ISSN (Online): 2583-7052

International Journal of Advanced Trends in Engineering and Management (IJATEM)
pp. 46-56

Article Title: **Retinal Fundus Image Analysis Using HGCA Mechanism for Automated Diabetic Retinopathy Diagnosis**

Retinal Fundus Image Analysis Using HGCA Mechanism for Automated Diabetic Retinopathy Diagnosis

Anuja S. B.[1], F. Ramesh Dhanaseelan[2*]

[1]Assistant Professor, Department of Master of Computer Applications, Narayanaguru College of Engineering, Manjalumoodu, Kanyakumari Dt, Tamilnadu

[2]Professor, Department of Master of Computer Applications, St Xavier's Catholic College of Engineering, Chunkankadai, Kanyakumari Dt, Tamilnadu

ABSTRACT

Diabetic Retinopathy (DR) is a leading cause of blindness worldwide. Early detection and accurate grading are crucial for effective treatment. This study proposes a computer-aided diagnosis system using image processing techniques to detect and grade DR from retinal fundus images. The proposed approach involves image preprocessing and enhancement, followed by feature extraction using texture analysis and vessel segmentation. A novel hybrid technique, referred to as Hybrid GCAM (HGCAM), is introduced for feature extraction. This technique combines the Global Channel Attention Mechanism (GCAM) with multi-scale feature refinement (MFR). It is mentioned here as Hybrid GCAM or HGCAM. GCAM – Global channel attention mechanism will extract global features along with local features. It increases robustness, it reduces computational complexity by concentrating on critical features, GCAM enhances detection of microaneurysms, hemorrhages, and other subtle lesions. By integrating GCAM and multiscale feature refinement the model is supposed to improve diabetic retinopathy detection accuracy, enhance feature representation and robustness, reduce computational complexity and can gain insights into feature importance. The system uses Support Vector Machine (SVM) and Convolutional Neural Networks (CNN) for classification. Early detection and treatment are critical to preventing vision loss, with multi-label SVM classification (MLC) playing a key role in DR detection and grading. Here we propose a system to diagnose diabetic retinopathy (DR) from colored fundus images, enabling early detection and treatment. Our proposed deep learning-based computer-aided diagnosis (CAD) system detects and analyzes retinal pathological changes without invasive procedures. The system comprises: Image preprocessing (noise reduction, quality enhancement) Feature extraction and classification. Our system demonstrates promising results, outperforming existing methods. It enables accurate DR diagnosis, facilitating timely treatment and preventing complications.

Keywords: DR – Diabetic Retinopathy, GCAM – Global Channel Attention Mechanism, SVM – Support Vector Machine, CAD – Computer Aided Diagnosis.

ISSN (Online): 2583-7052

International Journal of Advanced Trends in Engineering and Management (IJATEM)
pp. 46-56

Article Title: **Retinal Fundus Image Analysis Using HGCA Mechanism for Automated Diabetic Retinopathy Diagnosis**

1 Introduction

Diabetic retinopathy (DR) is a devastating complication of diabetes, affecting millions worldwide. Prolonged elevated blood sugar levels damage retinal blood vessels, leading to vision impairment and potential blindness. DR progresses silently, often unnoticed until irreversible damage occurs. Early detection is crucial, as timely treatment can prevent vision loss. The condition manifests in two stages: non-proliferative (NPDR) and proliferative (PDR). NPDR is characterized by microaneurysms, hemorrhages, and hard exudates, while PDR involves neovascularization, vitreous hemorrhage, and retinal detachment. NPDR is a curable stage of diabetic retinopathy by diabetic control methods and proper medication. NPDR can be classified in to three stages as mild NPDR, Moderate NPDR and Severe NPDR. Meanwhile Proliferative Diabetic Retinopathy (PDR) is a severe complication of diabetes, marked by abnormal blood vessel growth on the retina. This leads to vitreous hemorrhage, causing sudden vision loss, floaters, and blindness.

