18), (19), and (20), where the TP, TN, FP, and FN are represented as true positive, true negative, false positive, and false negative respectively.

The ratio of the number of correctly predicted classifiers to the overall predictions is known as the accuracy of the model. The result in the amount of variation of the feature value occurred by an influence is the sensitivity of the model. The performance of the model is validated using the parameters of accuracy, sensitivity, specificity, MCC, and error rate which were calculated by using Eqs. (16), (17), (18), (19), and (20) respectively. The prediction was improved by an efficient MCC performance value. The ratio of the false positive rate to the summation of the false positive and true positive is the result of the error rate.

$$Accuracy = \frac{TN+TP}{TN+TP+FP+FN} \quad (16)$$

$$Sensitivity = \frac{TP}{FN+TP} \quad (17)$$

$$Specificity = \frac{TN}{TN+FP} \quad (18)$$

$$MCC = \frac{TN \times TP - FP \times FN}{\sqrt{(TP+FP) \times (FP+TN) \times (FN+TP) \times (FN+TN)}} \quad (19)$$

$$Error\ rate = \frac{FP}{FP+TP} \quad (20)$$

4.1 Quantitative evaluation

This section evaluates the T-LMVO model which gives effective results for validating the input retinal OCT image and noor eye hospital medical images. The experimental evaluation was performed on various classification techniques of K-nearest neighbor (KNN), random forest (RF), DE, and multi-support vector machine (MSVM) with the parameters of accuracy, specificity, sensitivity, MCC, and error-rate in both cases of with feature and without feature selection as shown in Table 1 and 2. The classification was done efficiently by using the MSVM algorithm for both datasets as compared to the existing machine learning classifiers. The

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Table 1. Performance results of the classification techniques without and with feature selection

Experimental results of the classification models without feature selection					
Algorithms	**Accuracy(%)**	**Sensitivity(%)**	**Specificity(%)**	**MCC(%)**	**Error-rate(%)**
KNN	89.26	88.05	90.43	87.56	10.74
RF	90.24	89.35	91.08	86.39	9.76
DE	86.87	87.00	89.30	84.50	13.13
MSVM	93.68	90.96	92.51	94.44	6.32
Experimental results of the classification models with feature selection					
Algorithms	**Accuracy(%)**	**Sensitivity(%)**	**Specificity(%)**	**MCC(%)**	**Error-rate(%)**
KNN	90.15	91.25	89.31	92.45	9.85
RF	91.03	92.99	90.89	89.31	8.97
DE	87.35	88.96	90.08	86.69	12.65
MSVM	98.95	99.02	97.61	98.92	1.05

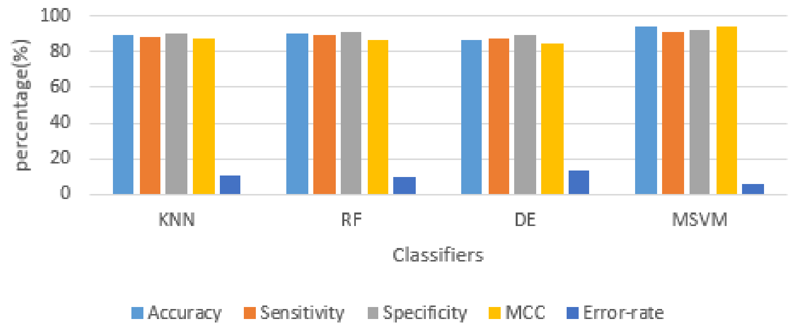

Figure. 4 Performance of various classifiers without feature selection

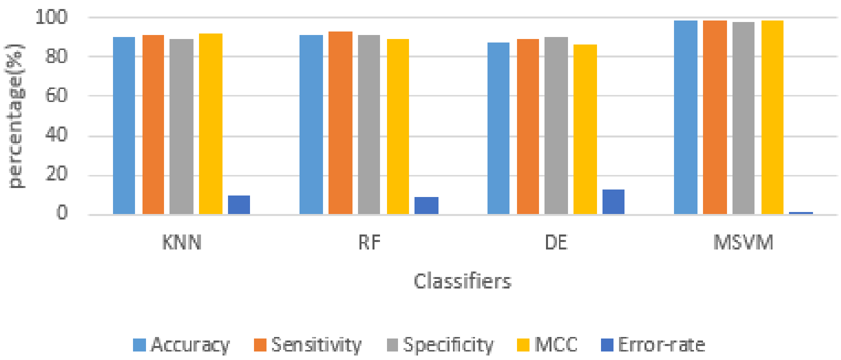

Figure. 5 Performance results of classification with feature selection

accuracy of the classification was improved by MSVM and the overfitting was reduced, where it was represented in graphical format with and without the process of feature selection. The performance of the T-LMVO was compared to the existing particle swarm optimization (PSO), artificial bee colony (ABC), and ant colony optimization (ACO) in Table 3 and 4. The proposed T-LMVO has shown improved performance in the following parameters such as accuracy of 98.95%, sensitivity of 99.02%, Specificity of 97.61%, MCC of 98.92%, and error rate of 1.05% for retinal OCT images with feature selection. The output of noor eye hospital images resulted in the accuracy of 98.99%, Sensitivity of 99.38%, specificity of 97.63%, MCC of 96.95% and the error rate of 1.01% with feature selection.

