Educational Administration: Theory and Practice
2023, 29(4), 627-634
ISSN: 2148-2403
https://kuey.net/
Research Article

Integrating Metaheuristics Methods To Detect Real-Life Glaucoma Problem Using Machine Learning Techniques

Abu Sarwar Zamani[1*], Aisha Hassan Abdalla Hashim[2]

[1*,2]Department of Electrical and Computer Engineering, International Islamic University Malaysia, Kuala Lumpur 53100, Malaysia

***Corresponding Author:** Abu Sarwar Zamani
(Sarwar_zamani@yahoo.com)

Citation: Abu Sarwar Zamani, et al, (2023) Integrating Metaheuristics Methods To Detect Real-Life Glaucoma Problem Using Machine Learning Techniques, *Educational Administration: Theory And Practice*, *29*(4), 627-634,
Doi: 10.53555/kuey.v29i4.5289

ARTICLE INFO

ABSTRACT

In glaucoma, the fluid pressure inside the eye rises, causing damage to the retinal nerve fibers, which is a common complication. Once damage to nerve fibers has occurred, it is impossible to regain vision. Glaucoma causes an increase in fluid pressure inside the eye, which damages the retinal nerve fibers, which is a common consequence. Once nerve fibers have been damaged, it is impossible to restore vision. Image processing, analysis, and computer vision techniques are becoming increasingly relevant in medical research as they become more significant in modern ophthalmology. There is no denying that ophthalmology is an interdisciplinary discipline, both in academic study and clinical practice today. Imaging technologies in ophthalmology increase diagnostic and observational capabilities. Fundus photography is the imaging approach that provides the most thorough fundus examination with the least amount of patient engagement and the most simple and inexpensive equipment. In detection of Glaucoma fundus images are vital. Optic disk in fundus images can indicate numerous eye diseases, particularly in cases of glaucoma, and can be used to measure aberrant characteristics. This article describes the categorization and detection of Glaucoma illness using Image Processing and Feature Selection. In this system, fundus photos are used as input. Using the CLAHE method, pictures are preprocessed to increase their quality. Following that, pictures are segmented using the K Means method. This segmentation aids in locating the region of interest in the input image. The Relied algorithm is then used to choose features. It aids in the improvement of categorization accuracy. The SVM-RBF, BPNN, and Nave Bayes algorithms are used for classification. SVM RBF is having better accuracy for classification of Glaucoma disease.

Keywords: Machine Learning, Image Processing, CLAHE, SVM RBF, Accuracy, Relief Algorithm, K Means

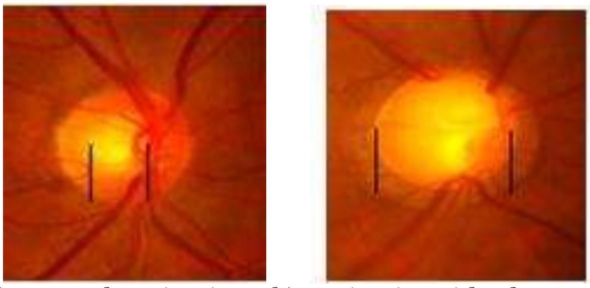
1. INTRODUCTION

Many disorders can only be detected and diagnosed with the use of medical photographs, which are increasingly ubiquitous. Using digital pictures, medical image processing aims to provide computational tools that aid in the measurement and visualization of disease and anatomical features. In today's health care environment, digital medical imaging is a must-have tool. In addition to providing a permanent record of patients, it can extract information regarding a wide range of disorders. The use of high-quality imaging aids in medical decision-making and can help cut down on the number of treatments that aren't really essential. As digital images and computational power continue to improve, so does ophthalmology in the 21st century. The utilization of digital images and processing power in ophthalmology is expanding as these technologies advance [1].
Increasingly important to modern ophthalmology, image processing, analysis, and computer vision techniques are becoming increasingly used in medical research [2, 3]. There is no disputing the fact that ophthalmology is a multidisciplinary subject, both in terms of academic study and clinical application today. In ophthalmology, imaging modalities improve diagnostic and observational capacities [4, 5]. Fundus photography is the imaging technique that offers the most comprehensive fundus examination with the least

amount of patient involvement and the least amount of expensive and basic equipment. However, the decision to adopt digital photography as an acceptable method of documenting the eye fundus has been the most significant single event in the medical research community. Many ailments might benefit from extracting information from the eye fundus, including glaucoma, heart problems, strokes, hypertension, peripheral vascular disease, and diabetic retinopathy, as has been proposed.