Retinal fibrosis and iris neo vascularization further exacerbate the condition, resulting in retinal detachment, glaucoma, and vision loss. Insufficient blood supply to the retina (retinal ischemia) also contributes to vision loss and blindness. Common symptoms include sudden vision loss, floaters, blurred vision, double vision, eye pain, redness, and sensitivity to light. Individuals with a prolonged history of diabetes (>10 years), poor blood sugar control, hypertension, high cholesterol, smoking habits, and family history are at increased risk. Prompt treatment, including laser photocoagulation, intravitreal injections, vitrectomy surgery, and retinal detachment repair, is vital to prevent irreversible vision loss. Regular eye exams are essential for early detection and effective management of PDR in diabetic patients. Accurate diagnosis relies on retinal imaging and expert evaluation. Advances in image processing and artificial intelligence offer promising solutions for automated DR detection, enabling early intervention and preserving vision.

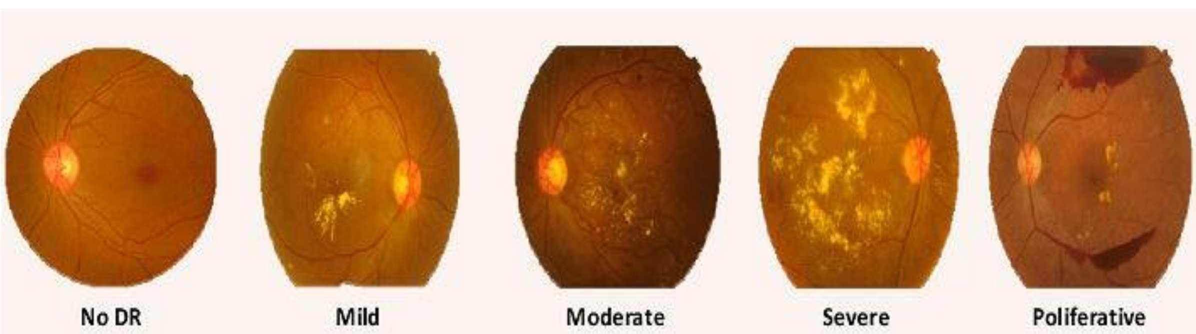

Figure 1: *Depicts normal eye and four stages of DR affected eye.*

2 Literature Review

International Journal of Advanced Trends in Engineering and Management (IJATEM)
pp. 46-56

2.1 Automatic Diabetic Retinopathy Grading System Based on Detecting Multiple Retinal Lesions

Eman Abdelmaksoud, et al [2021] proposed a novel Multi-Label Computer-Aided Diagnosis (ML-CAD) system for diabetic retinopathy grade diagnosis, applicable to diverse datasets. This system leverages nine public benchmark datasets: DRIVE, CHASEDB1, STARE, HRF, ID Rid, DIARETDB1, MESSIDOR, and E-ophtha. At first, the proposed system preprocesses the image by filtering and enhancing the contrast. Then, it utilizes GLRLM to determine the normal and DR images. Next it prepares the DR images by post processing steps for U-Net model which is then trained four times on the four variations (hemorrhages, exudates, Blood Vessels, and microaneurysms). The system extracts feature which are then used by the MLSVM for ML classification. Finally, we computed 6 performance matrices averages of the proposed ML- CAD system. The model proved that it is reliable and robust. It can be applied on the real world as it can be applied won different color fundus images with different cameras' settings, and different patients.

2.2 Multi-Scale Attention Network for Diabetic Retinopathy Classification

Mohammad T. Al Antaryetal [2021] this study introduces a novel Multi-Scale Attention Network (MSA-Net) for diabetic retinopathy (DR) classification, enhancing retinal image analysis. To boost representation power, a multi-scale attention mechanism is integrated into high- level feature representations. This mechanism employs Atreus convolution, processing input features at various scales, and generates attention maps through convolutional layers. These maps prioritize informative regions, suppressing weaker ones. Additionally, multi-level and multi-scale representation layers are incorporated to augment performance. Multi task learning training yields superior results compared to existing literature. Experimental outcomes validate the proposed model's effectiveness and efficiency in DR diagnosis and classification, showcasing significant clinical application potential.