The retinal OCT images were taken as the input images, which are used to predict disease from the image. Table 1 represents an efficient MSVM classification algorithm for retinal OCT images, resulting in high performance in the retinal disease classification without selecting the features where the accuracy of 93.68%, the sensitivity of 90.96%, specificity of 92.51%, 94.44% of MCC, and error rate consists of 6.32% and with the feature selection results evaluated are accuracy of 98.95%, the sensitivity of 99.02%, specificity of 97.61%, 98.92% of MCC, and error rate consists of 1.05%. The MSVM shows efficient results compared to the existing machine learning classifiers like K-nearest

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Table 2. Performance results of the classification techniques without and with feature selection

	Accuracy (%)	Sensitivity (%)	Specificity (%)	MCC (%)	Error-rate (%)
Performance of classification without feature selection					
KNN	88.66	87.45	89.99	86.61	11.34
RF	85.75	84.84	82.86	83.67	14.25
DE	90.45	87.32	86.12	89.75	9.55
MSVM	92.44	93.72	94.96	91.54	7.56
Performance of classification with feature selection					
	Accuracy (%)	**Sensitivity (%)**	**Specificity (%)**	**MCC (%)**	**Error-rate (%)**
KNN	90.19	89.32	91.69	92.37	9.81
RF	88.14	89.90	87.45	89.70	11.86
DE	92.94	88.04	90.60	93.84	7.06
MSVM	98.99	99.38	97.63	96.55	1.01

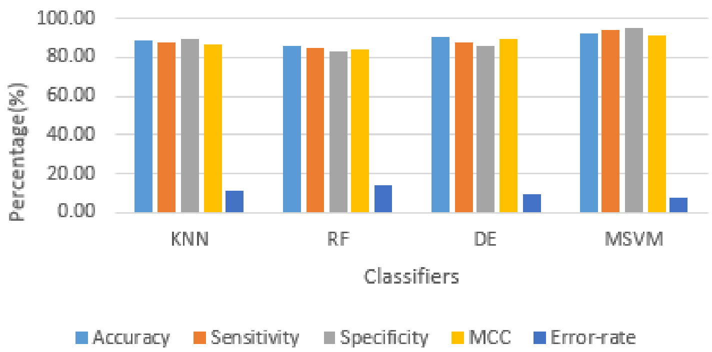

Figure. 6 The experimental results of the classification models without feature selection

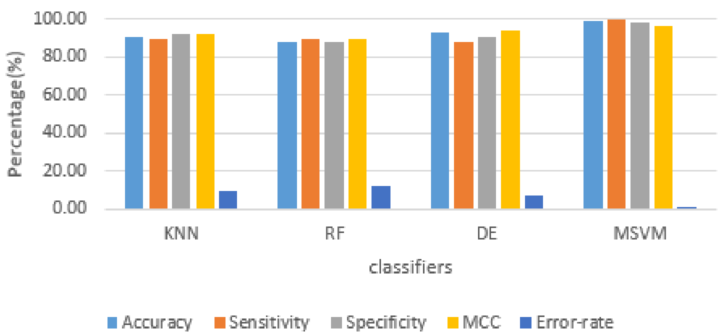

Figure. 7 The experimental results of the classification models with feature selection

neighbor (KNN), random forest (RF), and differential evolution (DE) algorithms. The MSVM improves the overall accuracy of a classification and minimizes overfitting. The graphical representation of Table 1 is represented in Figs. 4 and 5.

4.1.1. OCT retinal images

The proposed MSVM algorithm results in efficient classification for selected features which leads to minimizing the complexity and improving the efficiency. The MSVM shows efficient results as shown in Figs. 4 and 5 for the retinal OCT images in retinal prediction for the with and without feature selection samples.

The noor eye hospital OCT images were taken as the input images, where the retinal disease was predicted using the T-LMVO feature selection process. Table 2 represents an efficient MSVM classification algorithm for Noor eye hospital OCT images, resulting in high performance in the retinal disease classification without extracting the features where the accuracy of 92.44%, sensitivity of 93.72%, specificity of 94.96%, 91.54% of MCC, and error rate consists of 7.56% and with the feature extraction, the results evaluated are accuracy of 98.99%, the sensitivity of 99.38%, specificity of 97.63%, 96.55% of MCC, and error rate consists of 1.01%. The MSVM results in efficient results compared to the existing machine learning classifiers like K-nearest neighbor (KNN), random forest (RF), and differential evolution (DE) algorithms. The MSVM improves the overall accuracy of a classification and minimizes overfitting. The graphical representation of Table 2 is represented in Figs. 6 and 7.