In glaucoma, the fluid pressure inside the eye rises, causing damage to the retinal nerve fibers, which is a common complication. Once damage to nerve fibers has occurred, it is impossible to regain vision.

The OD is a prominent feature of a retinal fundus picture and can be found 3 to 4 mm nasally of the fovea on the retinal fundus image. It has an average width of 1.76mm horizontally and a height of 1.92mm vertically. In the typical fundus, the OD is the most prominent feature, and the size of the disc varies from person to person, occupying between 10% and 15% of the picture. Odds ratio (OD) changes can indicate numerous eye diseases, particularly in cases of glaucoma, and can be used to measure aberrant characteristics [6]. Figure 1 shows Fundus Images of Normal Optic Disc and Optic Disc with Glaucoma.



a) Normal Optic Disc b) Optic Disc with Glaucoma

Figure 1: Fundus Images of Normal Optic Disc and Optic Disc with Glaucoma

Literature survey contains an in depth study of existing methods for Glaucoma detection. Methodology section represents Image Processing and Feature Selection based classification and Detection of Glaucoma disease. Fundus images are used as input in this framework. Images are preprocessed to improve images using the CLAHE algorithm. Then images are segmented using K Means algorithm. This segmentation helps in identification of region of interest in the input image. Then feature selection is performed by Relied algorithm. It helps in improving the classification accuracy. Classification is performed by SVM-RBF, BPNN and Naïve Bayes algorithm. Result section contains analysis and discussion of input data set and results obtained by machine learning techniques.

2. LITERATURE REVIEW

The HSI approach allows for the separation of picture intensity from its corresponding colour component. In the picture enhancing process, local contrast augmentation of this intensity component is particularly beneficial. In addition, the RGB transformation has been made possible with no loss of color richness in the photos. In the HSI model, color and noise reduction are both closer to what humans are familiar with. On the I band of the HSI model, Median Filtering (MF) and zero/edge padding removal are used. On the basis of the HSI color approach's intensity measurements, the local adaptive contrast method improves contrast [7]. However, the immediate consequence on this model is that the noise might be improved with a little tweak of contrast. CLAHE was established in Nayomi et al. [8] for the I band of the HSI using MF and contrast limited adaptive histogram equalization (CLAHE).
Noise was a serious issue with color fundus pictures since it was present to a larger degree. For this problem, several previous research have used Median Filtering (MF) and convolution with a smoothing kernel as a basis for their solutions. In addition, a "shade corrected" photograph was created by removing a minor intensity variation in the green plane image background during the pre-processing step. Reduce the backdrop picture from a green image to get the desired shade alteration. The background picture is determined by using an MF to smooth out the green image. For example, Lee et al. [9] used 56 × 56 MFs to generate a shade-corrected picture. A Low-Pass Filter (LPF) or a Multi-Pass Filter (MF) should be used to smooth the real picture, and the background image should have the biggest retinal attribute possible. In order to do shade correction, the 3 x 3 mean filtering models were combined with the Gaussian kernel. In order to reduce noise and eliminate unnecessary pixels, pre-processing is employed. Smoothing and normalizing were utilized as shade correction techniques due to an inadequate conversion of the image.

OCT and HRT were used in a model created by Nayak et al. (2009) to identify glaucoma. It is based on the medical fundus photographs acquired from Kasturba Medical College. Using digital photos as a starting point, the procedure begins with pre-processing and thresholding. Morphological procedures are currently being applied to the pre-processed picture. Operations on the optic disc and blood vessels are carried out using morphological methods. Medical photographs were used to diagnose glaucoma because of the fuzzy set uncertainty. HRT was used to extract features from the fuzzy sets. Using Optic Disc topography characteristics, HRT was able to differentiate between normal and glaucomatous fundus images. An artificial neural network (ANN) was used to train an unsupervised neural network in the presented technique. There were two classes of statistical treatment: the "abnormal" class and "normal." In order to make the created system even better, additional various photographs will be taken into account [10].