2.3 A Novel Diabetic Retinopathy Detection Approach Based on Deep Symmetric Convolutional Neural Network

Tieyuan et al [2021], this study presents a deep convolutional network with a symmetric structure for detecting various lesions in diabetic retinal images. The symmetrical design enhances complex feature extraction, boosting detection accuracy. Our feature filtering module employs convolution, max pooling, and average pooling layers, which are compared experimentally. Results reveal superior overall accuracy with pooling operations over convolutional operations. Notably, max pooling excels in hard exudate detection (sensitivity: 97.1%, specificity: 96.8%), while average pooling improves microaneurysm detection (sensitivity: 91.0%, specificity: 96.3%). Future work aims to refine the model for simultaneous, accurate detection of multiple objects in diabetic retinopathy images.

2.4 Automated Microaneurysms Detection in Retinal Images Using Radon Transform and Supervised Learning: Application to Mass Screening of Diabetic Retinopathy

Meysam Tavakoli et al [2021] This paper presents an intelligent approach to Microaneurysm (MA) detection, employing both unsupervised and supervised techniques. Initially, retinal images undergo preprocessing to minimize background variations, ensuring accurate detection. Key landmarks like the optic nerve head and retinal vessels are identified and masked using the Radon transform (RT) and multi-overlapping windows. Subsequently, MAs are detected and counted by combining RT with a supervised support vector machine classifier. The method was validated on three public datasets and a local database comprising 749 images. Performance evaluation metrics included sensitivity, specificity, and FROC analysis. Results showed 100% sensitivity in DR detection, 93% specificity in MA detection: 95.7% sensitivity in MA detection, the advantages include accurate detection of retinal vessel location, finding accurate dimension of vessels, and reduced number of false positives.

2.5 An Enhanced Residual U-Net for Micro aneurysms and Exudates Segmentation in Fundus Images

Caixia Kou et al [2020] introduced an Enhanced Residual U-Net (ERU-Net) for segmenting Microaneurysms (MAs) and Exudates (EXs) in fundus images. ERU-Net features three U-paths, combining up sampling and down sampling paths, to enhance feature fusion and capture detailed information. A residual block is incorporated to extract representative features. Experimental evaluations on values of 0.9956, 0.9962, 0.9801, 0.9866, 0.9679, and 0.9609 for Mas and EXs segmentation, outperforming the original U-Net. ERU-Net also shows competitive results compared to traditional methods, CNNs, and recent U-Nets. Additionally, ERU-Net achieves the highest Jaccard index of 0.994 for optic disc segmentation on the DRISHTI-GS1 dataset. The results indicate ERU-Net's potential for medical image segmentation. Future work will explore ERU-Net's applicability to other medical image segmentation tasks.

3 Proposed Methodology

3.1 Preprocessing

In the proposed model we do the first step by acquiring an eye image by using fundus cameras. The image thus obtained may contain noise, low contrast, blurriness which will increase the risk

ISSN (Online): 2583-7052

International Journal of Advanced Trends in Engineering and Management (IJATEM)
pp. 46-56

of causing false positives and error during DR detection. So we preprocess the image by using CLAHE. CLAHE is a preprocessing technique employed in Diabetic Retinopathy (DR) detection to enhance contrast and correct uneven illumination in retinal images. This adaptive histogram equalization method divides the image into small regions, called tiles, and applies histogram equalization to each tile. Contrast limiting prevents over-amplification of noise, preserving delicate retinal structures. CLAHE enhances microaneurysms, hemorrhages, and exudates visibility. It Improves vessel segmentation and optic disc detection, Reduces effects of non-uniform illumination and shading and Increases robustness of feature extraction and classification algorithms. By applying CLAHE, retinal images become more suitable for analysis, enabling accurate detection of DR-related lesions and features. Also we use a Gaussian-Un sharp Masking filter combination to enhance retinal fundus images for Diabetic Retinopathy (DR) detection. This preprocessing technique uses a dual-filter approach; first it Smoothens images with Gaussian filtering (σ = 1-2), reducing noise and then it amplifies edges and details via Un sharp Masking (radius=2-5, amount=0.5-1.5). The Gaussian-Un sharp filter combination will boosts micro aneurysm, hemorrhage, and exudate visibility, It refines vessel segmentation and optic disc detection, minimizes noise and artifacts also it Preserves delicate retinal structures. This combined filter enhances image quality, facilitating accurate DR detection and feature extraction.