4.1.2. OCT images from noor eye hospital

The MSVM algorithm shows efficient classification results for the selected features which lead to minimize the complexity and improves efficiency. The MSVM shows efficient results which was represented in Figs. 6 and 7 for the noor eye hospital in retinal prediction for the with and without feature selection samples.

Table 3 and 4 represents the quantitative analysis of proposed T-LMVO with the conventional methods such as PSO, ACO, and ABC. The experimental validation was performed on both SD-OCT and noor eye hospital data and achieved an accuracy of 98.99%, sensitivity of 99.38%, specificity of 97.63%, MCC of 96.95% and the error rate of 1.01%.

The conventional optimization techniques such as PSO, ACO, and ABC have limitations such as more error rate, ineffective feature selection approach, and low specificity. The proposed T-LMVO has resulted in less error rate and better specificity values. The proposed approach has achieved better results due to the advantages of tournament selection such as effective time complexity, not susceptible to optimal biasing, and no requirement of fitness scaling or sorting.

4.2 Comparative analysis

The proposed T-LMVO is compared with the existing methods such as CNN [27], MascularNet [28], EOCT [29], and HCTNet [30] in the Tables 5 and 6. The T-LMVO is compared with CNN [27], MascularNet [28] on noor eye hospital dataset in Table 5. The T-LMVO is compared with EOCT [29], and HCTNet [30] on OCT images dataset in Table 6.

From Table 5 and 6, it is observed that the proposed method achieved better values than the existing methods due to the advanatges of tournament based feature selection in classifing the retina diseases. The compared conventional methods has limitations of high error rate, poor image grading, high error rate, low specificity, low detection accuracy, high training time. To overcome these limitations a tournament based feature selection mechanism is developed through this research which has an advantage of effective time complexity, not susceptible to optimal biasing, and no requirement of fitness scaling or sorting. The LMVO balances the exploitation and exploration algorithms by reducing the local optimum, maximizing the accuracy, and faster the convergence.

Table 3. Different optimization algorithms for retinal SD- OCT images

	Accuracy (%)	**Sensitivity (%)**	**Specificity (%)**	**MCC (%)**	**Error rate (%)**
PSO	92.32	51	23	51	7.68
ACO	94.58	80	24	10	5.42
ABC	96.22	82	68	72	3.78
Proposed T-LMVO	98.95	99.02	97.61	98.92	1.05

Table 4. Different optimization algorithms for images of noor eye hospital

	Accuracy (%)	**Sensitivity (%)**	**Specificity (%)**	**MCC (%)**	**Error-rate (%)**
PSO	92.53	94.72	93.37	91.16	7.47
ACO	93.58	92.38	94.25	92.19	6.42
ABC	95.42	96.85	94.80	95.92	4.58
Proposed T-LMVO	98.99	99.38	97.63	96.95	1.01

Table 5. Comparison table of the implemented method with the noor eye hospital dataset

Author	Method	Accuracy (%)	Sensitivity (%)	Specificity (%)
Mesut Togacar [27]	CNN	97.49	N/A	N/A
Sapna S. Mishra [28]	MascularNet	94.18	94.62	N/A
This study	T-LMVO	98.99	99.38	97.63

Table 6. Comparison table of the implemented method with the OCT dataset

Author	Method	Accuracy (%)	Sensitivity (%)	Specificity (%)
Esraa Hassan [29]	EOCT	97.47	98.36	96.15
Zongqing Ma [30]	HCTNet	91.56	88.57	N/A
This study	T-LMVO	98.95	99.02	97.61

5 Conclusion

The efficient T-LMVO model was proposed for the accurate prediction of retinal disease prediction which gives high-performance results in selection, classification and feature extraction. The normalization technique is used for preprocessing of the input images and the feature extraction takes place using the GLCM and local ternary patterns where the textural vectors minimize the gap between the features vectors that are extracted. The proposed T-LMVO for feature selection was presented for the input Retinal OCT image and noor hospital retinal images for prediction of the retinal diseases. The macular problems including the AMD, CNV, and DME are presented in the sample input images. The selected features were classified using the MSVM technique and when compared to the existing methods the proposed T-LMVO feature selector results in the accuracy of 98.95%, sensitivity of 99.02%, specificity of 97.61%, MCC of 98.92% and an error rate of 1.05% for retinal OCT images and for the images of noor eye hospital it shows the accuracy of 98.99%, sensitivity of 99.38%, specificity of 97.63%, MCC of 96.95% and the error rate of 1.01%. Overall, the proposed T-LMVO shows better stability, higher optimization accuracy, and better robustness. Further, hybrid deep learning techniques are presented for efficient predictions of retinal diseases and to increase the accuracy and minimize the error rate. The prediction of retinal disease in diagnosis patients was improved and reduced the problem of image misinterpretation.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

For this research work all authors' have equally contributed in conceptualization, methodology, validation, resources, writing—original draft preparation, writing—review and editing.

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