An automated diagnostic approach for the identification of glaucoma was developed by Bock et al. [11] and used extensively in digital fundus images. After preprocessing a picture, feature extraction, and classification were carried out using the newly devised approach. The photos were taken from a local database and distorted to remove the inconsistencies in the backdrop. During image capture, the brilliant speckles were spotted from a variety of perspectives. In order to extract generic and appearance-based features from glaucomatous pictures, the obtained image has to be preprocessed. Fast Fourier Transform (FFT) characteristics including pixel intensity values and B-spline coefficients were retrieved from the data set. Using Principal Component Analysis (PCA), each of these characteristics was calculated individually and yielded a low-dimensional picture for categorization. Probabilistic SVM classifier was utilized to aggregate the information for glaucoma prediction by using two stages. Following an examination, it was found that a specific categorization had improved. One benefit of early categorization improvement was that it lowered feature dimension. However, patients needed extensive clinical studies.

A model created by Chang et al. [12] could distinguish between glaucoma and non-glaucoma fundus images when used to assess pupillography. Controlled stimulus intensities, multiple intensities, and a variety of stimulus patterns were all used to examine pupillary responses. Pupilometer prototypes were produced by using the new approach. Based on pupillary and intensity variances, patterns, and hues, the pupilometer provided replies. A three-pronged strategy was devised, the first of which included comparing the images from two observers' eyes. Second, the reaction to stimuli from each eye's field was compared, and the pupil response for each subject was calculated. The Akaike criteria were used to build the associative models, and a fivefold cross validation was also carried out on the results. A drawback of pupillography was that the aberrant pupillary light responses were also found in other ocular and neurologic disorders. Other eye diseases were misdiagnosed as a result of this.

Glaucoma may be detected utilizing optic disc localization, hybrid feature set, and classification approaches developed by Akram et al. [13]. The system was tested using both a local dataset and a public dataset from the Armed Forces Institute of Ophthalmology, both of which were available online. Pre-processing, feature extraction, and classification were the three key components. To accurately identify glaucoma, the Mediods-based classifier was applied. The 2-D Gabor wavelet vascular pattern was used in the pre-processing stage to enhance the picture for improved visibility. After obtaining the pre-processed picture, a thresholding strategy was used to separate tiny vessels from larger vessels. In order to accurately depict and identify glaucoma, the new technique employed a precise collection of characteristics. A multivariate m-model called K-Nearest Mediods was developed to accurately identify glaucoma. It was, however, not possible to discern between photos of glaucoma in the same class and those of glaucoma outside of the same class.

Empirical Wavelet Transform was used by Maheshwari et al. [14] to construct an automated diagnosis method for identifying glaucoma in fundus images (EWT). EWT was used to do a decomposition on the fundus images, and then the correntropy characteristics were obtained and broken up into EWT components. The EWT components were disassembled into their component pieces according to their frequency, beginning with the highest and moving down to the lowest possible frequency. In order to rank the features in accordance with the recovered correntropy features that come from the EWT decomposition, the t-value feature selection technique is used. Feature selection algorithms are put to use to isolate certain aspects of an image in order to ascertain whether or not the image is normal or whether or not it contains glaucomatous symptoms. In this method, a classifier known as the Least Squares Support Vector Machine (LS-SVM) was applied. Kernels based on the Radial Basis Function and the Morlet wavelet were used in the LS-SVM classification (RBF). For the classification accuracy to be improved, the kernel functions and parameter selections will need to be improved.

In order to decompose photos in a repeatable way, Maheshwari et al. [15] created the Variational Mode Decomposition (VMD) approach. It was determined whether or whether the image was too coarse, too smooth, or too irregular in its pixelation. The entropy in fractal dimension characteristics were able to capture the pixel intensity variations efficiently. The ReliefF method was used to choose the features, and the results were impressive. For non-linear kernel function maps, these characteristics were given to Least Squares-SVM and Radial Basis Function (RBF). Then, glaucoma and normal fundus pictures are categorized.

It was found that owing to the wide variety of publically available datasets, the created approach had a limitation in terms of accuracy for changes in lighting of the picture.