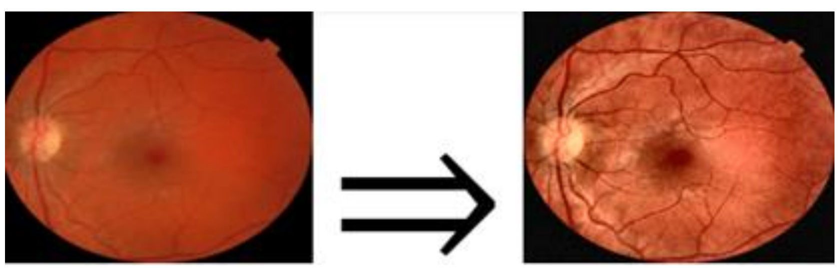

Figure 2: *Preprocessed image after CLAHE*

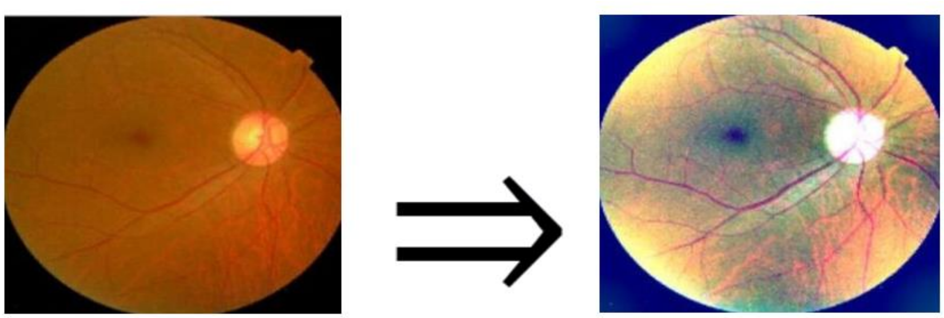

Figure 3: *Enhanced image after applying The Gaussian-Un sharp filter.*

International Journal of Advanced Trends in Engineering and Management (IJATEM)
pp. 46-56

3.2 Feature Extraction

Feature extraction in image processing involves identifying and extracting meaningful information from images to describe their content, properties, or characteristics. This process transforms raw image data into relevant features, enabling efficient analysis and classification. Common features extracted include texture, shape, color, spatial, and frequency characteristics. Techniques employed for feature extraction encompass edge detection, corner detection, blob detection, texture analysis, color space transformations, and convolutional neural networks. By reducing data dimensionality and highlighting essential information, feature extraction enhances image representation, improves classification accuracy, and facilitates various applications such as image classification, object detection, segmentation, recognition, and analysis. Here we use a novel hybrid idea for feature extraction, Global Channel Attention Mechanism with Feature Refinement Mechanism. Hybrid GCAM (HGCAM) is a technique used to refine feature extraction by highlighting important channels in deep learning models. In Diabetic Retinopathy (DR) image analysis, HGCAM helps emphasize relevant features.

3.2.1 How GCAM works

- Global Average Pooling: Pool feature maps across spatial dimensions (height and width) to capture global context.
- Channel Attention: Compute attention weights for each channel using a convolutional layer and sigmoid activation.
- Channel-wise Multiplication: Multiply attention weights with original feature maps to emphasize important channels.

Feature Refinement with GCAM (Hybrid GCAM). Here we use Multiscale Feature Refinement (MFR) for feature refinement along with GCAM. It is mentioned as HGCAM, is a powerful technique that enhances image analysis by extracting features at multiple scales, capturing both local and global details. This approach refines feature representation, improving model performance in various computer vision tasks. MFR comprises four key components: multi- scale feature extraction via dilated convolutions and pyramid pooling, scale-wise feature processing using convolutional layers and attention mechanisms, feature fusion preserving local and global context, and refinement modules applying attention and normalization techniques. By analyzing features at multiple scales, MFR captures comprehensive information, reducing noise and emphasizing critical details. This leads to improved accuracy in image classification, object detection, and segmentation tasks, as well as robustness to scale variations. MFR has diverse applications, including medical image analysis for diabetic retinopathy detection and remote sensing. By providing announced understanding of images, MFR elevates performance in

International Journal of Advanced Trends in Engineering and Management (IJATEM)
pp. 46-56

computer vision tasks.

