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# Diabetic Retinopathy, The Automated of Detection of Retinal Fundus Images with Probabilistic Neural Networks (PNN)

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ABSTRACT

Diabetic retinopathy and normal retinal diseases need a detection approach, in this case, to make the decision to diagnose diabetic retinopathy through retinal fundus images. The application aims to identify diabetic retinopathy through fundus imagery using Probabilistic Neural Network. The method we use involves the Probabilistic Neural Network (PNN) in the process of testing image data through the retina fundus. The results of this study have achieved detection of the accuracy of recognition of the range in reading images through the retina fundus of 88.9%, and The estimation of σ≥ 0.8 is the best benefit of smoothing boundaries to recognize diabetic retinopathy by utilizing the Probabilistic Neural Network, this shows the detection of research is quite high.

Keywords: PNN Method, Retinal Fundus, Image Processing, Diabetic Retinopathy Detection.

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## INTRODUCTION

Retinopathy is a condition that influences crafted by the eye's retina, which is the nerve layer that is in the rear of the eye and which catches the picture the eye sees and sends its data to the cerebrum with the goal that it very well may be deciphered by the mind. Diabetic Retinopathy (DR) is a difficulty of diabetes mellitus (DM) in the eye that assaults the retinal veins which causes the most perpetual visual impairment, victims experience diminished visual capacity as well as will unexpectedly lose vision if there has been exceptionally serious harm to the retina. Clinical assessment of patients with diabetic retinopathy is done in one manner, to be specific direct perception by a specialist on the retinal picture of a patient taken utilizing a fundus camera. The consequences of the retinal picture will be dissected by a specialist, this assessment generally requires a high focus in breaking down the picture. Past examination has been directed on the recognizable proof of diabetic retinopathy by a few strategies. In 2013, Dillak and Bindery utilized Backpropagation fake neural systems in recognizing diabetic retinopathy. The element extraction strategy utilized is 3D-GLCM Projection. Optical plate disposal is done on the retinal picture to improve exactness. The exactness got in this investigation was 94%. Resulting research led by Febriani, 2014, is the recognizable proof of diabetic retinopathy Modified k-Nearest Neighbour acquired ends. Utilizing the Modified k-Nearest Neighbour (Mk-NN) technique can distinguish diabetic retinopathy through retinal pictures with an exactness of 87.3%, affectability 92.1%, and particularity of 81%. The means before distinguishing proof are picture cutting, downsizing, green channel picture development, picture quality improvement, picture extraction highlight preparing utilizing GLCM. In this investigation, the creators propose the Probabilistic Neural Network strategy.

Probabilistic Neural Network (PNN) is a neural system strategy that utilizes the rule of measurable hypothesis, to be specific Bayesian Classification to supplant the heuristic rule utilized by the Backpropagation calculation Specht, 1994. This calculation has been generally utilized as a result of its capacity to process information quicker than different strategies. Then again, the Probabilistic Neural Network (PNN) technique was picked in light of the fact that it is one kind of neural system that has been demonstrated to have a genuinely elevated level of precision in recognizing, in particular an exactness of 96%.

## RELATED WORK

In this research, Fundus image processing results will be breaking down by an ophthalmologist, and investigation is done physically which requires an elevated level of focus. In this way we need a methodology that can recognize diabetic retinopathy and as a contribution to wellbeing experts in settling on choices in the distinguishing proof of Diabetic Retinopathy through the fundus retinal picture so as to acquire precise assessment results. Diabetic Retinopathy can create through 4 phases:

### 1. Delicate Non-proliferative Retinopathy

Little zones of inflatable like expanding in little retinal veins, called microaneurysms, happen at the most punctual phases of the infection. This microaneurysms can discharge liquid into the retina.

### 2. Moderate Non-proliferative Retinopathy

As the infection advances, solid veins of the retina can grow and change shape. They may likewise lose the capacity to ship blood. The two conditions cause trademark changes in the presence of the retina and can add to DME.