Using a modified version of the U-Net neural network, Sevastopolsky et al. [16] were able to successfully segment optical discs and cups. Prediction and segmentation findings took a long time using the previous approaches. An automated optic segmentation procedure was designed to solve the shortcomings of the current method, which reduced training and prediction time, and simplified the software. DRIONSDB, RIM-ONE, and DRISHTI-GS databases were utilized to test the new technique. Adaptive histogram equalization was used in the pre-processing step (CLAHE). Equalizing the color across the picture areas leads in an interpolated shift in contrast. Image segmentation and Dice score calculation are performed on pre-processed images. Among deep learning solutions with less parameters, the proposed technique had the lowest prediction time. Segmentation can be more difficult since the optic cup's boundary is more difficult to recognize.
Using ensemble learning and entropy sampling, Zilly et al. [17] developed an algorithm for detecting glaucoma. It was found that picking informative places to calculate entropy solved the problem of computational complexity. When the experiment began, the photos were obtained from the DRISHTI-GS dataset. Using convolutional filters for picture quality enhancement, the dataset's images were preprocessed. The approach that was created made use of CNN architectures and segmented retinal pictures. Segmentation of the optic cup and disc is performed on the pre-processed picture. The ground truth image was divided into four pieces by human specialists in the image's optic disc and cup. As soon as the convolutional filters were applied, the hand-crafted elements vanished. The number of samples was sampled uniformly, and the sampling entropy values produced results. The CNN was utilized to classify the newly produced features. A new approach was created; however, it didn't include any abnormal cases [28].

A deep learning algorithm for retinal fundus pictures was developed by Chai et al. [18,24] to automatically detect glaucoma. The hospital's dataset of eye illness patients was used in the development of the approach. Features are extracted from the generated model based on the optical disc and cup sizes. The nasal, superior, and temporal sections were employed in the feature extraction method, which yielded characteristics for categorization. A Convolutional Neural Network (CNN) model consisting of Multi-Branch Neural Network (MB-NN) comprising three benchmark sets surpassed the extracted features for classification. It was incorporated in the computer vision algorithms as an initial logistic regression model. However, in order to improve the model's performance, the produced model dataset has to be expanded.

Use of time-invariant feature CDR and wavelet transform features has been created to identify glaucoma. Venu Eye Institute & Research Centre provided the data for this study. To begin the preprocessing stage, the ROI portion of the photos was stripped out. It was necessary to use the pre-processed image in order to get the average coordinates of pixels with the highest intensity. The optic disc was calculated after morphological procedures based on dilation had been performed. The V channel is used to separate the foreground optic disc pixels from those in the background. The Fuzzy C-Means (FCM) method was used to differentiate the optic disc and optic cup from the retinal rim and the peripheral area. Anisotropic Dual-Tree Complex Wavelet Transform was used to extract the image's wavelet properties (ADTCWT). SVM using a linear polynomial kernel function, random forest, ADaBoost, and the Multi-Layer Perceptron classifiers have all been used to classify the retrieved features. It was utilized, however, as a starting point for further evaluation of the characteristics.
In the early stages of glaucoma, fundus pictures can be used to design new CAD tools. Deep learning was utilized to diagnose mild glaucoma at any stage using the CAD tool. The new technology uses a CNN architecture to diagnose glaucoma more accurately and automatically. The key benefit of employing CNN is that the complete image was collected for the purpose of analyzing the characteristics. Filtered images were blended into a single image without the need for complex feature construction. Memory and processing time were saved since the new technique skipped feature extraction, feature ranking, and dimensionality reduction stages. In order to classify all of the glaucoma pictures, the created approach used CNN. In order to do the experiment properly, CNN needs a larger quantity of photographs. When the number of pictures grows, so does the number of layers in the CNN method, which takes longer to process.

3. METHODOLOGY

Figure 2 illustrates the Image Processing and Feature Selection based categorization and Detection of Glaucoma illness that will be discussed in this part. Images of the fundus are read into this framework as the input. The CLAHE algorithm is used to preprocess photographs in order to increase the quality of the photos. After that, the K Means method is used to segment the pictures. The identification of the area of interest in the input picture is made easier with the aid of this segmentation. After then, the Relied algorithm will take care of the feature selection. It contributes to the overall improvement of the categorization accuracy. SVM-RBF, BPNN, and the Naive Bayes algorithm are used in the classification process.