- Initial Feature Extraction: Extract features from DR image using convolutional layers.
- GCAM Application: Apply GCAM to refine features, highlighting important channels.
- Feature Refinement: here we combine refined features using MFR with initial features obtained from GCAM, using concatenation or addition

3.2.2 Benefits in DR Image Analysis

- Enhanced lesion detection: HGCAM highlights channels with relevant lesion information.
- Improved feature representation: Refined features capture subtle changes in retinal images.
- Increased accuracy: HGCAM-enhanced features lead to better DR detection and classification. Integration with Deep Learning Models:

1. Convolutional Neural Networks (CNNs): Integrate HGCAM into CNN architectures.
2. Transfer Learning: Apply HGCAM to pre-trained models for DR image analysis.

By incorporating HGCAM, deep learning models can focus on relevant features, leading to improved performance in Diabetic Retinopathy image analysis.

3.3 Classification

Classification in Diabetic Retinopathy (DR) detection using image processing is pivotal for early identification and personalized treatment. Automated screening enabled by image processing classification reduces manual grading errors, allowing for timely interventions and improved patient outcomes. Accurate classification facilitates disease progression monitoring, minimizing costly complications and enhancing research on DR. By leveraging image processing techniques, classification revolutionizes DR detection, ensuring precise diagnoses and advancing medical research. This leads to better patient care, reduced healthcare costs, and improved vision preservation. Overall, classification in DR detection using image processing is a game-changer in preventing vision loss and enhancing patient well-being. Here we use Multilabel SVM Classifier for Classification and grading of different stages of diabetic retinopathy. The Multilabel Support Vector Machine (SVM) Classifier is a sophisticated algorithm that excels in classifying and grading Diabetic Retinopathy (DR) images with remarkable accuracy. By assigning multiple labels to each image, it precisely detects the severity of DR, distinguishing between various stages such as mild, moderate, and severe. This classifier's exceptional capability to handle complex DR images with diverse lesions and features sets it apart.

Leveraging multilabel classification, it identifies multiple DR stages, detects various lesions like microaneurysms and hemorrhages, and grades DR images with high precision. Here this method will give an output of the given image as Diabetic retinopathy or not. If it is a diabetic retinopathy

International Journal of Advanced Trends in Engineering and Management (IJATEM)
pp. 46-56

affected eye image then it will mark the stage in which the eye is, that is mild, moderate, and severe or PDR. Outperforming single-label classifiers, the Multilabel SVM Classifier boasts strengths in handling multiple labels and grades, robustness to image variability, and exceptional accuracy in DR detection and grading. As a valuable tool for automated DR screening, it enables early detection, personalized treatment, and improved patient outcomes. Its advanced capabilities make it an indispensable asset in the fight against DR-related vision loss.

3.4 Performance Metrics

The performance of the proposed method is compared to other approaches using the following metrics: accuracy, sensitivity, specificity. These metrics are mathematically calculated as follows:

a) Accuracy= $\frac{TP+TN}{TP+FP+TN+FN}$

b) Sensitivity= $\frac{TP}{TP+FN}$

c) Specificity= $\frac{TN}{TN+FP}$

Table 1: *Performance comparison between proposed method & previous work for DR classification*

Method	Accuracy	Specificity	Sensitivity
SVM	95.1	86.1	91.9
Inception V3	78.7	85.3	63.6
VGG	80	86.6	85.3
ResNet	74.6	85.7	57.1
Proposed Method	95.3	87.5	90.4

These findings surpass existing published results, demonstrating the effectiveness of our approach.