### 3. Extreme Non-proliferative Retinopathy

A lot more veins are blocked, consequently diminishing blood gracefully to the retinal area. This territory secretes development factors that signal the retina to develop fresh blood vessels.

### 4. Proliferative Diabetic-retinopathy (PDR)

At this propelled stage, development factors discharged by the retina trigger the multiplication of fresh blood vessels, which develop along the internal surface of the retina and into the glassy gel, the liquid that fills the eye. The fresh blood vessels are delicate, which makes them will in general hole and drain. The going with scarring can agreement and cause retinal separation - retinal withdrawal from the fundamental tissue, for example, backdrop stripping off a divider. Retinal separation can cause lasting loss of vision.

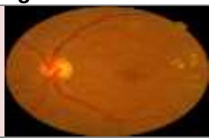
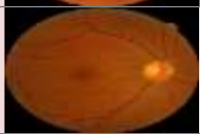
### 5. Gray Level Co-Occurrence Matrix

Highlight extraction means to remove novel highlights in the picture that will be utilized as contribution to the explanation stage. Highlight extraction completed in this examination utilizing the Gray-Level Co-Occurrence Matrix (GLCM) strategy. GLCM is a lattice that speaks to a local connection between two pixels in a grayscale picture in different ways of direction and spatial separation. GLCM is a n × n grid, where n is the quantity of dark levels held by grayscale pictures. The GLCM technique starts by shaping a union framework, which is L x (L communicating the measure of dim level) with the grid component (I, j) which is a joint likelihood dissemination of neighbouring pixel sets with a specific separation (cover) and a certain angle the rakish direction of the GLCM is 0º, 45º, 90º and 135º

## RESULT AND DISCUSSION

Result this study, information went into the framework are pictures sourced from Methods for Evaluating Segmentation and Indexing strategies Dedicated to Retinal Ophthalmology (MESSIDOR). The information is chosen and partitioned into two classifications to be specific ordinary and diabetic retinopathy (DR).

**Table 1: Retina Fundus Image Data**

| | | | | |
|---|---|---|---|---|
| A. | 1 | img_ diabetic retinopathy _1 |  | √ |
| B. | 2 | img_ diabetic retinopathy _2 |  | √ |
| C. | 3 | img_ diabetic retinopathy _3 |  | √ |
| D. | 4 | img_ diabetic retinopathy _4 |  | √ |
| E. | 5 | img_ diabetic retinopathy _5 |  | √ |
| F. | 6 | img_ diabetic retinopathy _6 |  | √ |
| G. | 7 | img_dr_7 |  | √ |