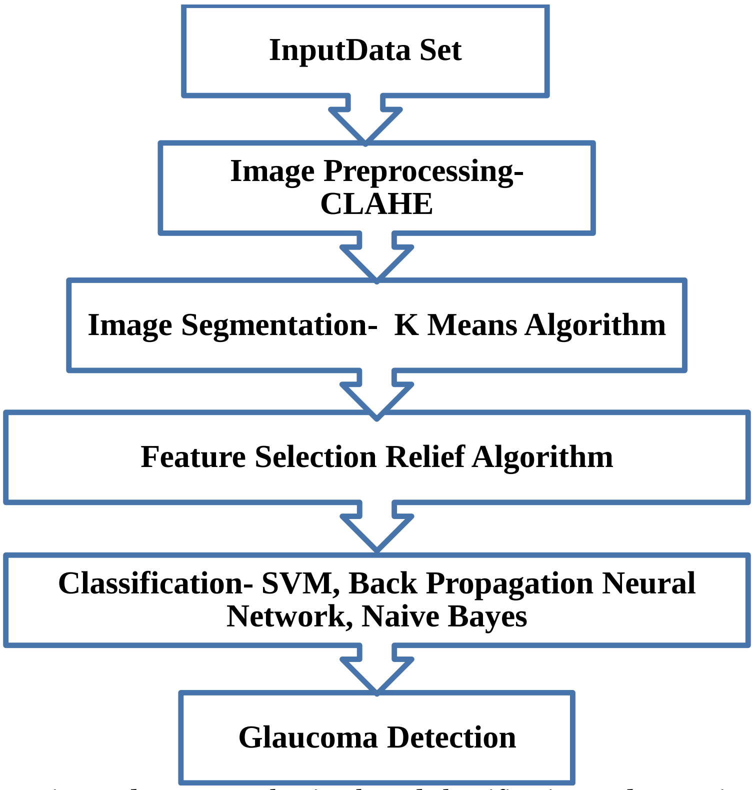


Figure 2: Image Processing and Feature Selection based classification and Detection of Glaucoma disease

Background extraction must be able to modify itself to fit the unique qualities of a specific image in order for an image to be properly recognized. Using CLAHE, the histogram is solely generated for the pixel's immediate surrounds. CLAHE restricts the maximum contrast adjustment that may be done by setting a maximum, or "clip level," to the height of the local histogram and hence the maximum contrast enhancement factor. The final image has less noise as a result of this. CLAHE excels for improving the appearance of small details in mammograms [19]. It is easy to detect the lesions when they are set against a white background. Despite the fact that this technique makes it simpler to distinguish between signal and noise, the resulting images nevertheless have a noticeable graininess.

In 1992, Kira and Rendell [20] devised the Relief algorithm, an instance-based learning approach, to cope with binary classification challenges. Individuals can use a filtering method to find feature-to-feature connections. By using nearest neighbors, feature statistics may be generated that account for how variables interact. But this technique does not account for any missing values or multi-class data in the dataset.

Machine learning technology based on computational learning theory, known as the Support Vector Machine (SVM), has been developed. Finding the appropriate classification function for categorizing the training dataset is at the heart of SVM's quest for accuracy. SVM may be used to address classification problems such as density estimates and pattern recognition. The training data is first mapped nonlinearly into a higher dimension, and then linearly separated [21,25]. The radial basis function (RBF), or RBF, is the favored choice. SVM performs better with RBF mode.

Haykin and Anderson developed the back propagation method, which is one of the most widely used learning algorithms. Simple pattern recognition and mapping tasks may be accomplished using BPN, which is suitable. Back Propagation is a learning process, not the network itself that takes examples as input and builds on them as output. In order to train the network to produce the correct output for every input pattern, algorithm examples of what the network must do will be provided. This modifies the weights of the network. A training pair is a pair consisting of an input and a target [22,26].

The theorem of Bayes provides the foundation for Bayesian classification. Simple bases, akin to the classification of end trees and chosen networks, are characterized by these Nave Bayesian Classification methods when applied to a big database. A subset of dependent characteristics can be represented using naive Bayes classification. P(x|c) is the posterior probability for each class in this technique. Predictions are made for each class with a higher likelihood.

$$P(x) = \frac{P(c)\,P(c)}{P(x)} \quad (1)$$

Where the $P(c|x)$posterior probability of each class given diabetes x attribute
$P(c)$ Is the likelihood value

$P(c)$ Prior Probability of diabetes class
P(x) is the prior probability of predictor
Each attribute conditionally forgives the subset class
Naive Bayes uses a similar method to predict different types of probabilities based on various attributes.