4 Conclusion

In this study, we presented a comprehensive approach for Diabetic Retinopathy (DR) detection using Global Channel Attention Mechanism with Feature Refinement and Multilabel SVM for classification and grading of DR images. Our method leverages the strengths of both attention mechanisms and multilabel classification to achieve accurate detection and grading of DR. The Global Channel Attention Mechanism effectively highlights critical features, while Feature Refinement enhances the quality of extracted features. The Multilabel SVM Classifier accurately assigns multiple labels, enabling precise grading of DR severity. Our approach demonstrates an improved accuracy in DR detection and grading, enhanced feature extraction and representation, effective handling of complex DR images, Robustness to image variability. This study contributes to the development of automated DR screening systems, enabling early detection, personalized treatment, and improved patient outcomes. Future research can explore integrating additional attention mechanisms and deep learning architectures to further enhance DR detection and grading accuracy. By harnessing the power of attention mechanisms and multilabel classification, our approach paves the way for advanced DR diagnosis and treatment, ultimately reducing the burden of vision loss in diabetic patients.

References

1. Thomas A. Ciulla; Armando G. Amador; Bernard Zinman, Year: 2003, “Diabetic retinopathy and diabetic macular edema: pathophysiology, screening, and novel therapies”, Diabetes care, Vol: 26, no: 9, pp. 2653 – 2664.

2. Razieh Ganjee; Reza Azmi; Mohsen Ebrahimi Moghadam, Year: 2016, “A novel micro aneurysms detection method based on local applying of Markov random field”, Journal of medical systems, Vol: 40, pp. 1 – 9.

3. Mrinal Haloi; Samarendra Dandapat; Rohit Sinha, Year: 2015, “A Gaussian scale space approach for exudates detection, classification and severity prediction”, arXiv preprint arXiv: 1505.00737.

4. Sharzil Haris Khan; Zeeshan Abbas; SM Danish Rizvi, Year: 2019, “Classification of diabetic retinopathy images based on customised CNN architecture”, In 2019 Amity International conference on artificial intelligence (AICAI), pp. 244 – 248.

5. Kedir M. Adal; Peter G. Van Etten; Jose P. Martinez; Kenneth W. Rouwen; Koenraad A. Vermeer; Lucas J. van Vliet, Year: 2017, “An automated system for the detection and classification of retinal changes due to red lesions in longitudinal fundus images”, IEEE transactions on biomedical engineering, Vol: 65, no: 6, pp. 1382 – 1390.

6. Juan Wang; Yujing Bai; Bin Xia, Year: 2019, “Feasibility of diagnosing both severity and features of diabetic retinopathy in fundus photography”, IEEE access, Vol: 7, pp. 102589 – 102597.

7. Meindert Niemeijer; Bram van Ginneken; Stephen R. Russell; Maria SA Suttorp-Schulten; Michael D. Abramoff, Year: 2007, “Automated detection and differentiation of drusen, exudates, and cotton-wool spots in digital color fundus photographs for diabetic retinopathy diagnosis”, Investigative ophthalmology & visual science, Vol: 48, no: 5, pp. 2260 – 2267.

8. Alan D. Fleming; Sam Philip; Keith A. Goatman; John A. Olson; Peter F. Sharp, Year: 2006, “Automated

assessment of diabetic retinal image quality based on clarity and field definition", Investigative ophthalmology & visual science, Vol: 47, no: 3, pp. 1120 – 1125.

9. Thomas Walter; Pascale Massin; Ali Erginay; Richard Ordonez; Clotilde Jeulin; Jean-Claude Klein, Year: 2007, "Automatic detection of micro aneurysms in color fundus images", Medical image analysis, Vol: 11, no: 6, pp. 555 – 566.

10. Meysam Tavakoli; Sina Jazani; Mahdieh Nazar, Year: 2020, "Automated detection of micro aneurysms in color fundus images using deep learning with different preprocessing approaches", In Medical imaging 2020: imaging informatics for healthcare, research, and applications, Vol: 11318, pp. 110 – 120.

11. Reza Azad; Maryam Asadi-Aghbolaghi; Mahmood Fathy; Sergio Escalera, Year: 2019, "Bi-directional ConvLSTM U-Net with densley connected convolutions", In Proceedings of the IEEE/CVF international conference on computer vision workshops, pp. 0 – 0.

12. Reza Azad; Maryam Asadi-Aghbolaghi; Mahmood Fathy; Sergio Escalera, Year: 2020, "Attention deeplabv3+: Multi-level context attention mechanism for skin lesion segmentation", In European conference on computer vision, pp. 251 – 266.