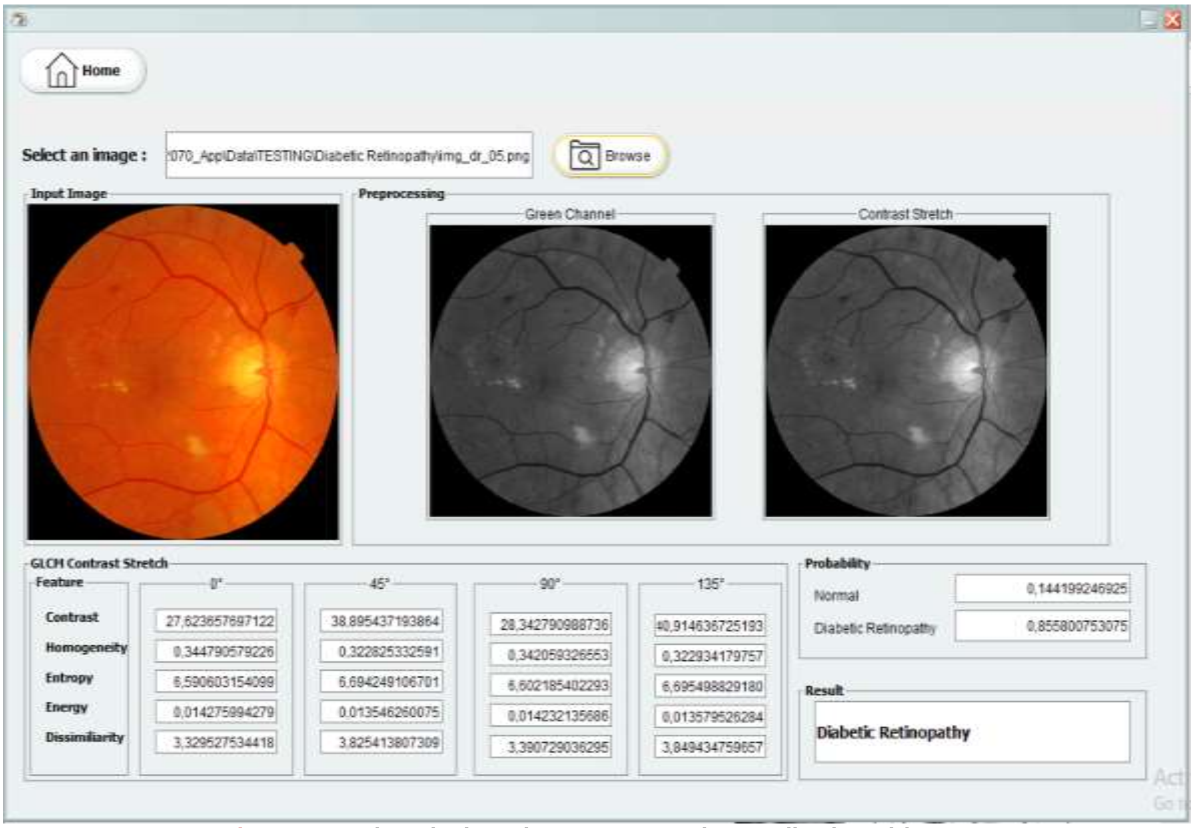



**Figure 1: Result Retinal Fundus Image Detection Application with PNN**

After the preparation is done, the framework testing should be possible on the testing page as appeared in Fig 1. On the testing page there is a peruse button that capacities to show a discourse box and select the picture to be tried. At that point subsequent to choosing the picture to be tried, the chose picture will show up in the picture input board and consequently handled to the pre-processing stage (green channel and difference extending). At that point the framework will show the element extraction esteem which comprises of the estimation of the GLCM results then the likelihood esteem results are shown in the "Possibility" board and the characterization results will show up in the "Result" board. This stage the information and framework will be tried. Information testing was performed utilizing 94 typical pictures and 112 diabetic retinopathy pictures as testing information, and 376 ordinary pictures and 444 diabetic retinopathy pictures as preparing information. The arrangement testing in PNN utilizes distinctive smoothing boundary (σ) values to discover what is the σ esteem that has the most noteworthy precision. The qualities of σ utilized are 0.1, 0.3, 0.5, 0.7 and 0.9. Testing with various σ expects to get the estimation of σ that can distinguish diabetic retinopathy with a serious extent of precision.

**Table 2: Information Retrieval and Pattern Recognition, Precision and Recall**

| Category | Relevant (a) | Don`t Relevant (b) | Total (a+b) | Don`t Found (c) | Total (a+c) | Recall [a/(a+c)] x 100% | Precision [a/(a+b)] x100% |
|---|---|---|---|---|---|---|---|
| DR | 86 | 8 | 95 | 9 | 93 | 91,4% | 92,7% |
| Normal | 93 | 19 | 112 | 19 | 112 | 82,7% | 84,6% |
| average | | | | | | 85,8% | 85,7% |

In data recovery and example acknowledgment, accuracy and review are two computations that are frequently used to quantify the exhibition of a framework constructed. Exactness is the degree of precision between the data mentioned by the client and the appropriate responses given by the framework. Review is the degree of achievement of the framework in rediscovering data. Review and exactness of the diabetic retinopathy recognizable proof framework through fundus pictures. The normal exactness is 88.9% and the review esteem is 88.9% on a size of 0% - 100%. In spite of the fact that the accuracy esteem is equivalent to the review esteem, the degree of viability of the data recovery framework in this examination has been supposed to be compelling. The adequacy of a framework is evaluated dependent on the hypothesis that was begat by Lancaster in 1991 which is important and unessential. Viability can be partitioned into two sections, in particular viable if the worth is above half and not successful if the worth is beneath half. As per Lee Pao's hypothesis in 1989, the perfect state of the adequacy of a malignancy order framework is if the proportion of review and precisions is the equivalent.