4. EXPERIMENTAL RESULT ANALYSIS

For examining the results of the framework, a series of experiments took place on fundus image dataset [23]. Total 100 images are used. 45 images are related Glaucoma and remaining 55 images are normal. For training purpose, 80 images were used. 35 images were having Glaucoma and remaining 45 images were normal. In this system, fundus photos are used as input. Using the CLAHE method, pictures are preprocessed to increase their quality. Following that, pictures are segmented using the K Means method. This segmentation aids in locating the region of interest in the input image. The Relied algorithm is then used to choose features. It aids in the improvement of categorization accuracy. The SVM-RBF, BPNN, and Nave Bayes algorithms are used for classification [27].
Five parameters accuracy, sensitivity, specificity, precision and recall are used in experimental analysis. Performance of machine learning algorithms on the basis of these five parameters is shown in figure 3. SVM RBF is having better accuracy for classification of Glaucoma disease.
Accuracy= (TP + TN) / (TP + TN + FP + FN)
Sensitivity = TP/ (TP + FN)
Specificity = TN/ (TN + FP)
Precision = TP/ (TP + FP)
Recall = TP/ (TP + FN)
Where,
TP= True Positive
TN= True Negative
FP= False Positive
FN= False Negative

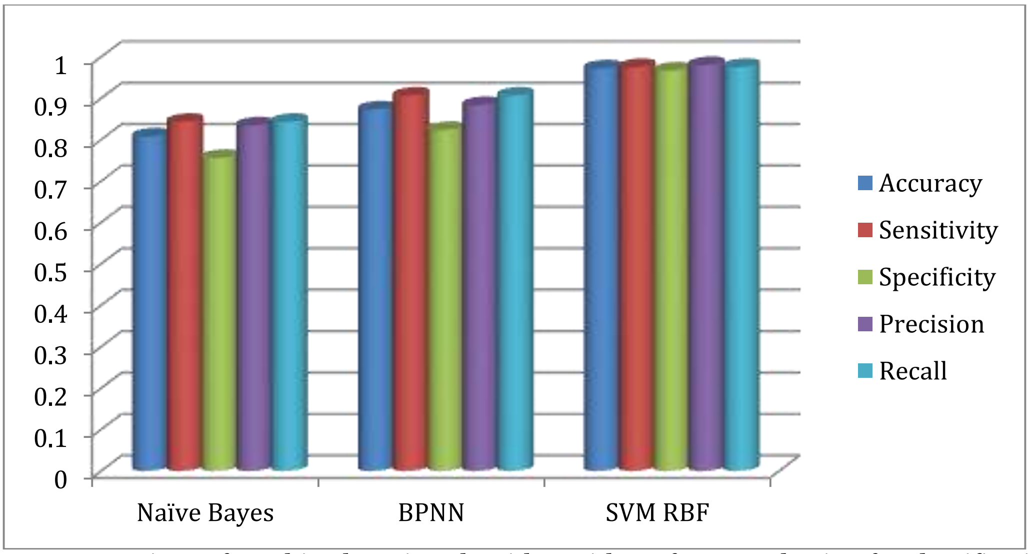


Figure 3: Comparison of Machine learning algorithm without feature selection for classification and detection of Glaucoma Disease

5. CONCLUSIONS

Glaucoma causes an increase in fluid pressure inside the eye, which damages the retinal nerve fibers, which is a common consequence. Once nerve fibers have been damaged, it is impossible to restore vision. Image processing, analysis, and computer vision techniques are becoming increasingly relevant in medical research as they become more significant in modern ophthalmology. This article is a representation of a classification and detection method for glaucoma that is based on image processing and feature selection. In order to improve the photos' overall quality, a preprocessing step known as CLAHE is performed on them. After that, the K Means technique is used to the images in order to segment them. The area of interest in the input picture may be more easily located with the assistance of this segmentation. After that, the Relied algorithm is used to the feature selection process. It is helpful in enhancing the accuracy of the categorizing process. For classification, the SVM-RBF method, the BPNN algorithm, and the Nave Bayes algorithm are used. The experimental analysis makes use of the following five parameters: accuracy, sensitivity, specificity, precision, and recall. When it comes to the categorization of glaucoma illness, SVM RBF has a higher degree of accuracy.