13. Zeng Zeng; Yang Xulei; Yu Qiyun; Yao Meng; Zhang Le, Year: 2019, "Sese-net: Self-supervised deep learning for segmentation", Pattern Recognition Letters, Vol: 128, pp. 23 – 29.

14. Noushin Eftekhari; Hamid-Reza Pourreza; Mojtaba Masoudi; Kamaledin Ghiasi-Shirazi; Ehsan Saeedi, Year: 2019, "Micro aneurysm detection in fundus images using a two-step convolutional neural network", Biomedical engineering online, Vol: 18, pp. 1 – 16.

15. Yung-Hui Li; Nai-Ning Yeh; Shih-Jen Chen; Yu-Chien Chung, Year: 2019, "Computer-assisted diagnosis for diabetic retinopathy based on fundus images using deep convolutional neural network", Mobile Information Systems 2019, no: 1, pp. 6142839.

16. Jen Hong Tan; Hamido Fujita; Sobha Sivaprasad; Sulatha V. Bhandary; A. Krishna Rao; Kuang Chua Chua; U. Rajendra Acharya, Year: 2017, "Automated segmentation of exudates, haemorrhages, micro aneurysms using single convolutional neural network", Information sciences, Vol: 420, pp. 66 – 76.

17. Yuji Hatanaka; Kazunori Ogohara; Wataru Sunayama; Mitsuhiro Miyashita; Chisako Muramatsu; Hiroshi Fujita, Year: 2018, "Automatic micro aneurysms detection on retinal images using deep convolution neural network", In 2018 International Workshop on Advanced Image Technology (IWAIT), pp. 1 – 2.

International Journal of Advanced Trends in Engineering and Management (IJATEM)
pp. 46-56

18. Rishab Gargeya; Theodore Leng, Year: 2017, Year: 2017, "Automated identification of diabetic retinopathy using deep learning", Ophthalmology, Vol: 124, no: 7, pp. 962 – 969.

19. Graham S. Scotland; Paul McNamee; Alan D. Fleming; Keith A. Goatman; Sam Philip; Gordon J. Prescott; Peter F. Sharp et al, Year: 2010, "Costs and consequences of automated algorithms versus manual grading for the detection of referable diabetic retinopathy", British Journal of Ophthalmology, Vol: 94, no: 6, pp. 712 – 719.

20. Varun Gulshan; Lily Peng; Marc Coram; Martin C. Stumpe; Derek Wu; Arunachalam Narayanaswamy; Subhashini Venugopalan et al, Year: 2016, "Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs", jama, Vol: 316, no: 22, pp. 2402 – 2410.

21. Eman Abdel Maksoud; Sherif Barakat; Mohammed Elmogy, Year: 2020, "A comprehensive diagnosis system for early signs and different diabetic retinopathy grades using fundus retinal images based on pathological changes detection", Computers in Biology and Medicine, Vol: 126, pp. 104039.

22. Michael David Abràmoff; Yiyue Lou; Ali Erginay; Warren Clarida; Ryan Amelon; James C. Folk; Meindert Niemeijer, Year: 2016, "Improved automated detection of diabetic retinopathy on a publicly available dataset through integration of deep learning", Investigative ophthalmology & visual science, Vol: 57, no: 13, pp. 5200 – 5206.

23. Valentina Bellemo; Zhan W. Lim; Gilbert Lim; Quang D. Nguyen; Yuchen Xie; Michelle YT Yip; Haslina Hamzah et al, Year: 2019, "Artificial intelligence using deep learning to screen for referable and vision-threatening diabetic retinopathy in Africa: a clinical validation study", The Lancet Digital Health, Vol: 1, no: 1, pp. e35 – e44.

24. Romany F. Mansour; Year: 2018, "Deep-learning-based automatic computer-aided diagnosis system for diabetic retinopathy", Biomedical engineering letters, Vol: 8, pp. 41 – 57.

25. Thippa Reddy Gadekallu; Neelu Khare; Sweta Bhattacharya; Saurabh Singh; Praveen Kumar Reddy Maddikunta; In-Ho Ra; Mamoun Alazab, Year: 2020, "Early detection of diabetic retinopathy using PCA-firefly based deep learning model", Electronics, Vol: 9, no: 2, pp. 274.