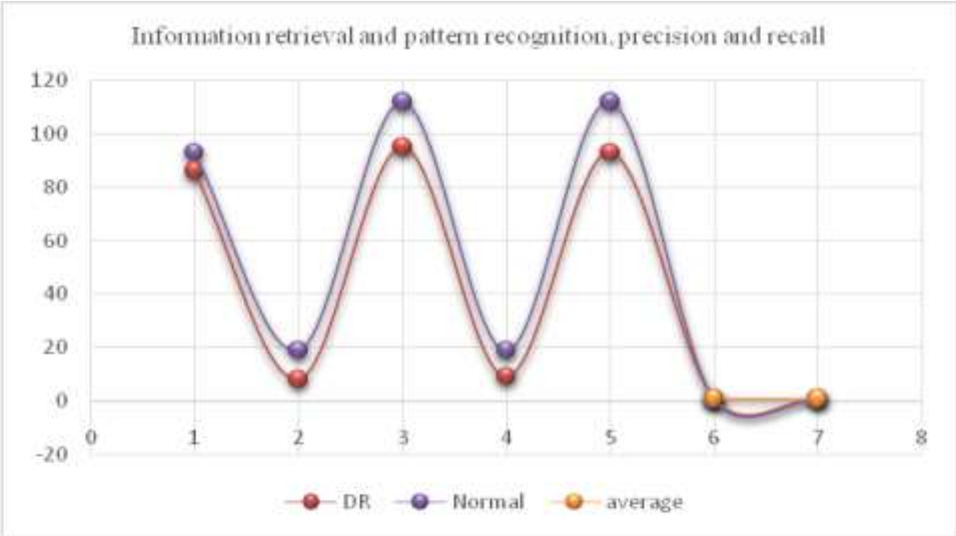



**Figure 2:** **Result Information Retrieval and Pattern Recognition, Precision and Recall**

The test results as appeared in Fig.2 where the x pivot on the diagram is the estimation of the smoothing boundary (σ) while the y hub is the consequence of the exactness esteem, the littler the estimation of σ, the precision got is additionally on the grounds that the estimation of σ is exceptionally powerful on the estimation of the likelihood thickness work. While the more prominent the estimation of σ, the higher the exactness acquired. The best exactness is acquired from the worth $\sigma \geq 0.8$.

From this conversation, it very well may be seen that the lower the estimation of σ, the lower the degree of exactness on the grounds that the estimation of σ influences the complete thickness of the likelihood esteem. The most noteworthy exactness is acquired with the worth $\sigma \geq 0.8$. The creator decides the utilization of σ in this investigation with an estimation of 0.9 which is the most noteworthy incentive on the utilization of σ with the expectation that this worth can get high precision. Subtleties of the grouping test results with the worth $\sigma = 0.9$.

## CONCLUSION

In this study, Probabilistic Neural Network technique can recognize diabetic retinopathy through retinal fundus pictures well which has an exact pace of 88.9%. In this investigation 720 preparing information and 253 testing information were utilized, which were obtained from the ophthalmology office utilizing a fundus camera. In light of framework testing, the estimation of the smoothing boundary (σ) significantly influences exactness. Since the littler the estimation of σ, the likelihood esteem is likewise littler, and the more prominent the worth, the more prominent the likelihood esteem. The estimation of $\sigma \geq 0.8$ is the best benefit of smoothing boundaries to recognize diabetic retinopathy by utilizing the Probabilistic Neural Network Method.