REFERENCES

[1] A. Almazroa, S. Alodhayb, E. Osman, E. Ramadan, M. Hummadi, M. Dlaim, M. Alkatee, K. Raahemifar, and V. Lakshminarayanan, "Retinal fundus images for glaucoma analysis: The riga dataset," Proc. SPIE, vol. 10579, Mar. 2018, Art. no. 105790B.

[2] S. S. Kanse and D. M. Yadav, "Retinal fundus image for glaucoma detection: A review and study," J. Intell. Syst., vol. 28, no. 1, pp. 43–56, Jan. 2019.

[3] Shabaz, M., & Kumar, A. (2019). SA Sorting: A Novel Sorting Technique for Large-Scale Data. In Journal of Computer Networks and Communications (Vol. 2019, pp. 1–7). Hindawi Limited. https://doi.org/10.1155/2019/3027578.

.[4] V. Jasti et al., "Computational Technique Based on Machine Learning and Image Processing for Medical Image Analysis of Breast Cancer Diagnosis", Security and Communication Networks, vol. 2022, pp. 1-7, 2022. Available: 10.1155/2022/1918379.

[5] Sharma, C., Bagga, A., Singh, B. K., & Shabaz, M. (2021). A Novel Optimized Graph-Based Transform Watermarking Technique to Address Security Issues in Real-Time Application. In V. Kumar (Ed.), Mathematical Problems in Engineering (Vol. 2021, pp. 1–27). Hindawi Limited. https://doi.org/10.1155/2021/5580098.

[6] J. I. Orlando, H. Fu, J. B. Breda, K. van Keer, D. R. Bathula, A. Diaz-Pinto, R. Fang, P. A. Heng, J. Kim, J. Lee, and J. Lee, "Refuge challenge: A unified framework for evaluating automated methods for glaucoma assessment from fundus photographs," Med. Image Anal., vol. 59, Jan. 2020, Art. no. 101570.

[7] Dhiman, G., Kaur, G., Haq, M. A., & Shabaz, M. (2021). Requirements for the Optimal Design for the Metasystematic Sustainability of Digital Double-Form Systems. In D. Meng (Ed.), Mathematical Problems in Engineering (Vol. 2021, pp. 1–10). Hindawi Limited.
https://doi.org/10.1155/2021/2423750.

[8] NayomiGeethanjaliRanamuka, RavindaGayanN. Meegama ,Detection of h ard exudates from diabetic retinopathy images using fuzzy logic, IET Image Processing, Volume 7, Issue 2, 2013 , pp. 121 – 130.

[9] Lee , S.C., Wang, Y. and Lee, E.T., 1999, May. Computer algorithm for auto mated detection and quantification of microaneurysms and h emorrhages (HMAs) in color retinal images. In Medical Imaging 1999: I mage Perception and Performance (Vol. 3663, pp. 61-71). International S ociety for Optics and Photonics.

[10] Badea , P., Danciu, D. and Davidescu, L., 2008, May. Preliminary results o n using an extension of gradient method for detection of red lesions on eye fundus photographs. In 2008 IEEE International Conference on Automation, Quality and Testing, Robotics (Vol. 3, pp. 43-48). IEEE.

[11] Bock, R, Meier, J, Nyúl, LG, Hornegger, J & Michelson, G 2010, 'Glaucoma risk index: automated glaucoma detection from color fundus images', Medical image analysis, vol. 14, no. 3, pp. 471-481.

[12] Chang, DS, Arora, KS, Boland, MV, Supakontanasan, W & Friedman, DS 2013, 'Development and validation of an associative model for the detection of glaucoma using pupillography', American journal of ophthalmology, vol. 156, no. 6, pp. 1285-1296. e1282.

[13] Akram, MU, Tariq, A, Khalid, S, Javed, MY, Abbas, S &Yasin, UU 2015, 'Glaucoma detection using novel optic disc localization, hybrid feature set and classification techniques', Australasian physical & engineering sciences in medicine, vol. 38, no. 4, pp. 643-655.

[14] Maheshwari, S, Pachori, RB &Acharya, UR 2016, 'Automated diagnosis of glaucoma using empirical wavelet transform and correntropy features extracted from fundus images', IEEE journal of biomedical and health informatics, vol. 21, no. 3, pp. 803-813.

[15] Maheshwari, S, Pachori, RB, Kanhangad, V, Bhandary, SV &Acharya, UR 2017, 'Iterative variational mode decomposition based automated detection of glaucoma using fundus images', Computers in biology and medicine, vol. 88, pp. 142-149.

[16] Sevastopolsky, A 2017, 'Optic disc and cup segmentation methods for glaucoma detection with modification of U-Net convolutional neural network', Pattern Recognition and Image Analysis, vol. 27, no. 3, pp. 618-624.

[17] Zilly, J, Buhmann, JM &Mahapatra, D 2017, 'Glaucoma detection using entropy sampling and ensemble learning for automatic optic cup and disc segmentation', Computerized Medical Imaging and Graphics, vol. 55, pp. 28-41.

[18] Chai, Y, Liu, H & Xu, J 2018, 'Glaucoma diagnosis based on both hidden features and domain knowledge through deep learning models',Knowledge-Based Systems, vol. 161, pp. 147-156.

[19] S. Sahu, A. K. Singh, S. P. Ghrera, and M. Elhoseny, "An approach for de-noising and contrast enhancement of retinal fundus image using CLAHE," Opt. Laser Technol., vol. 110, pp. 87–98, Feb. 2019.

[20] R. Urbanowicz, M. Meeker, W. La Cava, R. Olson and J. Moore, "Relief-based feature selection: Introduction and review", Journal of Biomedical Informatics, vol. 85, pp. 189-203, 2018. Available:

10.1016/j.jbi.2018.07.014.

[21] C. Wu, H. Chen, J. Chen and C. Lee, "Glaucoma Detection Using Support Vector Machine Method Based on Spectralis OCT", Diagnostics, vol. 12, no. 2, p. 391, 2022. Available: 10.3390/diagnostics12020391.

[22] J. Parab, M. Sequeira, M. Lanjewar, C. Pinto and G. Naik, "Backpropagation Neural Network-Based Machine Learning Model for Prediction of Blood Urea and Glucose in CKD Patients," in IEEE Journal of Translational Engineering in Health and Medicine, vol. 9, pp. 1-8, 2021, Art no. 4900608, doi: 10.1109/JTEHM.2021.3079714.

[23] Wheyming song, March 31, 2020, "1450 fundus images with 899 glaucoma data and 551 normal data.", IEEE Dataport, doi: https://dx.doi.org/10.21227/4bcp-2z21.

[24] Jasti, V. D. P., Zamani, A. S., Arumugam, K., Naved, M., Pallathadka, H., Sammy, F., ... & Kaliyaperumal, K. (2022). Computational technique based on machine learning and image processing for medical image analysis of breast cancer diagnosis. *Security and communication networks*, *2022*, 1-7.

[25] Akhtar, M. M., Shatat, A. S. A., Al-Hashimi, M., Zamani, A. S., Rizwanullah, M., Mohamed, S. S. I., & Ayub, R. (2023). MapReduce with Deep Learning Framework for Student Health Monitoring System using IoT Technology for Big Data. *Journal of Grid Computing*, *21*(4), 67.

[26] Zamani, A. S., Hashim, A. H. A., Shatat, A. S. A., Akhtar, M. M., Rizwanullah, M., & Mohamed, S. S. I. (2024). Implementation of machine learning techniques with big data and IoT to create effective prediction models for health informatics. *Biomedical Signal Processing and Control*, *94*, 106247.

[27] Zamani, A. S., Deepa, S., Ritonga, M., Kaliyaperumal, K., & Bangare, M. L. (2022). Machine Learning Techniques for Automated and Early Detection of Brain Tumor. *International Journal of Next-Generation Computing*, *13*(3).

[28] Nancy, P., Murugesan, G., Zamani, A. S., Kaliyaperumal, K., Jawarneh, M., Shukla, S. K., ... & Raghuvanshi, A. (2023). Detection of brain tumour using machine learning based framework by classifying MRI images. *International Journal of Nanotechnology*, *20*(5-10), 880-896.