## CONFLICT OF INTEREST

None

## REFERENCES

1. Fong DS, Aiello L, Gardner TW, King GL, Blankenship G, Cavallerano JD, Klein R. Retinopathy in diabetes. *Diabetes care* 2004; 27(1): s84-s87.
2. Vidyasari R, Sovani I, Mengko TLR, Zakaria H. Vessel enhancement algorithm in digital retinal fundus microaneurysms filter for nonproliferative diabetic retinopathy classification. *In 2nd International Conference on Instrumentation, Communications, Information Technology, and Biomedical Engineering* 2011: 278-281.
3. Sabrina, E. Classification of Diabetic Retinopathy uses the Learning Vector Quantization (LVQ) Method. *Journal of Electrical Engineering* 2017; 6(2): 97-103.
4. Sinthanayothin C, Boyce JF, Williamson TH, Cook HL, Mensah E, Lal S, Usher D. Automated detection of diabetic retinopathy on digital fundus images. *Diabetic medicine* 2002; 19(2): 105-112.
5. Usher D, Dumskyj M, Himaga M, Williamson TH, Nussey S, Boyce J. Automated detection of diabetic retinopathy in digital retinal images: a tool for diabetic retinopathy screening. *Diabetic Medicine* 2004; 21(1): 84-90.
6. Xu K, Feng D, Mi H. Deep convolutional neural network-based early automated detection of diabetic retinopathy using fundus image. *Molecules* 2017; 22(12): 2054.
7. Akram UM, Khan SA. Automated detection of dark and bright lesions in retinal images for early detection of diabetic retinopathy. *Journal of medical systems* 2012; 36(5): 3151-3162.
8. Abramoff MD, Niemeijer M, Russell SR. Automated detection of diabetic retinopathy: barriers to translation into clinical practice. *Expert review of medical devices* 2010; 7(2): 287-296.
9. Silberman N, Ahrlich K, Fergus R, Subramanian L. Case for automated detection of diabetic retinopathy. *In AAAI Spring Symposium Series* 2010.
10. Carrera EV, González A, Carrera R. Automated detection of diabetic retinopathy using SVM. *In IEEE*

*XXIV International Conference on Electronics, Electrical Engineering and Computing (INTERCON)* 2017: 1-4.

11. Syah R, Nasution MK, Elveny M, Arbie H. Optimization Model for Customer Behavior with Mars and KYC System. *Journal of Theoretical and Applied Information Technology* 2020; 98(13): 2616-2627.
12. Ravishankar S, Jain A, Mittal A. Automated feature extraction for early detection of diabetic retinopathy in fundus images. *In IEEE Conference on Computer Vision and Pattern Recognition* 2009: 210-217.
13. Shahin EM, Taha TE, Al-Nuaimy W, El Rabaie S, Zahran OF, Abd El-Samie FE. Automated detection of diabetic retinopathy in blurred digital fundus images. *In 8th International Computer Engineering Conference (ICENCO)* 2012: 20-25.
14. Srinivasan PP, Kim LA, Mettu PS, Cousins SW, Comer GM, Izatt JA, Farsiu S. Fully automated detection of diabetic macular edema and dry age-related macular degeneration from optical coherence tomography images. *Biomedical optics express* 2014; 5(10): 3568-3577.
15. Syah BR, Nasution MKM, Elveny M, Nababan EB, Sembiring S. Managing Schema of Knowledge Accelereration (KAE) Model to Big Data Customer Behavior Using Business Metrics. *International Journal of Supply Chain Management* 2020: 9(5).
16. Selvathi D, Prakash NB, Balagopal N. Automated detection of diabetic retinopathy for early diagnosis using feature extraction and support vector machine 2012.
17. Lin GM, Chen MJ, Yeh CH, Lin YY, Kuo HY, Lin MH, & Cheung CY. Transforming retinal photographs to entropy images in deep learning to improve automated detection for diabetic retinopathy. *Journal of ophthalmology* 2018: 1-6.
18. Elveny M, Syah R, Nasution MKM. Taxonomy Business Model to Customer Behaviour in E-Metric Ecosystem. *Journal of Advanced Research in Dynamical and Control Systems* 2020; 12(7): 99-104. http://doi.org/10.5373/JARDCS/V12I7/20201989
19. González-Gonzalo C, Sánchez-Gutiérrez V, Hernández-Martínez P, Contreras I, Lechanteur YT, Domanian A, Sánchez CI. Evaluation of a deep learning system for the joint automated detection of diabetic retinopathy and age-related macular degeneration. *Acta Ophthalmologica* 2020; 98(4): 368-377.
20. Harini R, Sheela N. Feature extraction and classification of retinal images for automated detection of Diabetic Retinopathy. *In Second International Conference on Cognitive Computing and Information Processing (CCIP)* 2016: 1-4.
21. Syah R, NasutionM, Nababan EB, Efendi S. Knowledge Acceleration Estimator (KAE) Model to Customer Behavior Using Business Metrics. *Journal of Theoretical and Applied Information Technology* 2020; 98(08):1301-1311.
22. Noronha K, Nayak KP. A review of fundus image analysis for the automated detection of diabetic retinopathy. *Journal of Medical Imaging and Health Informatics* 2012; 2(3): 258-265.
23. Rao MA, Lamani D, Bhandarkar R, Manjunath TC. Automated detection of diabetic retinopathy through image feature extraction. *In International Conference on Advances in Electronics Computers and Communications* 2014: 1-6.
24. Syah R, Nasution MKM, Husein I. Dynamic Control Financial Supervision (OJK) for Growth Customer Behavior using KYC System. *International Journal of Advanced Science and Technology* 2020; 29(8): 1110 – 1119.
25. Kaur J, Sinha HP. Automated detection of diabetic retinopathy using fundus image analysis. *International Journal of Computer Science and Information Technologies* 2012; 3(4): 4794-4799.
26. Sun JK, Cavallerano JD, Silva PS. Future promise of and potential pitfalls for automated detection of diabetic retinopathy. *JAMA ophthalmology* 2012; 134(2): 210-211.
27. Bhardwaj C, Jain S, Sood M. Appraisal of pre-processing techniques for automated detection of diabetic retinopathy. *In Fifth International Conference on Parallel, Distributed and Grid Computing (PDGC)* 2018: 734-739.
28. Samanta A, Saha A, Satapathy SC, Fernandes SL, Zhang YD. Automated detection of diabetic retinopathy using convolutional neural networks on a small dataset. *Pattern Recognition Letters* 2020.
29. Fleming AD, Goatman KA, Philip S, Williams GJ, Prescott GJ, Scotland GS, Olson JA. The role of haemorrhage and exudate detection in automated grading of diabetic retinopathy. *British Journal of Ophthalmology* 2010; 94(6): 706-711.
30. Zeng X, Chen H, Luo Y, Ye W. Automated detection of diabetic retinopathy using a binocular siamese-like convolutional network. *In IEEE International Symposium on Circuits and Systems (ISCAS)* 2019: 1-5.
31. Syah R, Nasution MKM, Nababan EB, Efendi S. Optimization Metrics Model: The Mobile Wallet for Merchant Ecosystem. *In Journal of Physics: Conference Series* 2020; 1566(1): 012124.
32. Akram MU, Tariq A, Anjum MA, Javed MY. Automated detection of exudates in colored retinal images for diagnosis of diabetic retinopathy. *Applied optics* 2012; 51(20), 4858-4866.
33. Welikala RA, Fraz MM, Dehmeshki J, Hoppe A, Tah V, Mann S, Barman SA. Genetic algorithm-based feature selection combined with dual classification for the automated detection of proliferative diabetic retinopathy. *Computerized Medical Imaging and Graphics* 2015; 43, 64-77.

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